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A LITERATURE REVIEW OF DRONE-TRUCK ROUTING PROBLEMS: CHALLENGES AND FUTURE RESEARCH DIRECTIONS

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Abstract. In recent years, new routing problems with high complexity have emerged in parallel with the diversification of collaborative operational activities carried out by drones with ground vehicles. There are two main factors that affect the complexity level of these new generation routing problems. The first factor is the synchronization of vehicles with very different characteristics to optimally perform operational tasks. The second factor is that unlike traditional routing problems such as transportation and logistics, healthcare, military and emergency operations, new generation problems have more complex objective and constraint spaces. In traditional routing problems, customers are represented by fixed points in a two-dimensional search space. In contrast, in agricultural spraying, which is a new generation routing problem, the areas to be sprayed are represented by irregular areas. The objective and constraint functions in next generation routing problems are specified as area-based rather than point-based because of this difference. This increases the geometric complexity of the objective and constraint spaces in next generation routing problems. This paper analyzes 108 publications on traditional and next generation routing problems published between 2015 and 2024. A comprehensive review of routing problems based on drone-truck cooperation is provided according to their application areas, mathematical models, and solution methods. Unlike the review studies in the literature, new routing problems in the field of agriculture are also included in this research and the mathematical complexity of these problems is presented for the first time. Current trends for future research on drone-truck based problems are discussed.

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1. Introduction

(a) Research motivation: Until the past decade, routing problems mainly focused on transportation and supply chain activities carried out using ground and sea vehicles. Due to the physical characteristics and constraints of these vehicles, they could only be used to optimize routing problems in limited sectors.

In recent years, significant advancements have been made in Unmanned Aerial Vehicle (UAV) technologies [1, 2]. As a result of research on hardware and software components of drones, significant improvements have

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been achieved in (i) their ability to perform swarm tasks, (ii) their endurance (operational time), (iii) their payload capacity, and (iv) their speed. In parallel with the developments in the capabilities of UAVs, there has also been a great increase and diversification in the areas where they are used. Due to the widespread use of drones, there have been two important changes in routing problems which are:

– New routing problems have emerged: The concept of smart (precision) farming has gained a new dimension within the framework of sustainable agricultural practices. In the context of smart spraying in agriculture, the use of a combination of ground vehicles and UAVs has facilitated efficient operations [3–6]. It was ensured that only diseased areas in agricultural fields were sprayed and the drug dosage could be adjusted. In this way, a significant improvement was achieved in precision spraying. In addition to smart spraying in agriculture, UAVs also play a major role in tasks such as vegetation monitoring, weed detection and mapping.
– Existing routing problems had to be re-modeled: UAVs have been used for cargo/transportation and other supply chain applications currently carried out by land and sea vehicles. The optimization models (objective functions, constraints, design parameters) of these problems need to be redesigned to accommodate the utilization of UAVs.

As evident from the above explanations, there have been significant changes in the optimization of routing problems carried out with UAVs in recent years. As a result of these changes, well-known routing problems have been redefined, and even new routing problems have emerged.

Joerss *et al.* predicted that autonomous vehicles will deliver 80% of all parcels in the next decade [7]. Especially popular logistics cargo companies such as Amazon, UPS and DHL use drones and trucks to deliver packages to customers [8]. The idea of using drones for delivery emerged during the 2020 Covid-19 pandemic to ensure social distancing and minimize the impact of the disease [9]. In the context of agriculture, when spraying or fertilizing an agricultural field with ground vehicles, there are negative impacts on many criteria, especially human and plant health, cost and time to complete the job. In order to overcome these negative impacts, operational activities have been carried out by ground vehicle-assisted drones [5, 6]. All these developments require an in-depth analysis of the current studies on routing problems, and this is crucial in providing researchers with the necessary new information and perspectives for their future work.

(b) Literature review: Murray and Chu (2015) introduced the studies in which drone-truck tandem carried out operational activities together [10]. Since 2015, many academic studies have been conducted in this field. Although drones have limited flight time and carrying capacity, their ability to utilize the airspace and move quickly is crucial. Drones used in conjunction with ground vehicles enable efficient operation management. Studies in the literature consider the specific constraints of drones (such as their number, battery consumption, carrying capacity, flight range, etc.) and trucks (such as their number, number of drones they can carry, considered distance metric, etc.). Optimization processes are carried out by introducing different procedures for drone-truck synchronization. In this study, 108 publications between 2015 and 2024 are analyzed. The review studies in the literature have mostly focused on the transportation and logistics application area. The operations of UAVs in agriculture have not been adequately addressed. In most of the review studies, mathematical models of the problems are left out of the scope of the studies.

During the literature review, journals with high impact value were examined. The most important issue during the review was to search using appropriate keywords. For this purpose, the search was conducted with combinations of frequently used keywords such as "drone", "UAV", "logistic", "distribution", "agriculture", "spraying", "routing", "truck". In addition to these keywords, critical keywords such as "Traveling Salesman Problem with Drone (TSP-D)", "The Flying Sidekick Traveling Salesman Problem (FSTSP)", "Parallel Drone Scheduling Traveling Salesman Problem (PDSTSP)" and "Vehicle Routing Problem with Drone (VRPD)" were also used. Thus, studies based on drone-truck cooperation are identified and analyzed.

(c) Research necessity: New routing problems involving drone-truck collaboration have emerged with the diversification of application areas where drones are used. Collaborative drone-truck routing in agriculture is one of these new routing problems. The objective functions and constraints of these problems are different from objective functions and constraints of the well-known logistics problems. For instance, in agricultural applications, drone operations can be longer and more complex than in transportation and logistics, healthcare, military and emergency operations. In the field of agriculture, drones continue their operations by both liquid replenishment and battery replacement. On the other hand, in other operations, drones usually make short-term deliveries to fixed points. In logistics problems, a point-based routing operation is performed for package delivery to customers, while area-based routing is considered for routing problems such as spraying, coverage, etc. in the agricultural application area. In the literature review, there are few studies on drone-truck collaborative routing in agricultural applications.

Drone-truck collaborative studies are optimized according to their objective functions and constraints. Optimization algorithms are divided into two as single-objective and multi-objective optimization according to their objective functions. Multi-objective optimization has not been sufficiently considered in drone-truck collaborative routing problems in the literature. In this regard, the following two deficiencies are noticeable. (i) In the literature, it is seen that in drone-truck collaborative studies involving multi-objective optimization, even though the objective functions are in conflict, they are tried to be solved with single-objective optimization algorithms instead of pareto-based approaches. (ii) In some studies, although appropriate methods are used, recent methods recently proposed for pareto-based multi-objective optimization are not used. These two deficiencies constitute a gap in the literature.

In recent years, learning-based solution approaches developed using artificial intelligence techniques have been used to solve optimization problems. However, very little work has been done in the literature on these solution approaches for solving drone-truck cooperative routing problems. Further research on learning-based solution approaches for drone-truck collaborative routing problems is important for several key reasons:

- Complexity and size: Learning-based solutions need more research on their ability to deal with increasingly large and complex network structures.
- Changing conditions and dynamic environments: Factors such as weather and road conditions, obstacles on the route, changes in delivery points, etc. can affect the solution. More research is needed on the ability of learning-based models to adapt to these factors.

(d) Innovation and main contribution: The innovations that this review brings to the literature can be stated as follows:

- This article is the most comprehensive and current research conducted on routing studies involving the drone-truck tandem in the literature. A total of 108 routing studies published between 2015 and 2024, involving the drone-truck tandem, were examined in this paper.
- The routing applications of the drone-truck tandem in the agricultural field were analyzed for the first time in this article.
- In drone-truck cooperative routing studies, heuristic, metaheuristic, and exact solution methods are generally offered as solution methods. This study presents learning-based solution approaches that have become popular in recent years and compared with other methods.
- Optimization models (mathematical definitions of objective and constraint functions) of current routing problems involving the drone-truck tandem are presented and the complexities of these models are discussed for the first time.
- This is the first time that the difference between multi-objective optimization and single-objective optimization in drone-truck collaboration studies has been discussed in such depth.

(e) A graphical summary of the organization of the paper: This paper mainly aims to review routing problems involving drones and trucks and present trends in operations research. The trends of existing research are reviewed and research directions for future work are summarized. The main criteria of the reviewed studies are compared and the similarities and differences of the studies are presented. Figure 1 shows the organization chart of the paper.

TABLE 1. Comparison of review studies in the literature.

Ref.	Years (num. of art. reviewed)	Math. Model	Multi-obj. opt.	Drone-truck cap.	App area	Inst.	Lear. sol.	Cont. and Def.
[11]	2001–2017, (217)	No	No	No	TL	No	No	Yes
[12]	2016–2018, (29)	No	No	No	TL	Yes	No	Yes
[13]	2002–2020, (120)	No	No	Yes	TL	No	No	Yes
[14]	2015–2020, (64)	No	No	Yes	TL	Yes	No	No
[15]	2005–2019, (79)	No	Yes	Yes	TL	No	No	No
[16]	2015–2020, (101)	No	Yes	Yes	TL	Yes	No	Yes
[17]	2015–2021, (20)	No	No	No	TL	No	No	Yes
[18]	2015–2020, (60)	Yes	No	Yes	TL	Yes	No	No
[19]	2015–2022, (45)	Yes	Yes	Yes	TL	Yes	No	No
This paper	2015–2024, (108)	Yes	Yes	Yes	TL, EM, DM, HM, AG	Yes	Yes	Yes

Notes. Years (num. of art. reviewed): The years between which articles were reviewed (how many articles were reviewed) are stated, Math. Model: Inclusion of mathematical models, Multi-obj. opt.: Whether studies examine multi-objective optimization, Drone-truck cap.: Detailed analysis of drone and truck capacity constraints, App area: Which areas are considered as application area?, Inst.: Considering the number of instances in the studies examined, Lear. sol.: whether the learning-based solution method was examined, Cont. and Def.: Presenting the contributions and deficiencies of the studies reviewed to the literature, TL: Transportation and Logistics, EM: Emergency Management, DM: Defense and Military, HM: Healthcare and Medical, AG: Agriculture.

2. An overview of review articles in the literature

Many academic studies on the future direction of operational activities involving drones take place in the literature. In addition to its use in logistics, it has recently found a role in agricultural activities for precision agriculture. Due to the constraints of the drone (flight time, payload capacity, etc.), collaborative studies with a ground vehicle (truck) have emerged since 2015. Although drone-truck-based systems have made significant progress in industrial applications in recent years, existing academic studies are not always aligned with real-world technological and operational developments. Existing literature studies lack a framework that effectively classifies relevant drone-truck-based systems and synthesizes existing research according to the operational design characteristics of these systems. Although there is a literature review of drone-only studies [11], it does not provide a systematic classification framework that distinguishes them from drone-truck-based studies. Studies examining drone-truck collaborative operations [12–19] are presented only in the transportation and logistics application area. Table 1 presents the criteria addressed by this study and the review studies in the literature.

Otto *et al.* provided a comprehensive review of optimization approaches for civil applications of UAVs such as routing operations, area coverage, search operations, data collection and communication link [11]. Khoufi *et al.* presented a review of 29 research studies between 2016 and 2018 [12]. In their study, the number of drones-trucks,

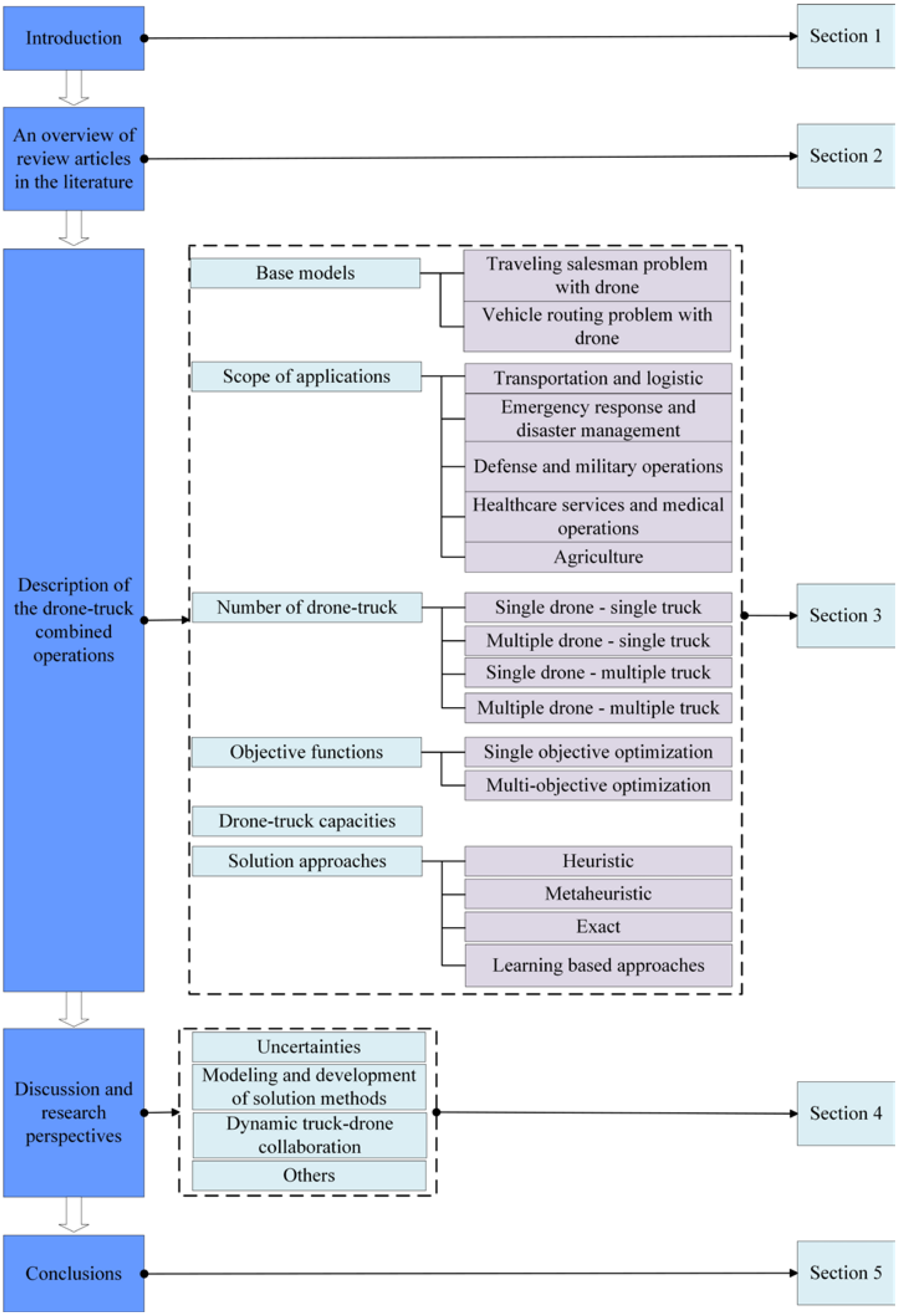

FIGURE 1. Organization chart of the paper.

application area and solution approaches were compared, and a general review is presented without addressing the specific constraints of drones and trucks. Chung *et al.* examined optimization approaches in the civil application of drone operations and drone-truck cooperative operations, including construction, agriculture, logistics, security, disaster management, and entertainment [13]. Macrina *et al.* examined the main contributions related to logistics systems where deliveries are provided by drones and trucks [14]. The problems used in the studies between 2015 and 2020 are classified. Rojas Viloria *et al.* classified the reviewed studies according to the objective function, solution methods, application areas, constraints, and whether it uses a complementary ground vehicle [15]. Moshref-Javadi and Winkenbach proposed a scalable classification framework that systematically traces the boundaries between a wide range of UAV-based logistics systems and associated operational planning problems [16]. The review of 101 research studies is presented in tables based on their objectives and methodology. Liang and Luo reviewed 60 research studies examining drone-truck cooperative routing problems [18]. Many criteria such as operation schemes of drone-truck cooperative routing problems and constraints of drones and trucks were discussed. It provides a comprehensive literature survey on the topic of drone-based package delivery systems. Zhang *et al.* (2023) proposed a taxonomy for the delivery problem in logistics [19]. Through the review of 45 research papers, a discussion on solution approaches, objective functions and constraints, and different delivery modes is presented.

This study comprehensively reviews current research articles according to their mathematical models, application areas, number of drones and trucks, optimization objective functions and problem solution methods. How the test instances were constructed, and the contributions and deficiencies of the reviewed studies to the literature are presented. The contributions of this paper are as follows:

- One hundred eight current studies between 2015 and 2024 have been analyzed in detail. The study is supported with detailed tables and figures for easy understanding by the researchers.
- Although three review studies were classified according to whether the objective functions were single or multiple, multi-objective optimization was not examined in depth. In this review study, multi-objective optimization is examined and discussed in depth.
- In addition to transportation and logistics, healthcare, military, and emergency operations, this paper examines drone-truck collaborative operations in smart agriculture in depth for the first time.
- Optimization models of routing problems involving drone-truck tandem are discussed for the first time in terms of complexity.
- A comparative analysis of learning-based solution approaches with other solution methods has been provided for the first time.

3. Description of the drone-truck combined operations

This section presents the basic models of drone truck tandem operations. In the subsections of this section, the base models (TSP-D and VRPD) are introduced.

3.1. Base models

Different types of operations emerge from delivery problems. In TSP-D, a drone is allowed to meet a truck at the node where it is launched to serve a node. Many studies have examined this problem [20–31]. There are problems where the drone is not allowed to rendezvous with the truck where it was launched from the truck. In this type of problem, the truck may meet the drone at a different node or arc. In this problem, known as FSTSP, there is synchronization between the drone and the truck [10, 32–34]. Many studies have also been conducted on PDSTSP where there is no synchronization between the drone and the truck [35–38]. Figure 2 shows the delivery operations of drone and truck in FSTSP and PDSTSP.

Figure 2 shows the delivery differences between drone and truck in FSTSP and PDSTSP. In FSTSP, the drone carries out the delivery process synchronously with the truck, whereas in PDSTSP, the drone(s) and the truck make independent cooperative deliveries.

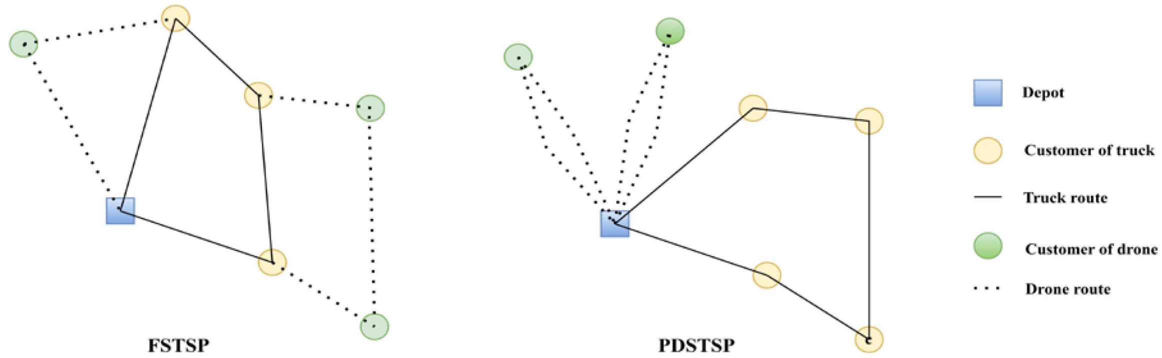

FIGURE 2. Drone-truck tandem operations in FSTSP and PDSTSP.

3.1.1. Traveling salesman problem with drone (TSP-D)

The drone sortie (i, j, k) is usually given as launch node i, served customer node j and meeting node k [10, 22, 29]. Roberti and Ruthmair used two index variables in their mathematical model, and this provides simplicity due to the smaller number of indices [31]. In this section, equations with two index variables are used in the mathematical models. For the TSP-D model, the study of Roberti and Ruthmair [31] is taken as a reference. The model is defined as grap $G = (V, A)$. The vertex set consists of the depot set $V = \{0, c+1\}$. Arc set is denoted as $A = \{(0, j)|j \in N\} \cup \{(i, j)|i, j \in N, i \neq j\} \cup \{(i, c+1)|i \in N\}$ and $N = \{1, \ldots, c\}$. The delivery times for truck and drone are $t_{i,j}^{T}$ and $t_{i,j}^{D}$ for $(i, j) \in A$, respectively. Let $x_{i,j}^{T} \in \{0, 1\}$ be a binary variable equal to 1 if the truck traverses arc $(i, j) \in A$, and let $x_{i,j}^{D} \in \{0, 1\}$ be a binary variable equal to 1 if the drone traverses arc $(i, j) \in A$. A customer point can be delivered by truck only or by drone only, or by both vehicles at the same time. The delivery operation with only truck is denoted as y_i^T, the delivery operation with only drone is denoted as y_i^D, and the delivery operation with both vehicles is denoted as y_i^C. a_i is a continuous variable that records the arrival time at each node, and M is defined as a very large number.

Drone flight endurance: The sortie time must be less than the drone endurance when the drone will deliver a package to the customer. Otherwise, this delivery should be assigned as a truck delivery. The drone flight endurance is defined as e, and the related constraints are given in equations (1) and (2) [31].

$$\sum_{i,j \in A} t_{i,j}^{D} x_{i,j}^{D} + \sum_{j,i \in A} t_{j,i}^{D} x_{j,i}^{D} \leq e + M\left(1 - y_i^D\right), \qquad \forall i, j \in N \tag{1}$$

$$x_{i,j}^{D} \leq x_{i,j}^{T}, \qquad \forall i, j \in A : t_{i,j}^{D} > e. \tag{2}$$

Weight-dependent flight range: One of the important constraints affecting the drone flight distance is the weight of the package carried by the drone. The drone battery capacity is defined as b, the weight d_i demanded for each customer, and the energy consumption of the drone moving from i to j depending on w is defined as $e_{i,j}(w)$. The battery energy consumption of a drone serving a customer $i \in N$ with weight d_i is defined as $b_{i,j}^{\text{on}} = e_{i,j}(d_i)$, while the battery energy consumption of an empty loaded drone is defined as $b_{i,j}^{\text{off}} = e_{i,j}(0)$. Considering the package weight carried by the drone, the drone flight range is given in equations (3) and (4) [31].

$$x_{i,j}^{D} \leq x_{i,j}^{T} \qquad \forall i, j \in A : b_{i,j}^{\text{off}} > b \tag{3}$$

$$\sum_{i,j \in A} b_{i,j}^{\text{on}} x_{i,j}^{D} + \sum_{j,i \in A} b_{j,i}^{\text{on}} x_{j,i}^{D} \leq b + M\left(1 - y_i^D\right), \qquad \forall i, j \in N. \tag{4}$$

Drone-truck synchronization: In drone-truck tandem operations, the simultaneous arrival of both vehicles at rendezvous points is a significant challenge. If the drone arrives at the rendezvous point early, it must wait until the truck picks it up, hovering in the air. The drone battery endurance should be taken into account for the drone waiting time. Otherwise, the drone has to land. The synchronization relationship between drone and truck is given in equation (5) [31].

$$\begin{aligned} & a_k - a_i \leq e\ M\left(2 - \ x_{i,j}^D - x_{j,k}^D\right) + M\left(1 - y_i^D\right), \\ & \quad \forall i \in N \cup \{0\},\ j \in N,\ k \in N\ \cup \{c+1\} : i \neq j \neq k,\ t_{i,j}^D + t_{j,k}^D \leq e. \end{aligned} \tag{5}$$

3.1.2. Vehicle routing problem with drone (VRPD)

In VRPD, the collaboration of multiple drones and multiple trucks is examined. The synchronization process between trucks and drones is more challenging than in TSP-D due to the multiple trucks and multiple drones. In this problem, as in TSP-D, only one vehicle can serve the customers. Wang and Sheu tried to minimize total logistics costs by introducing certain constraints for the VRPD problem [39]. In their study, trucks take drones loaded with customer packages from the depot point to the hub point, called docking centers. Drones are launched from the hub point to make deliveries to customers. The VRPD is defined as a graph $G = (V, A)$. Vertex set $V = \{0, c+1\}$ consists of the set of depots and $A = \{(i,j)|i,j\ \in V,\ i \neq j\}$ is the arc set. The set of customers is $C = \{1, \ldots, c\}$ and a set of docking hub nodes is $O = \{o_1, \ldots, o_m\}$. K and D denote the truck and drone sets, respectively. The delivery times for truck and drone are $t_{i,j}^T$ and $t_{i,j}^D$ for $(i,j) \in A$, respectively. F^T, is defined as the fixed cost of truck operation. The unit delivery costs of the truck and the drone are denoted as C^T and C^D, respectively. M is defined as a very large number. The definitions of binary variables are presented below equations (6)–(9) [39]:

$$x_{i,j,k} = \begin{cases} 1, & k \in K,\ \ (i,j) \in A,\ \text{independent truck} \\ 0, & \text{others} \end{cases} \tag{6}$$

$$y_{i,j,d} = \begin{cases} 1, & d \in D,\ \ (i,j) \in A,\ \text{independent drone} \\ 0, & \text{others} \end{cases} \tag{7}$$

$$u_{i,j,k} = \begin{cases} 1, & k \in K,\ \ (i,j) \in A,\ \text{with several drones} \\ 0, & \text{others} \end{cases} \tag{8}$$

$$y_{i,j,k,d} = \begin{cases} 1, & k \in K \text{ and } d \in D\ \ (i,j) \in A \\ 0, & \text{others.} \end{cases} \tag{9}$$

The objective function is to minimize the total costs, including fixed costs and drone-truck delivery costs. The objective function is given in equation (10) [39].

$$\min F^T\left(\sum_{0,j\in A}\sum_{k\in K} x_{0,j,k} + \sum_{0,j\in A}\sum_{k\in K} u_{0,j,k}\right) + C^T\sum_{i,j\in A}\sum_{k\in K} t_{i,j}^T\left(x_{i,j,k} + u_{i,j,k}\right) + C^D\sum_{i,j\in A}\sum_{d\in D} t_{i,j}^D(y_{i,j,d}). \tag{10}$$

Drone flight endurance: The sortie time of the drone when delivering a package to the customer must be less than the maximum flight time T^D (the maximum time the drone spends from the depot or hub to the delivery point). Otherwise, this delivery should be assigned as a truck delivery. $v_{i,d}^D$ is defined as the total flight time of the drone $d \in D$ from the depot or hub to the node $i \in V$. Accordingly, the constraints on drone flight endurance are given in equations (11) and (12) [39].

$$v_{i,d}^D \leq T^D, \qquad \forall d \in D,\ i \in V \tag{11}$$

$$v_{j,d}^D \geq v_{i,d}^D + t_{i,j}^D + M\left(1 - y_{i,j,d}\right), \qquad \forall d \in D,\ i \in O \cup \{0\},\ (i,j) \in A. \tag{12}$$

Weight-dependent flight range: The payload capacity of the drone is L^D, and the weight of the package requested by customer $i \in C$ is g_i. The package carried by drone $d \in D$ moving from the depot or hub at customer $i \in C$

is denoted by $w_{i,d}$. Accordingly, equations (13) and (14) give weight-dependent constraints [39].

$$w_{i,d} \leq L^D, \qquad \forall d \in D,\ i \in C \tag{13}$$

$$w_{j,d} \geq w_{i,d} + g_j + M\left(1 - y_{i,j,d}\right), \qquad \forall d \in D,\ j \in C,\ (i,j) \in A. \tag{14}$$

The main features of the drone and truck of the studies discussed in Table 2 were examined. The objective function, solution method and mathematical models in the studies were also compared. The columns represent the reference of the study (*#ref*), the objective function (*#obj*), number of drones, trucks, depots (*#d,t,d*), whether packages are picked up from customers (*#pick*), drone multi-visit (*#mvisit*), the drone release (*#release*), synchronization between drone and truck (*#sync*), characteristics of drones (*#charc*), problem solution methods (*#sol*), whether the mathematical model is included in the study (*#math*), and application area of study (*#app*), respectively.

According to Table 2, 83% of the reviewed publications include single-objective optimization, while the remaining 17% include multi-objective optimization. It was observed that 20% of the reviewed publications used deterministic algorithms, while 80% used heuristic or metaheuristic solution methods. The reason for the less frequent use of deterministic solution approaches is because of their tendency to get trapped in local solution traps when solving high-dimensional problems.

3.2. Scope of applications

In this section, the studies are classified according to the application area. The studies are divided into three areas. These are transportation and logistics, emergency response and disaster management, defense and military operations, healthcare services and medical operations, and agriculture, respectively. As a result of the literature review, the yearly distribution of the drone delivery problem, the yearly distribution of the operations in agriculture, and the yearly distribution of the reviewed publications between 2015 and 2024 are shown in red, green and blue colors in Figure 3, respectively.

Figure 3 shows that there has been a significant increase in the number of publications on drones in recent years. In parallel, the increase in the field of agriculture in recent years is remarkable. Overall, drone routing studies appear to be a mature research field that has reached a certain level of saturation, whereas agricultural drone operations remain an emerging research area. The studies analyzed in the study were selected from recent studies.

3.2.1. Transportation and logistics

The transportation and logistics industry is experiencing strong growth. In recent years, with the e-commerce industry driven by online access, there has been growing interest in new delivery operations. The development of e-commerce is increasing the number of parcels delivered to customers around the world every year. In 2022, China exceeded expectations with a volume of 100 billion parcels, reaching 108 billion parcels. In 2027, this volume is expected to reach 200 billion parcels. In India, it is estimated to increase from 2.7 billion in 2021 to 5.3 billion in 2027 and in the US from 21 billion parcels in 2021 to 28.0 billion by 2027 [127].

Traditional cargo delivery is done using road vehicles such as trucks, vans and motorcycles. These vehicles deliver packages within and between cities. The disadvantages of these traditional cargo deliveries are: (i) it can cause problems such as traffic jam and air pollution. (ii) it can increase the delivery time of packages. (iii) it carries risks such as lost or damaged packages. In response to the rapidly increasing number of packages, various solutions have been sought to provide quality delivery services. Murray and Chu introduced the algorithm that drones can be used together with trucks for parcel delivery and the trend in this field has increased [10]. Joerss *et al.* predicted that autonomous vehicles will deliver 80% of all parcels in the next decade [7]. Since then, famous logistics companies such as Amazon, UPS and DHL have started to use drones for parcel delivery. In 2018, Workhorse Group has announced that it has patented the HorseFly delivery truck-launched drone package delivery system [128]. The patented HorseFly truck-launched drone delivery system works as follows:

(i) The truck driver places the package on the drone and then the drone launches.

TABLE 2. Summary of the primary features Drone-Truck combinatorial studies.

#ref	#obj	#d,t,d	#pick	#mvisit	#release	#sync	#charc	#sol	#math	#app
[2]	Cost	m,1,1	No	No	Node/Arc	Yes	HM	LR	Yes	TL
[3]	Cost	m,1,1	–	–	Node/Arc	Yes	HT	M	Yes	AG
[4]	Time	m,1,1	–	–	Node/Arc	Yes	HT	M	Yes	AG
[5]	Time	m,–,1	–	–	–	–	HT	M	Yes	AG
[10]	Time	1,1,1	No	No	Node	Yes	HM	H	Yes	TL
[20]	Cost	1,1,1	No	No	Node	Yes	HM	H	Yes	TL
[21]	Time	1,1,1	No	No	Node	Yes	HM	E	No	TL
[22]	Cost	1,1,1	No	No	Node	Yes	HM	H	Yes	TL
[23]	Time, cost	1,1,1	No	No	Node	Yes	HM	M	Yes	TL
[24]	Cost	1,1,1	No	No	Node	Yes	HM	H	No	TL
[25]	Waiting time, min-bat	1,1,1	No	No	Node/Arc	Yes	HM	H	Yes	TL
[26]	Cost	1,1,1	No	No	Node	Yes	HM	H	No	TL
[28]	Time	1,1,1	No	Yes	Node	Yes	HM	H	Yes	TL
[29]	Time	1,1,1	No	No	Node	Yes	HM	M	Yes	TL
[30]	Time	1,1,1	No	No	Node	Yes	HM	E	Yes	TL
[31]	Time	1,1,1	No	No	Node	Yes	HM	E	Yes	TL
[33]	Time	m,1,1	No	No	Node	Yes	HM	M	No	TL
[34]	Time	1,1,1	No	No	Node	Yes	HM	H	No	TL
[35]	Time	m,m,m	Yes	Yes	Node	No	HM	H	Yes	TL
[37]	Time	m,1,1	No	No	Node	Yes	HM	H	Yes	TL
[39]	Cost	m,m,1	No	Yes	Node	No	HM	E	Yes	TL
[40]	Truck time, time	m,1,1	No	Yes	Node	Yes	HM	M	Yes	TL
[41]	Time	1,1,1	No	No	Node/Arc	Yes	HM	LR	Yes	TL
[42]	Cost	m,m,1	Yes	Yes	Node/Arc	Yes	HM	M	Yes	TL
[43]	Cost, waiting time, and service reliability	m,1,1	Yes	Yes	Node	Yes	HM	H	Yes	TL
[44]	Time	m–m	–	–	–	–	HM	–	Yes	AG
[45]	Distance	m–1	–	–	–	–	HM	M	Yes	AG
[46]	Time	m,1,1	Yes	No	Node	Yes	HT	LR	Yes	TL
[47]	Waiting time	m,1,1	No	No	–	Yes	HM	LR	Yes	TL
[48]	Time, cost	1,1,1	No	No	Node	Yes	HM	E	Yes	TL
[49]	Cost	m,m,1	No	Yes	Node/Arc	Yes	HM	E	Yes	TL
[50]	Time, cost	m,m,1	No	No	Node/Arc	Yes	HT	LR	Yes	TL
[51]	Cost	m,m,1	No	Yes	Node	Yes	HM	H	Yes	TL
[52]	Cost	m,m,1	No	No	Node	Yes	HM	E	Yes	TL
[53]	Time	m,–,1	–	–	–	–	HT	M	No	AG
[54]	Cost, min-dep	m,m,1	No	No	Node	Yes	HM	H	Yes	TL
[55]	Time	m,–,1	No	–	–	–	HT	H	Yes	TL
[56]	Cost	m,m,1	Yes	Yes	Node	Yes	HM	H	Yes	TL
[57]	Cost	m,m,1	No	No	Node	Yes	HM	M	Yes	TL
[58]	Cost	m,m,1	No	No	Node	Yes	HM	M	Yes	TL
[59]	Time	m,–,1	–	–	–	–	HT	M	Yes	AG
[60]	Min-bat	m,m,1	Yes	–	–	–	HM	E	Yes	TL
[61]	Cost	m,m,1	No	Yes	Node	Yes	HM	H	Yes	TL
[62]	Time, cost	m,1,m	No	Yes	Node/Arc	Yes	HT	H	Yes	TL
[63]	Cost	m,m,1	No	No	Node	Yes	HM	H	Yes	TL
[64]	Cost	m,m,1	No	Yes	Node	Yes	HM	H	Yes	TL
[65]	Max-pro	m,m,1	No	Yes	Node	Yes	HM	M	Yes	TL
[66]	Cost	m,m,1	No	No	Node	Yes	HM	E	Yes	TL
[67]	Time	1,1,1	No	No	Node/Arc	No	HM	H	Yes	TL
[68]	Time	m,m,1	No	No	Node	Yes	HM	E	Yes	TL
[69]	Time	1,1,1	No	No	Node	Yes	HM	E	Yes	TL
[70]	Time	m,1,1	No	No	Node	Yes	HM	E	Yes	TL
[71]	Time	1,1,1	No	No	Node	Yes	HM	E	Yes	TL
[72]	Time	m,1,1	No	No	Node	Yes	HM	M	Yes	TL
[73]	Time	m,1,1	No	Yes	Node	Yes	HM	M	Yes	TL
[74]	Time	1,1,1	No	Yes	Node/Arc	Yes	HM	H	Yes	TL, EM
[75]	Time	1,1,1	No	No	Node	Yes	HM	H	Yes	TL
[76]	Cost	1,1,1	No	Yes	Node	Yes	HM	H	Yes	TL
[77]	Time	m,1,1	No	Yes	Node/Arc	Yes	HM	H	Yes	TL
[78]	Cost	m,1,1	No	No	Node/Arc	Yes	HM	M	Yes	TL

TABLE 2. continued.

#ref	#obj	#d,t,d	#pick	#mvisit	#release	#sync	#charc	#sol	#math	#app
[79]	Time	m,m,1	No	Yes	Node	Yes	HM	H	Yes	TL
[80]	Max-cus	1,1,1	No	No	Node	No	HM	H	No	TL
[81]	Time, cost	m,1,1	No	No	Node/Arc	Yes	HM	LR, H	Yes	TL
[82]	Time	m,1,1	No	No	Node	Yes	HT	H	Yes	TL
[83]	Cost, max-ser	m,m,1	No	No	Node	Yes	HM	M	Yes	TL
[84]	Cost	m,m,1	No	Yes	Node/Arc	Yes	HM	H	Yes	TL
[85]	Time	1,1,1	No	No	Node/Arc	No	HM	E	Yes	TL
[86]	Time	1,1,1	No	Yes	Node/Arc	Yes	HM	E, H	No	TL
[87]	Time	1,1,1	No	No	Node	Yes	HM	H	No	TL
[88]	Time	m,m,1	No	No	Node	Yes	HM	H, M	Yes	TL
[89]	Time	m,m,1	No	No	Node	Yes	HT	H	Yes	TL
[90]	Time	1,1,1	No	No	Node	Yes	HM	H	Yes	TL
[91]	Time	m,m,1	No	No	Node/Arc	Yes	HM	H	Yes	TL
[92]	Cost	m,m,1	No	No	Node	Yes	HM	H	Yes	TL
[93]	Min-CO^2, cost	m,m,1	No	No	Node	Yes	HM	M	Yes	TL, EM
[94]	Cost	m,1,1	Yes	Yes	Node	Yes	HM	H	Yes	TL
[95]	Time	m,m,1	No	No	Node	Yes	HM	E	Yes	TL
[96]	Time	1,1,1	No	Yes	Node/Arc	Yes	HM	H	Yes	TL
[97]	Time	m,1,1	No	Yes	Node/Arc	Yes	HM	M	Yes	TL
[98]	Time	m,m,1	No	Yes	Node	Yes	HM, HT	H	Yes	TL
[99]	Time	1,1,1	No	No	Node	Yes	HM	E	Yes	TL
[100]	Time	1,1,1	No	No	Node	Yes	HM	H	No	TL
[101]	Time	m,1,1	No	No	Node/Arc	Yes	HM	H	No	TL
[102]	Time	1,1,1	No	No	Node	Yes	HM	H, E	Yes	TL
[103]	Time	m,1,m	Yes	No	Node	Yes	HM	M	Yes	TL
[104]	Time	m,m,1	No	No	Node	Yes	HM	H	No	TL
[105]	Max-cus	m,m,1	No	No	Node	Yes	HM	H	No	TL
[106]	Time	m,m,1	No	Yes	Node	Yes	HM	H	Yes	TL
[107]	Time	m,1,1	No	No	Node	Yes	HM	M	Yes	TL
[108]	Min. of unsprayed area	1,–,1	–	–	–	–	HM	M	Yes	AG
[109]	Time	1,1,1	No	Yes	Node/Arc	Yes	HM	H, M	Yes	TL
[110]	Time	m,m,1	No	No	Node	Yes	HM	–	No	TL
[111]	Cost, distance	–,d,1	–	–	–	–	HM	M	Yes	AG
[112]	Distance	m,–,1	–	–	–	–	HM	M	Yes	AG
[113]	Cost	m,m,m	Yes	Yes	Node/Arc	Yes	HM	M	Yes	TL
[114]	Time, distance	m,–,1	–	–	–	–	HM	M	Yes	AG
[115]	Max-cov	m,–,1	–	–	–	–	HM	LR	Yes	AG
[116]	Max-cov	1,–,1	–	–	–	–	HM	H	No	AG
[117]	Time, energy	m,–,1	–	–	–	–	HM	H	Yes	AG
[118]	Time	m,–,1	–	–	–	–	HM	M	Yes	AG
[119]	Cost	1,–,1	–	–	–	–	HM	M	Yes	AG
[120]	Time	m,m,1	Yes	Yes	Node/Arc	Yes	HM	M	No	EM
[121]	Cost	m,m,1	No	Yes	Node	Yes	HM	H	Yes	EM
[122]	Time	m,–,m	No	Yes	–	–	HT	H	Yes	EM
[123]	Cost	1,1,1	No	No	Node/Arc	Yes	HM	E	Yes	DM
[124]	Cost	m,1,1	No	No	Node/Arc	Yes	HM	M	Yes	DM
[125]	Time	m,1,1	No	Yes	Node/Arc	Yes	HT	M	Yes	HM
[126]	Cost	m,m,1	No	Yes	Node/Arc	Yes	HT	E	Yes	HM

Notes. m: multi, time: Minimizing the total completion time of the job, cost: Minimization of the total cost of completion of the job, truck time: minimization of truck time, max-cus: Maximizing the number of customers served in a day, min-bat: Battery consumption minimization, waiting time: Minimization of waiting time, min-CO2:Minimization of CO2 ratio, max-ser: Maximize customer service level, max-pro: Maximize total profit, min-dep: Minimizing depreciation, max-cov: Maximization the coverage area, energy: Minimization energy consumption, HM: Homogeneous, HT: Heterogeneous, LR: Learning based approach, H: Heuristic, M: Metaheuristic, E: Exact, TL: Transportation and Logistics, AG: Agriculture, EM: Emergency Management, DM: Defense and Military, HM: Healthcare and Medical.

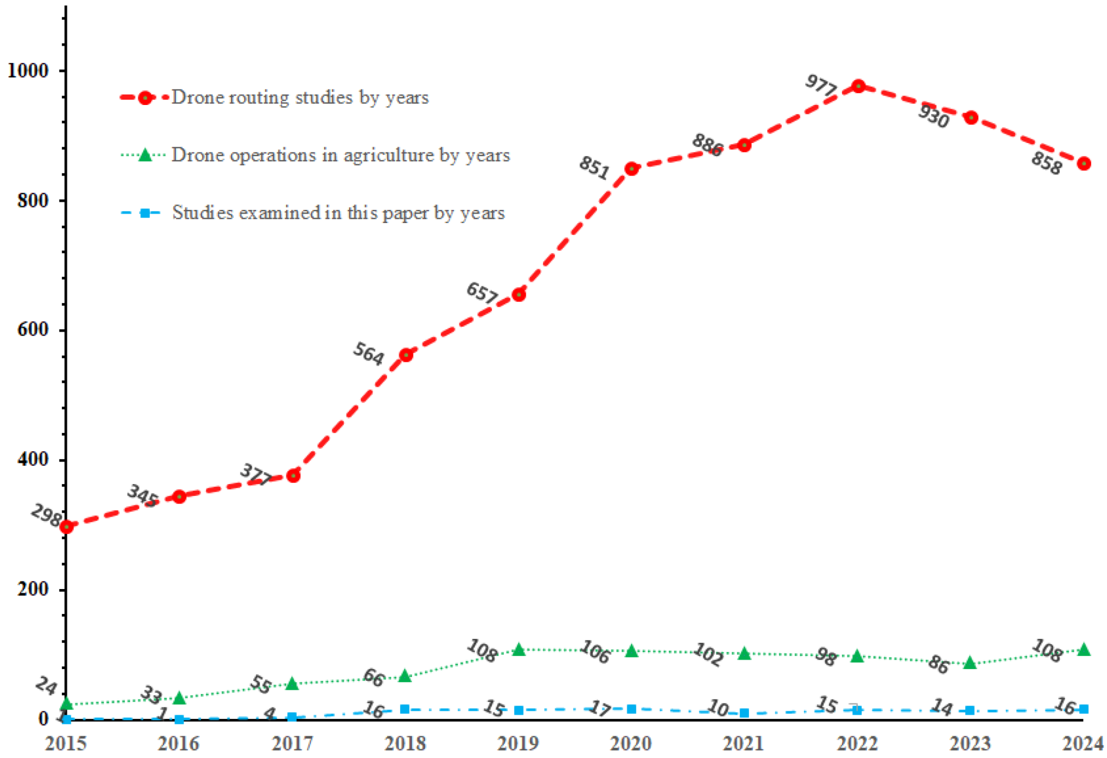

FIGURE 3. The distribution of publications in the literature by years.

(ii) The launched drone autonomously takes off from the top of the delivery truck and flies to the delivery location.
(iii) The drone automatically descends at the delivery location and delivers the package.
(iv) The drone returns to the delivery truck at a specific stop. For its next delivery, a new delivery package is loaded and the battery is replaced with a new fully charged battery.

3.2.2. Emergency response and disaster management

Emergency Response and Disaster Management is a field that emphasizes the need for rapid and effective response in emergencies. The capacity of advanced technologies, such as drones, to provide rapid and flexible response in emergencies is at the center of research in this field. Drones have the ability to quickly deliver aid to hard-to-reach areas by traversing damaged infrastructure [129]. Moreover, truck-drone collaboration play an important role in ensuring effective distribution of resources in disaster situations [120]. Moreover, emergency management and disaster response strategies require continuously updated systems to cope with dynamic uncertainties and changing demands [129]. In this context, efficient allocation of resources across multiple warehouses and the ability to respond quickly in emergency situations are key to success in disaster response [121]. Advanced optimization techniques and heuristic algorithms are used to improve the efficiency of these processes [130].

The dynamic truck-UAV collaboration strategy aims to increase both time and resource efficiency by utilizing trucks to transport supplies to emergency areas [120]. This strategy enables UAVs to work together with trucks to overcome limited range and payload capacity. Thus, UAVs can reach farther by taking off from trucks, and at the same time, trucks can quickly deliver supplies when road conditions deteriorate [131]. Thus, by ensuring the timely arrival of emergency relief supplies after a disaster, the efficiency of rescue operations is increased.

In addition, multi-depot vehicle routing problems enable more efficient use of UAVs and trucks in emergency logistics [122, 130, 132]. Such collaborative approaches provide flexibility and resilience in disaster management while enabling the most efficient use of resources.

3.2.3. *Defense and military operations*

The use of UAVs and drone technology in military operations also influences geopolitical dynamics. In particular, the use of small and lightweight UAVs in civilian domains enables states to enhance their military capabilities, while the application of these technologies in the context of terrorism and asymmetric warfare poses a threat to international security [133]. This situation leads to a reshaping of defense policies and complicates military operations. Military operations have undergone a significant transformation in recent years, especially with the widespread adoption of unmanned aerial vehicles. Drone technology is effectively utilized for tasks such as target identification and intelligence gathering in conflict zones, and it also plays a role in civilian applications, such as the transport of food and medical supplies [133]. This transformation increases the integration of military operations with civilian life, thus bringing the concept of "everyday militarism" to the forefront. The incorporation of military applications into daily life subjects society to increased military surveillance, raising concerns regarding civil rights [134].

The combination of drones and trucks is being researched in the literature to enhance the effectiveness of drones with limited flight ranges in military operations [123]. The study addresses issues related to the tandem routing of drones and trucks, particularly discussing how solutions can be presented under sparse demand conditions. It emphasizes that the use of drones in military operations can also improve logistics and distribution services. Tian *et al.* (2022) examine target surveillance operations through the collaboration of a truck and multiple drones. This study focuses on optimizing the routes required for monitoring multiple targets, going beyond traditional military operations. The truck, by carrying drones, provides a broader surveillance area, thereby increasing the effectiveness of military missions. It is noted that drones extend the range of the truck, allowing for the surveillance of more targets [124].

3.2.4. *Healthcare services and medical operations*

Drones play a significant role in minimizing the impacts of the pandemic on healthcare services and optimizing the distribution of medical supplies. The COVID-19 pandemic has increased the utilization of drones in the health sector, showcasing the potential of this technology [135]. Drones provide a secure and rapid alternative for both medication and vaccine distribution, facilitating access to healthcare services in rural and hard-to-reach areas [136]. Research indicates that healthcare workers generally exhibit a positive attitude towards the use of drones for the delivery of medical supplies and vaccines. For instance, 54.2% of healthcare workers indicated that employing drones for medical supply delivery is a good idea. Moreover, factors such as leadership innovativeness and delivery risk emerge as significant elements influencing this positive attitude [136].

Deliveries made by drones present a faster and more environmentally friendly alternative compared to traditional methods [125, 137]. During the COVID-19 pandemic, the use of drones has enabled the rapid delivery of critical supplies, thereby reducing the risk of transmission through human contact [135]. However, the effectiveness of drones is constrained by various challenges, including weather conditions, payload capacities, and regulatory frameworks [135].

Luo *et al.* (2024) examine a collaborative delivery system involving one truck and multiple heterogeneous drones in the context of the COVID-19 pandemic. The study introduces the Multiple Visits Traveling Salesman Problem with Multiple Heterogeneous Drones (MTSP-MHD) model, which allows a truck to carry a fleet of heterogeneous multi-visit drones for cooperative deliveries. The study employs a combination of k-means clustering, nearest neighbor search, and greedy strategies (KNG) to formulate feasible solutions. This research emphasizes the integration of drone technology to enhance delivery processes during the pandemic, making them more efficient and cost-effective [125]. Another study investigates a multi-drone and multi-truck collaborative delivery system for the delivery of emergency medical supplies. The research addresses the routing problem in

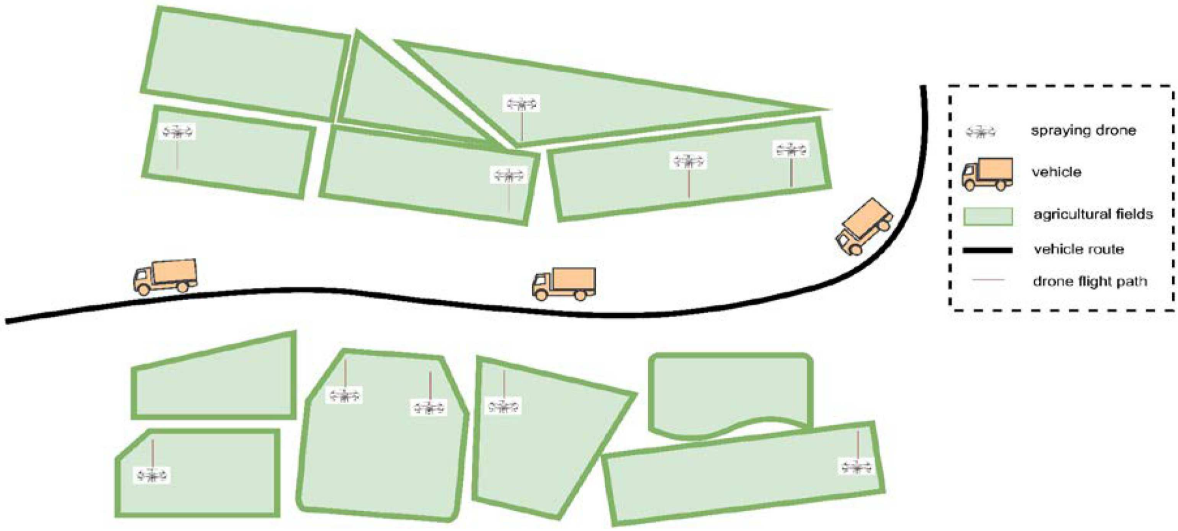

FIGURE 4. Spraying operation of the sub-divided agricultural field with a ground vehicle supported drones.

a medical supply network and aims to improve delivery efficiency using a complex model and hybrid algorithms [126].

In conclusion, it is evident that drones hold a crucial position in healthcare services, especially in pandemic situations, and that the wider adoption of this technology is warranted [135, 136]. In the future, it is critical for policymakers and health organizations to understand the attitudes towards this new technology and the potential barriers to its integration into healthcare services [136].

3.2.5. Agriculture

The processes of spraying, fertilization, mapping or remote sensing of agricultural fields as required by precision agriculture are among the most frequently studied topics recently. According to traditional methods in agriculture, spraying or fertilizing of fields is conducted by human hands or with the help of ground vehicles. Different operations are carried out for spraying and fertilization processes with the use of drones in agriculture. The use of drones to improve the efficiency of agriculture is relatively innovative [3–5, 53, 59, 138, 139].

Xu *et al.* conducted operations on spraying sub-regions in agricultural fields using multiple drones [4]. By using multiple drones with different characteristics (heterogeneous), the superior features of the drones were utilized. In the spraying of sub-areas, the completion time of the job is minimized with the GA algorithm designed specifically for the problem. A different algorithm was created to plan the route of the ground vehicle and determine the location where the ground vehicle will launch the drone and meet the drone. The ground vehicle serves as a mobile depot for the drones. The ground vehicle assists for the spraying operation of the drone which carries the spraying liquid and has a certain flight range. The amount of liquid the drone carries for spraying and the duration of its flight are limited. The ground vehicle tries to overcome these limitations of the drone and waits for the drone at a location close to the area where the drone will spray. Thus, the movement time of the drone without spraying is reduced and the flight time of the drone is used efficiently. Figure 4 below shows the spraying operation of the ground vehicle-assisted drone.

Figure 4 shows that the agricultural field is divided into sub-areas. These fields are sprayed by drones. The role of the ground vehicle is to act as a mobile depot for the drones. The ground vehicle arrives at the appropriate location for resupplying the drones (replacement of the spraying liquid and battery) and tries to utilize the flight time of the drone efficiently [3, 4].

The health status of the plants in that field is very important when spraying an agricultural field. Li *et al.* tried to minimize the completion time of spraying agricultural field with drones by considering the health status of the field [53]. The health status of the agricultural field was examined according to the Normalized Difference Vegetation Index (NDVI) and the diseased fields were sprayed efficiently. According to the NDVI index, 4 different spraying intensities were determined and heterogeneous drones were used to spray this agricultural field.

In order to minimize the cost of a ground-assisted drone spraying operation, Mukhamediev *et al.* considered 3 components; personnel costs, drone usage cost and flight cost [3]. The fitness function created accordingly is given in equation (15) [3].

$$Fit = (W + S) * P \tag{15}$$

where Fit is the total cost of the overflight, W is the cost associated with the wear of the drone, S is the cost associated with the work of personnel and the vehicle, and P is the penalty.

Drone wear and tear cost (W): The cost of the risks in the take-off and landing of the drone, the flight cost and distance-related costs [3].

$$W = \sum_{1}^{l} W_{\text{cycle}} + W_{\text{km}} * d + W_{\text{h}} * h \tag{16}$$

where l corresponds to the number of drones. W_{cycle} is the take-off and landing costs of the drone (this includes the risk of damage to the drone during take-off and landing). W_{km} is the flight cost per km and W_{h} is the flight cost per hour. The d is the distance travelled by the drone and the h is the time.

Personnel costs (S): This corresponds to the cost of the mobile platform and the wage of the personnel for each drone take-off and landing [3].

$$S = T_{\text{total}} * S_{\text{hourly}} + N_{\text{starts}} * \; S_{\text{per-start}} \tag{17}$$

where S is the total payment made to the personnel in charge. T_{total} is the total flight time in hours, S_{hourly} is the cost per flight hour, N_{starts} is the number of take-off and landing cycles and $S_{\text{per-start}}$ is the cost for each take-off and landing cycle. While determining the personnel wage, the drone flight time and the total number of take-offs and landings of the drone are taken into consideration.

Long flight time penalty (P_{hard}): If the drone flight time exceeds the specified maximum flight time, it is penalized hard. The cost of drone wear and tear and personnel costs are multiplied by an exponential penalty.

$$P_{\text{hard}} = 1 + 1000^{T_{\text{total}} - T_{\max}}. \tag{18}$$

If the maximum flight time is exceeded by values smaller than the maximum flight time (in case of optimization failure), a soft penalty P_{soft} is applied.

$$P_{\text{soft}} = 1 + \frac{T_{\text{total}} - T_{\text{borderline}}}{T_{\max} - T_{\text{borderline}}} \tag{19}$$

where T_{total} is the total flight time, $T_{\max}$ is the maximum flight time and $T_{\text{borderline}}$ is the borderline crossing time exceeding the maximum time. The penalty function can be generally expressed as in equation (20).

$$P = \begin{cases} P_{\text{hard}}, & T_{\text{total}} > T_{\max} \\ P_{\text{soft}}, & T_{\text{total}} \geq T_{\text{borderline}} \text{ and } T_{\text{total}} \leq T_{\max}. \end{cases} \tag{20}$$

There are differences between the use of the drone in operations such as spraying, fertilization or mapping in agricultural field and the delivery of packages to customers in transportation and logistics application area. There is also a similar drone routing in healthcare, military and emergency operations as in transportation and

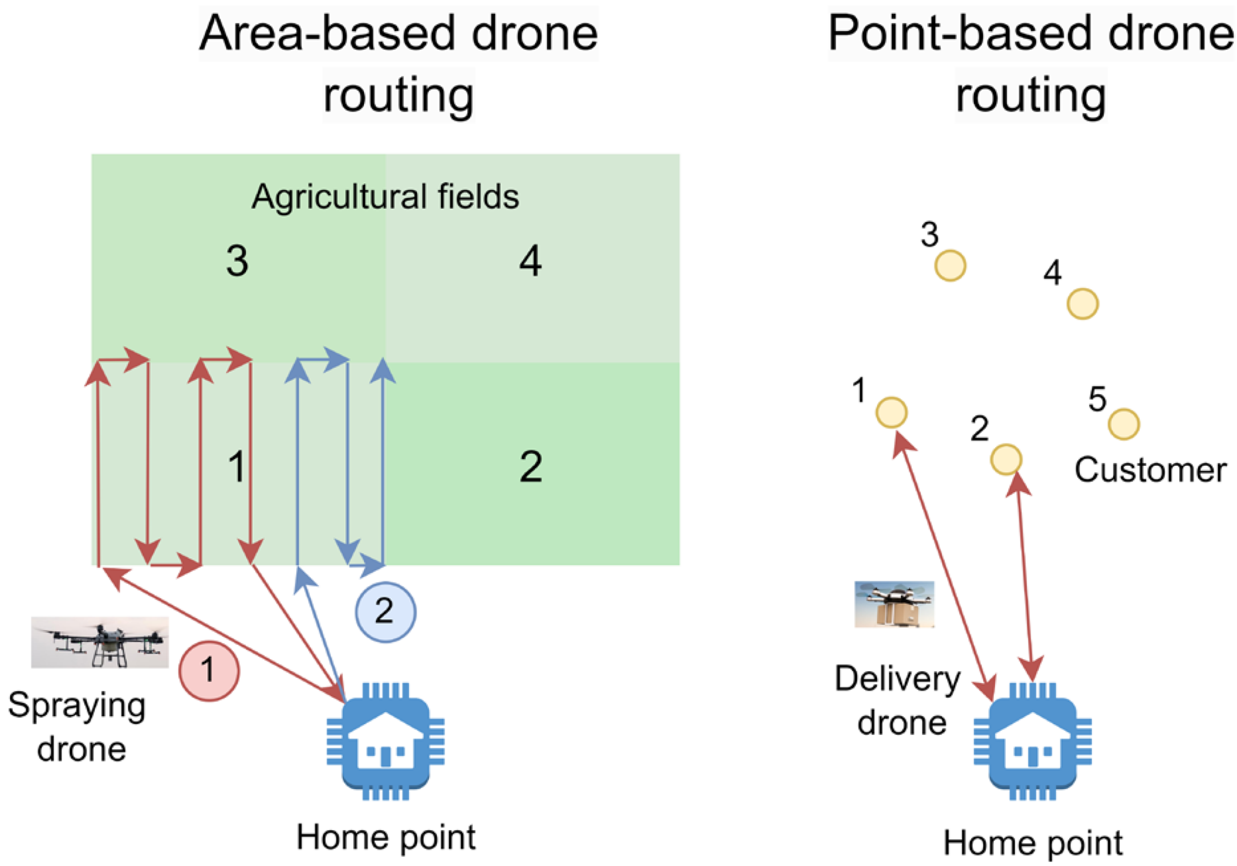

FIGURE 5. Presentation of area-based drone routing and point-based drone routing.

logistics application areas. When the spraying operation of the drone in the agricultural field is considered, it is known that there is a certain weight of spraying liquid to be carried by the drone and a certain flight time of the drone. The drone ensures the spraying of sub-agricultural areas, which can vary in size. Depending on the flight time and the amount of spraying liquid, the drone moves to the depot location each time to supply the spraying liquid or battery and then returns to the agricultural sub-area location. The drone completes the spraying task when it returns to the depot location after completing the spraying according to the specified constraints. Figure 5 shows the area-based routing of the drone for spraying in agricultural areas and the point-based routing for operations such as package delivery to customers and emergency medicine delivery.

Figure 5 shows a drone routing for transportation and logistics, healthcare, military, emergency and agriculture application areas. Area-based drone routing is related to the agriculture area, while point-based drone routing is related to the logistics area. The operations such as package delivery to customers and emergency medicine delivery in Figure 5 are quite different from the drone routing process in agriculture. In the parcel delivery of the drone to the customer node, since the customer has only one location (lat, lon), the drone only needs to go to the customer location once. In this operation process, the drone completes its task once it reaches the customer node and arrives at the home location again. According to these explanations, agricultural problems such as spraying, fertilization, and mapping appear to be more complex than those in transportation and logistics, healthcare, military, and emergency operations. Therefore, the algorithm for solving routing problems in agriculture needs to be designed in a problem-specific way. Thus, drone-truck based operations for precision farming in the field of agriculture are of more interest to researchers in the future and this application area tends to receive increasing attention.

3.3. Number of drone-truck

There are many different types of operations based on the cooperation between UAVs and ground vehicles, depending on the number of drones and trucks. The variability of the number of drones assigned to each truck is an important factor affecting the operation process. Depending on the number of drone-truck vehicle types, four delivery operations were analyzed; single drone and single truck, multiple drones and single truck, single drone and multiple trucks and multiple drones and multiple trucks scenarios.

3.3.1. Single drone and single truck

The most basic type of operation in which drone and truck are used together in delivery problems is the study using single drone and single truck [10]. The study describes the optimization of a single truck and single drone scenario to minimize job completion time. The truck and the drone cooperate to serve customers. Some customers are served by the truck while others are served by the drone. Due to the flight time constraint of the drone and the payload weight constraint, the truck is forced to serve some customers. For the truck, the distance traveled was calculated using the Manhattan distance metric, while for the drone, the distances between nodes were calculated using the Euclidean metric. Murray and Chu proposed a mixed integer linear programming (MILP) formulation and three heuristic methods based on the nearest neighbor, savings, and sweep algorithms.

Agatz *et al.* introduced a truck-drone cooperative study known as TSP-D. In the TSP-D optimization problem, multiple visits of the combined node are allowed, which is not allowed in the FSTSP formulation [20]. Also, unlike FSTSP, the drone is allowed to rendezvous at the node where it was launched from the truck. The truck node is the node where customers are visited only by trucks and the drone node is the node where customers are visited only by drones. The combined node is visiting by both trucks and drones. In the combined node, the drone is located on the truck. This proposed model showed that the delivery process with single drone and single truck is better than the delivery process with only truck.

Luo *et al.* formulated a 0–1 integer programming model for a two-echelon ground vehicle and UAV cooperated routing problem (2E-GU-RP) with a single ground vehicle and a single UAV [109]. Different from the main depot and destination locations, the meeting locations of the ground vehicle and the drone were determined by considering the destination locations. The drone is allowed to serve more than one customer in one flight. There are three critical decisions to be made for the study; determining the route of the ground vehicle, determining the parking locations where the ground vehicle will stop (to launch and rendezvous with the drone), and determining the routing of the UAV to its current destinations. Two heuristics are proposed to solve the model. Test instances were created using randomly generated destinations in the range 25–200 and the performance of these two heuristics were compared with these instances.

3.3.2. Multiple drone and single truck

Multiple drone and single truck cooperation is presented as an extended variant of the single drone and single truck operation type. In this type of collaboration, multiple drones and a single truck are used. Murray and Chu introduced the collaboration of multiple drones and single trucks for delivery [10]. In some of the studies in the literature, drones only deliver to customers, while in others, both delivery and pickup are performed [43]. The operation of picking up packages from customers was introduced to the literature by Ham [35]. In the study where the job completion time is minimized, multiple visits are allowed for a customer node. It is reported that up to 100 customer test instances can be solved with the heuristic algorithm.

Ferrandez *et al.* conducted a delivery operation using single ground vehicle with multiple drones [33]. Customer nodes were clustered using k-means method. A test instance with 100 customers was tried to minimize the job completion time with GA. Chang and Lee [101] and Salama and Srinivas [81] also used the k-means clustering method in their studies. They worked on the minimization of the objective function determined by the heuristic algorithm. The truck carrying the drones uses the node at the center point of the clusters as a stop. The delivery to the customer nodes is carried out through these drones.

Peng *et al.* presented an extended multiple drone and single truck delivery operation to deliver parcels to customers [103]. Also, package pickup from customers is included in the study. Minimization of job completion time and job completion cost are considered separately. The Minimum Visit Cost Crossover (MVCC) algorithm was proposed to increase the functionality of the algorithm and to produce a new solution with less cost. Peng *et al.* also tried to optimize the same objective functions [97]. In the proposed hybrid GA, the Low Visit Cost Crossover algorithm (LVC) is proposed to prevent premature convergence and provide a better distribution in the population.

Kim and Moon showed that the Traveling Salesman Problem with a Drone Station (TSP-DS) can be divided into TSP and parallel identical machine scheduling problems [37]. A synchronized package delivery operation of a single truck with multiple drones was conducted. The TSP-DS is formulated based on mixed integer programming.

Karak and Abdelghany presented a hybrid heuristic by extending the Clarke and Wright algorithm to minimize routing costs [94]. Multiple drones are included with a single ground vehicle, allowing multiple visits to customers and parcel pickups from customers.

Poikonen and Golden introduced a drone energy function by taking into account the weight of the parcel carried by the drones [86]. In this way, the problem is expressed mathematically by considering that drones can carry more than one parcel.

Murray and Raj integrated a heterogeneous fleet of drones into logistics delivery operations [82]. Heterogeneous drones have different characteristics (carrying capacity, flight time, etc.). A mathematical model is presented by considering the energy consumption of the drone in flight. The problem is optimized by heuristic algorithms with the MILP created.

Cavani *et al.* used a decomposition approach with exact solution to solve TSP with Multi Drone (TSP-MD) [70]. For the problem, delivery operations were carried out using multiple drones and single truck. MILP model, valid inequalities, and a decomposition method are presented to find optimum solutions for solving the problem. Boccia *et al.* preferred an exact solution method for solving the FSTSP using the branch-and-cut algorithm [71]. Luo *et al.* extended TSP-MD and proposed the Multi-visit Travelling Salesman Problem with Multi Drone (MTSP-MD) problem and MILP algorithm [73]. This algorithm allows drones to visit multiple customer nodes. The multi-start tabu search (MSTS) algorithm was designed to solve the problem. The test instances presented by Solomon [140] with up to 100 customers were used in their study.

Euchi and Sadok created MILP for the VRPD problem [72]. In the algorithm, multiple drones and one ground vehicle are considered. A hybrid genetic algorithm is proposed to solve the problem effectively. The proposed hybrid GA was able to solve up to 200 generated test instances in accordance with the objective function.

Drone and truck cooperative operations, which are mostly used in logistics, are also seen in agricultural operations [4]. This is the first study in which drones and ground vehicles are used collaboratively for spraying operations in agriculture.

3.3.3. Single drone and multiple truck

In the reviewed publications, there are no studies involving single drones and multiple trucks. This variation is not seen as a very practical problem and may be a special case of the multi-drone multi-truck variation.

3.3.4. Multiple drone and multiple truck

In recent years, the need for fast and efficient parcel delivery to customers has increased with the growth in the e-commerce sector. In this context, multiple drone and multiple truck collaboration provides significant potential by increasing delivery speed and reducing delivery costs. The most complex drone-truck tandem operation is the multiple drone and multiple truck variation. While the single drone and single truck variation is NP-hard, this variation further increases the complexity of the optimization process [35, 39, 51, 52, 54, 56–58, 60, 61, 63, 64, 68, 79, 83, 84, 88, 89, 91, 92, 95, 98, 104, 105, 110, 141]. The separate delivery routes of the drones and trucks, the locations where the drones will be launched, the locations where the drones will meet the trucks, and which truck will meet which drone are all very important in this combination. Some of the studies using multiple drones and multiple trucks are presented below.

Wang *et al.* addressed the problem from a worst-case point of view [141]. Several different worst-case scenarios are organized and inferences are made from these scenarios. In their work, VRPD with multiple drones and multiple trucks is introduced. According to the presentation, once the drone is launched from the truck, the drone is not allowed to meet different trucks. Poikonen *et al.* extended the results of the problem previously considered from a worst-case point of view [110]. They also showed that the VRP has more practical relevance to Amdahl's Law. Di Puglia Pugliese and Guerriero [142] and Ham [35] present the Vehicle-Drone Routing Problem with Time Windows (VDRPTW). Their study is an extension of VRP with Time Windows (VRPTW) introduced to the literature by Desrochers *et al.* [143]. Kuo *et al.* used multiple drones and multiple trucks considering the time window constraint [57].

Schermer *et al.* used the route-first cluster-second heuristic method to solve the VRPD [104]. Numerical experiments were performed on large-scale instances and the performance of the heuristics was observed. Ulmer and Thomas conducted a study on large-scale instances [105]. They presented a comprehensive Markov decision process model for the dynamic VRP. Real-world problems are included in the optimization, in which the objective is to maximize the number of customers served in a working day.

Kitjacharoenchai *et al.* presented the MILP model of The Multiple Travelling Salesman Problem with Drones (mTSPD) [88]. Adaptive Insertion Heuristic (ADI) heuristic algorithm is proposed for the solution of the problem. The algorithm consists of two steps; generating mTSPD solutions and applying removal and insertion operators to the first mTSPD solution to find the solution. GA, combined k-means/nearest neighbor and random cluster/tour heuristics are proposed as solution methods. The experimental results show that the proposed model using multiple drones and multiple trucks along with the heuristic provides shorter delivery completion time than simply using trucks alone, multiple trucks, and single drone and single truck in the operation. Schermer *et al.* proposed a drone assignment and scheduling problem that minimizes job completion in the VRPD problem [89]. Valid inequalities are introduced to improve the performance of the solutions. The proposed metaheuristic algorithm is tested using a heterogeneous fleet of drones with up to 100 customers.

Luo *et al.* introduced the one-to-one pickup and delivery problem with multi-trucks and multi-visit drone (OPDP-MTMV). In this type of delivery, there are multiple trucks equipped with a drone [56]. The energy consumption of the drones, which can carry more than one parcel in each flight, depends on the payload weight and flight time. Iterated local search (ILS) is proposed for the mathematically modeled problem.

Schermer *et al.* proposed a heuristic combining variable neighborhood search and Tabu Search to solve the VRPD and En Route Operations (VRPDERO), an extension of VRPD [91]. They used small instances up to 10 customers and large instances up to 50 customers as test instances. Masmoudi *et al.* studied VRPD Equipped with Multi-Package Payload Compartments (VRP-D-MC) [65]. In the scenario where a drone is allowed to carry multiple packages, the drone can serve multiple customers in one sortie. In their study, the flight time of the drone is included as a function of energy consumption.

Sacramento *et al.* formulated the problem similar to the FSTSP problem with a time window constraint [92]. Adaptive Large Neighbourhood Search (ALNS) was proposed for solving large problems up to 200 customers.

Delivery problems involve operations using either independent drones or drones attached to trucks. Wang *et al.* proposed a hybrid truck-drone delivery (HTDD) algorithm to solve the delivery problem [98]. They used multiple trucks, multiple drones attached to the truck and multiple independent drones. Kitjacharoenchai *et al.* proposed a MIP model and two heuristics, the drone-truck route construction and the large neighborhood search (LNS), to solve their two-echelon problem (2-echelon VRPD -2EVRPD-) [79]. Two trucks and four drones were used in the study where multiple visits of drones were allowed. The performance of the study was observed using the test instances presented by Augerat [144].

Meng *et al.* developed a two-stage solution approach consisting of three main components to handle large-sized instances using multiple trucks and multiple drones [51]. Drones are organized to have simultaneous delivery and pickup capabilities.

3.4. Objective functions

There are different objective functions in the optimization of problems in drone-truck collaborative operations. In this section, the objective functions used in the studies are reviewed. According to the number of objective functions presented in the studies, they are divided into two as single-objective optimization and multi-objective optimization.

3.4.1. Single objective optimization

This section examines single objective function studies. Accordingly, the objective functions are given in three subsections; minimization of time, minimization of completion cost and others.

Minimization of the time: Among the studies on drone-truck routing problems, the most common objective function is the minimization or makespan [4, 10, 21, 23, 28–31, 33–35, 37, 62, 67–75, 77, 79, 81, 82, 85–91, 95–102, 104, 106, 107, 110, 141]. Minimizing the job completion time is very important in parcel delivery problems. When analyzed regarding logistics operations, the delivery of the cargo package to the customers within the appropriate time is appreciated by the customers. It is quite important for cargo companies to use the time during the day efficiently.

Optimization of job completion time or makespan affects drone and truck routes. In operations where drone and truck serve customers, the two types of vehicles wait for each other at the rendezvous location. In this case, the resulting waiting time can significantly affect the completion time of the job.

Salama and Srinivas presented mathematical models for the minimization of job completion time and cost using a fleet of trucks and drones [81]. To utilize the drone fleet, drones are launched simultaneously from a truck parked at the center of customer locations.

Murray and Raj used multiple drones and single truck to minimize the completion time of a job [82]. Different scenarios were implemented by varying the endurance (speed and flight range) of the drones. They consider a last-mile delivery service where the packages are ready in the depot before the delivery is made.

Minimization of the cost: The cost of completion should be considered as an important factor in the decision-making processes of companies. Optimizing cost can improve the efficiency and profitability of the delivery process [145]. It is important to carefully analyze and optimize the cost of completion in drone and truck collaborative delivery operations.

Kuo *et al.* [57] tried to minimize the total travel costs of drones and trucks. The objective of the vehicle routing problem with drones and time windows (VRPTWD) model they studied is to minimize the travel cost corresponding to the fuel cost of the truck and drone. These travel costs are derived from Sacramento *et al.* [92].

Peng *et al.* gave the total delivery cost as the sum of the distance cost of the ground vehicle and the total distance cost of the UAVs [97]. Studying an extension of VRPD, Wang and Sheu presented a MIP algorithm for the minimization of logistics costs and introduced the branch-and-price method exact solution method [39].

Considering the payload capacity and flight distances of drones, Karak and Abdelghany [94] studied deals with minimizing the routing cost of the drone and the ground vehicle. In their study, delivery and pickup are allowed to be performed and extend the Clarke and Wright algorithm for multimodality.

Using sidewalk robots and drones, Deng *et al.* tried to minimize the total delivery cost by considering the waiting costs, delivery costs per unit and capital costs of both types of vehicles [78]. The results show that as the number of customers increases, there is more potential to save on capital costs.

Li *et al.* introduced the two-echelon vehicle routing problem with time windows and mobile satellites (2E-VRP-TM) [84]. Four different functions are presented to minimize the total cost; the variable cost of vans, the operating cost of UAVs, the conversion of the cost of possible waiting times of UAVs, and the conversion of the cost of possible waiting times of vans.

Meng *et al.* considered a variant of the combined truck-drone routing problem that allows drones to serve multiple customers and provide both pickup and delivery services in each sortie [51]. The transportation costs of the truck and the drone are considered separately when calculating the total delivery cost. The transportation cost of the truck is taken proportional to the travel distance, while that of the drone is taken proportional to the battery energy consumed. Tamke and Buscher, stating that the speed of the drone affects the energy consumption, used the speed-dependent energy consumption in their problem [52]. In their study, they formulated a comprehensive MIP that aims to minimize the operating costs, which consist of the fuel consumption costs of trucks, the costs of drivers and the energy costs of drones.

Other objective functions: There are studies using different objective functions other than optimization of cost and time in drone-truck tandem operations. The operational cost of vehicles whose fuel consumption is based on petroleum sources is mostly due to the travel distance. Accordingly, CO2 emissions to the environment are directly affected by fuel usage. Chiang *et al.* presented a green vehicle-routing problem (GVRP) [93]. In this study, they showed that the optimal delivery of parcels with the help of UAVs will save energy and reduce carbon emissions.

Dayarian *et al.* studied the routing problem by aiming to deliver the maximum number of packages to the customer within a day [80]. The study, which introduces the vehicle routing problem with drone resupply (VRPDR), is the first study to propose the use of drones to resupply the delivery vehicle. Das *et al.* tried to minimize travel costs and maximize customer service levels based on on-time deliveries [83]. They developed a multi-objective optimization model with these two conflicting objectives.

Zhang and Li proposed an explored cooperative vehicle-drone distribution network (CVDDN) for perishable products in pandemic situation [54]. Aiming to minimize the total cost and value loss for logistics distribution, the results of the case study in Chengdu province showed the comprehensiveness and high performance of the proposed CVDDN optimization.

The first study using synchronized drone-truck tandem operations in agriculture has recently appeared [4]. Besides minimizing the completion time of the job, the flight of the drone without spraying was also minimized. Thus, the efficient flight time of the drone is increased. In their study, the agricultural field was divided into 22 sub-areas and sprayed with multiple drones and single trucks. The determination of the locations where the truck will launch the drone and where the drone will rendezvous with the truck has been studied.

3.4.2. Multi-objective optimization

In drone-truck collaboration, drones and trucks cooperate together to carry out operation processes according to different application areas. To increase the effectiveness of this collaboration, decisions need to be made about how to plan the tasks of the drones and trucks. These decisions often consider more than one objective function. A single objective function is optimized in single-objective optimization. This objective function usually represents delivery time, cost or environmental effect. In single objective optimization, the problem has a single optimal solution. In contrast, in multi-objective optimization, multiple objective functions are optimized. Multi-objective optimization can help drones and trucks plan their missions more efficiently. For example, in multi-objective optimization, it may be desirable to optimize both delivery time and cost. Thus, in this case, the tasks of the drones and trucks can be planned in a way that best meets both objective functions. Figure 6 shows the distribution of the studies according to the number of single objective and multi-objective optimizations and the multi-objective optimization algorithms used.

According to Figures 6 and 8 of the drone-truck collaboration studies included multi-objective optimization. The solution approaches of these multi-objective studies are also shown in Figure 6.

Multi-objective optimization is basically divided into two categories: (i) when the objective functions are in conflict and (ii) when the objective functions are not in conflict. These two different cases change the approach used to solve the problem. In a multi-objective optimization problem with conflicting objective functions, metaheuristic algorithms used to solve single objective optimization problems cannot be used. Since the objective functions are in conflict, pareto-based [83], indicator-based [146] or decomposition-based [147] approaches are used. Among these, pareto-based approaches are the most widely used. For example, drones may need to fly faster to reduce delivery time. However, flying drones faster may increase fuel consumption and increase cost. Pareto optimal solutions are those that maximize one objective function while minimizing other objective functions. The challenges of multi-objective optimization in the drone-truck cooperative routing problem can be summarized as follows:

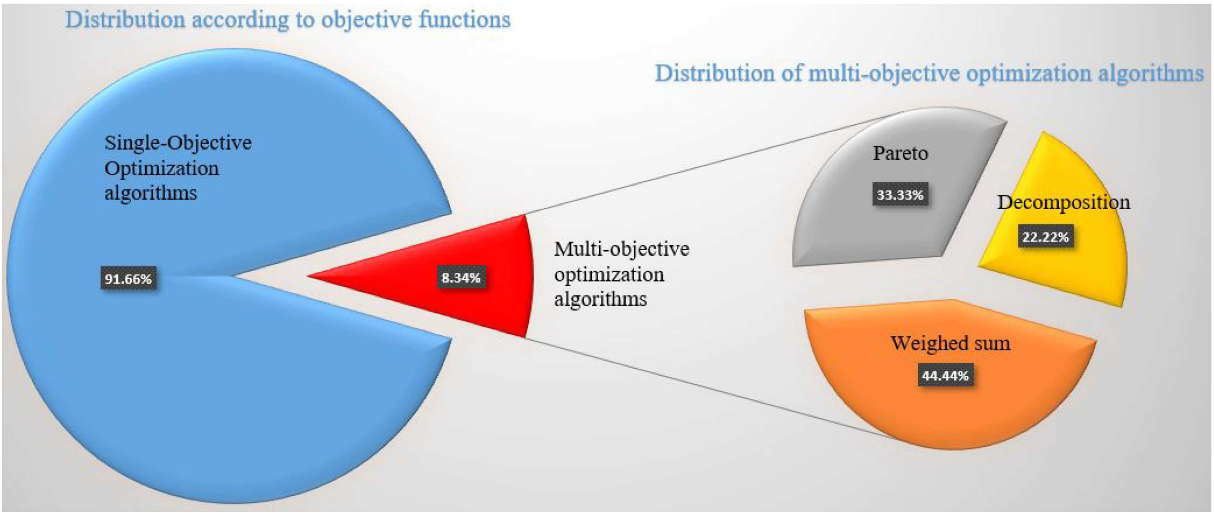

FIGURE 6. Distribution of the reviewed studies according to the number of objective functions and multi-objective optimization algorithms.

Complexity of the problem: The drone-truck collaborative routing problem is a complex problem with a large number of variables and constraints. This makes the multi-objective optimization problem even more complex.

No single optimal solution: There is no single solution that simultaneously optimizes all objectives. Instead, a set of Pareto optimal solutions exists, each representing a trade-off between different objectives.

As can be seen in Figure 6, multi-objective optimization has been used very little in drone truck collaborative studies. However, multi-objective optimization is one of the most frequently studied topics especially in recent years. In the literature, there are some recent approaches for multi-objective optimization such as clustering-based [148] and Dynamic Switched Crowding [149]. Using these approaches in drone-truck collaborative routing problems and investigating their performance is considered as an important research topic. Thus, researchers can fill this gap in the literature in their future studies.

3.5. Drone-truck capacities

A drone is an aerial vehicle that can carry loads up to a certain limit and has a limited time in the air. These two constraints must be taken into account in order for the drone to serve target customer locations. If the drone is unable to serve a customer, a truck must provide delivery to that customer. Salama and Srinivas [81] and Meng *et al.* [51] included load-dependent flight distance in their research instead of assuming a fixed flight distance, since the flight range of the drone depends on the payload in practical applications [90, 150]. In delivery operations, depending on the weight of the parcel to be delivered, only trucks are allowed to serve some customers. Huang *et al.* modeled basic characteristics, including delivery time, energy consumption and battery charge, as time-dependent for a drone [85]. Tamke and Buscher extended the flight of the drone with the same constant speed in each sortie, enabling it to fly at different speeds in each sortie [52]. One truck can carry multiple drones and each drone is assigned its own specific truck. Drones can only be launched from the assigned truck (except for the depot) and can rendezvous with the same truck. In problems where there is synchronization between drone and truck, the ratio of drone speed to truck speed is important. Cengiz *et al.* explained that when this speed ratio is not fixed but dynamically varied according to the weight carried by the drone, it positively affects the completion time [151].

The constraints set for the drone and truck collaborative studies should be at a level that can simulate real-world problems. However, the constraints included in the study in accordance with real-world conditions

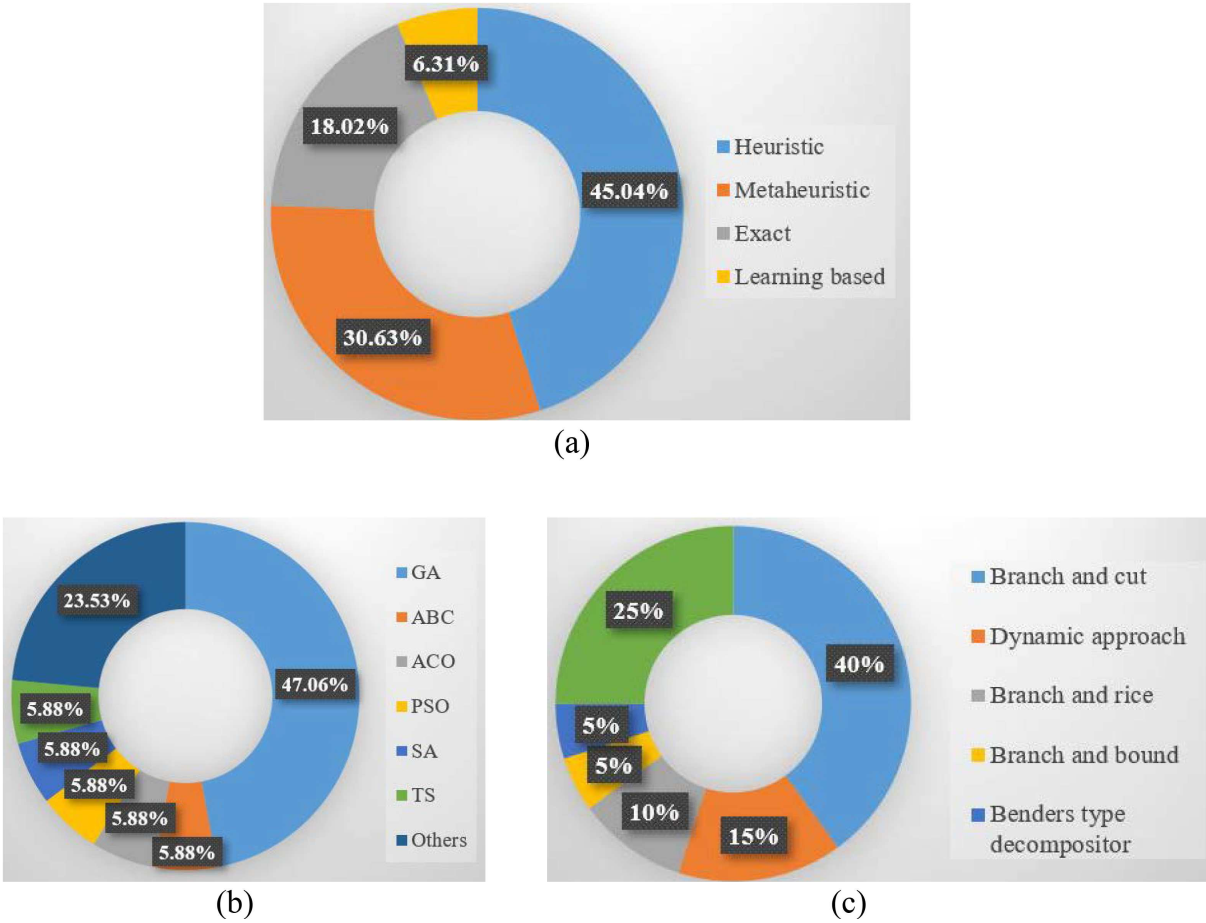

FIGURE 7. (a) distribution of the analyzed studies by solution method, (b) distribution of metaheuristic algorithms, (c) distribution of algorithms with exact solutions.

increase the complexity of the problem, which is already NP-hard. Accordingly, it is necessary to provide an efficient solution method for solving the problem.

Battery depletion is a very important constraint for drones. The energy expenditure of drones when they climb in a three-dimensional space is different from the energy expenditure when they land. When drone-truck collaborative studies are examined, there are very few studies that consider the battery depletion of drones in three-dimensional real-world conditions. Due to this literature gap, future studies of the researchers will significantly contribute to the literature.

3.6. Solution approaches

There are different solution methods for drone-truck collaborative problem types. In this section, the studies are categorized as heuristic, metaheuristic, exact and learning based solution methods. The advantages of the presented solution methods over each other are discussed in depth. Figure 7a shows the distribution of the analyzed studies by solution method, Figure 7b shows the distribution of metaheuristics, and Figure 7c shows the distribution of algorithms with exact solutions.

3.6.1. Heuristic

Drone-truck operations are inherently NP-hard problems. It is not feasible to use commercially available MILP solvers such as Gurobi and CPLEX to solve the problem with large instances Schermer *et al.* [89] because it is quite common for algorithms to get stuck in local search traps so researchers have focused on heuristic algorithms to solve these problems.

Murray and Chu presented a heuristic for the route determination and assignment process for the FSTSP problem [10]. They used single drone and single truck to serve 10 customer locations. For the task assignment process, the problem is first solved like the TSP solution and the customers are assigned to the truck. The heuristic determines the customers to be served by the drone and removes them from the truck route. By comparing the cost of assigning a customer location to a truck or a drone, the appropriate assignment is implemented. Ha *et al.* tried to minimize the total operating costs considering waiting costs in the routing problem solved [22]. As an extension of Murray and Chu [10], they developed a hybrid heuristic consisting of GRASP and local search. Kitjacharoenchai *et al.* proposed an Adaptive Insertion Heuristic (ADI) algorithm for solving the mTSPD problem [88].

3.6.2. Metaheuristic

Metaheuristic algorithms provide general and high-level methods for solving complex optimization problems. These algorithms aim to find high-quality solutions that balance multiple objectives and constraints using population-based search strategies, adaptive mechanisms and intelligent exploration strategies. There are the following differences in the selection of metaheuristic optimization algorithms for drone truck collaborative routing problems:

(i) *Problem-specific adaptations*: Metaheuristic optimization algorithms can be specially designed for routing problems. For example, some algorithms can be specifically designed to reduce the length or cost of routes.
(ii) *Search strategy*: Metaheuristic optimization algorithms can use different search strategies in routing problems. These strategies help to explore different parts of the solution space. For example, a tabu search algorithm generates new solutions by ignoring solutions that have been examined in the past. This ensures that the algorithm does not get stuck with the same solutions. However, there are also near-neighborhood search strategies (exploitation) to explore solutions that are close to the current solution and far-neighborhood (exploration) search strategies to explore solutions that are far from the current solution. In order to improve the solution performance of the metaheuristic algorithm, it is necessary to effectively balance exploration and exploitation. For example, a FDB guidance selection mechanism has been developed for the selection of solution candidates to achieve the balance between exploration and exploitation.
(iii) *Control parameters*: Metaheuristic optimization algorithms can use different control parameters in routing problems. These parameters affect the behavior of the algorithm. For example, in genetic algorithms, parameters such as chromosome length and mutation rate affect the performance of the algorithm.

The main metaheuristics used in the literature are Genetic Algorithm (GA), Artificial Bee Colony algorithm (ABC), Ant Colony Optimization algorithm (ACO), Simulated Annealing algorithm (SA), Tabu Search (TS) and others. Figure 7b shows the distribution of the number of uses of these solution methods among the 25 references. The most preferred metaheuristic algorithm for solving the drone-truck routing problem is GA with 15 reference studies.

3.6.3. Exact

Exact algorithms are algorithms that guarantee the solution of a problem. Exact-solution algorithms for drone truck routing problems try to find the best solution by considering all possible solutions to the problem. These algorithms can require a lot of time and memory depending on the dimension of the problem. Exact solution algorithms are also used in the solution of drone-truck collaborative problems. Studies conducted with exact solution methods use fewer test instances compared to other solution methods. The use of exact solution methods for a prior understanding of the problem has become very important. Bouman *et al.* is the

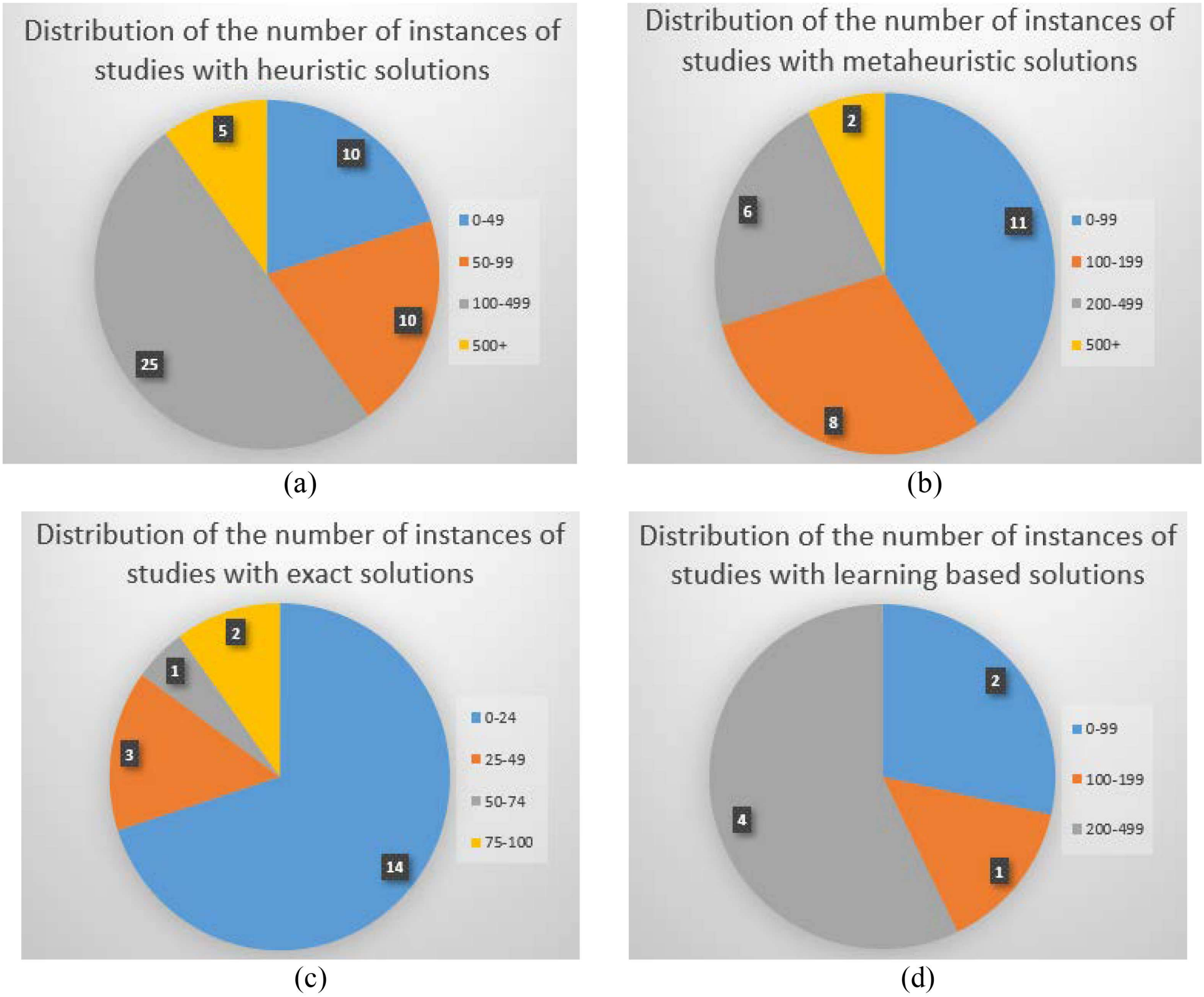

FIGURE 8. (a) distribution of the number of instances of studies with metaheuristic solutions, (b) distribution of the number of instances of studies with heuristic solutions, (c) distribution of the number of instances of studies with exact solutions, (d) distribution of the number of instances of studies with learning based solutions.

first study that solves problems with up to 20 customers with the exact solution approach [21]. They used a three-pass dynamic method to solve the VRPD problem. The fact that problems solved by commercial solvers (Gurobi and CPLEX) take a long time and have been effective in developing exact solution methods. Wang and Sheu developed a branch-and-price algorithm with multiple drones and trucks [39]. Their algorithm minimized the objective function value faster than the Gurobi solver. Figure 8c shows the distribution of exact solution approaches used in the reviewed publications. According to Figure 8c, among the exact solution approaches, branch and cut is one of the more frequently used methods. Figure 8 shows the distribution of the number of instances considered in the analyzed studies according to the solution methods.

When the four different solution approaches given in Figure 8 are analyzed, the number of instances considered in the algorithms with exact solutions in Figure 8c is considerably lower than the other solutions. In Figure 8c, 70% of the studies using the exact solution approach considered 0–24 instances. In the study with the largest number of instances, the number of instances is in the range of 75–100. Exact solution algorithms work by considering all possible solutions to the problem, so small-sized instances are used. As the size of the problem increases, the running time and memory requirements of exact solution algorithms increase. Therefore, as the problem dimension increases, heuristic, metaheuristic or learning based solution approaches should be used.

3.6.4. Learning based approaches

Learning-based routing is one of several approaches used to solve routing problems, such as heuristic, exact and metaheuristic algorithms. These approaches are a new and exciting way to tackle routing problems, leveraging the power of machine learning and artificial intelligence. These methods go beyond traditional mathematical optimization algorithms and offer advantages in handling complex scenarios and adapting to dynamic environments [152].

Supervised Learning: Models learn from established successful routes, utilizing training data to predict optimal or near-optimal solutions for new problems. This methodology depends on thoughtfully crafted features that encapsulate pertinent information about the problem and its surrounding context. Commonly employed techniques include neural networks, decision trees, and support vector machines. Ermağan *et al.* created a learning-based algorithm to solve the drone routing problem [153]. The learning-based algorithm with a heuristic algorithm called Learning and Flying (L&F) yielded solutions with an average optimality gap of around 5% for instances tested up to 40 nodes.

Reinforcement Learning: Recently, reinforcement learning has received increasing attention for solving routing problems. This approach provides a more intuitive and adaptive learning process as the algorithm learns and adapts to different scenarios without relying on clear rules or predefined comprehensive models. The algorithm can effectively route and optimize vehicle movements in complex road networks by utilizing the power of reinforcement learning, resulting in better performance and more efficient decision making [47]. Beginning with Bello *et al.* [154] who used pointer networks to solve the TSP, learning-based solution methods have given comparable results with heuristic optimization algorithms. Khalil *et al.* used the DQN algorithm to solve the combinatorial optimization problem, including the TSP [155]. Many studies have commonly adopted the encoder-decoder structure to directly learn routing policies. In this approach, the encoder, a neural network, is tasked with learning the graph representation based on a given input. The encoder's output is then fed into the decoder, another neural network, which focuses on learning the routing policy considering the current state of the graph. Various neural network architectures, such as fully attention-based models and LSTM-based models, have been proposed for both the encoder and decoder components [156]. The attention mechanism, a technique that seeks critical relationships between inputs or between inputs and outputs, is employed for enhanced performance. In contrast, LSTM, a type of recurrent neural network, is specifically designed to capture both long and short-term dependencies within sequential data. Research conducted by Nazari *et al.* [157], and Kool *et al.* [158] has highlighted the effectiveness of end-to-end learning, where machine learning methods alone are applied, in addressing routing problems. Specifically, Kool *et al.* [158] show cased the superiority of the attention model, which utilizes multiple layers of multi-head attention to grasp node representations. This outperformance was noted in comparison to previous models, including the one by Nazari *et al.* [157], which employed a simpler representation model consisting of a single layer of single-head attention.

Zhang *et al.* routed a fleet of homogeneous vehicles using a multi-agent model with a reinforcement learning approach [159]. Bogyrbayeva *et al.* focused on routing using a single-agent model [160]. Bogyrbayeva *et al.* focus on developing an end-to-end model for TSP-D, which can provide a basis for integrated and iterative methods as well [161]. Arishi *et al.* proposed a two-stage machine learning approach, namely clustering and routing, to solve the parking lot and traveling salesman problem with homogeneous drones (PLTSPHD) [2]. In the first stage, a constrained k-means clustering algorithm is proposed to cluster delivery locations based on the maximum flight range and the number of drones available per truck. In the second stage, a deep reinforcement learning model is developed to find the optimal route among all constrained clusters.

Table 3 presents a comparison of the heuristic, metaheuristic, exact and learning based solution methods according to certain features.

Table 3. Comparison of approaches to solving optimization problems.

Feature	Heuristic	Metaheuristic	Exact	Learning based
Solution Quality	Can produce very efficient solutions	May be less efficient	Guarantees the optimal solution	Can be both efficient and fast
Dynamic Adaptability	Can adapt well to dynamic environments	May not adapt as well	Adaptability is limited	Can adapt well to dynamic environments
Complexity	Can be more complex to develop and implement	Relatively simple	Can be very complex	Less complex than exact algorithms
Speed	Can be slower to train but fast to execute	Often very fast	Can be very slow	Can be fast or slow depending on the algorithm
Computational Resources	May require significant training data and resources	Require less computational resources	Require significant computational resources	Require less computational resources than exact algorithms

4. Discussion and research perspectives

This section identifies future research directions based on the publications reviewed. Issues such as uncertainties, limitations and environmental expectations in the reviewed publications are discussed.

4.1. Uncertainties

The uncertainties in road and air networks is a challenge to the execution of operational tasks. On the road, natural disasters (such as accidents, hurricanes, floods and storms) and human disruptions (such as traffic accidents, protests, political conflicts) can occur. In air traffic, factors such as rainfall, fog, storms, wind and extreme temperatures can negatively play a role. The flight of UAV is seriously affected by these negative factors. In particular, these factors can cause changes in the flight speed, battery consumption and flight range of the UAV.

Safety and security are very important in drone flight. Negative factors affecting the airway may jeopardize drone flight safety and security. The emergence of these negatives will also negatively affect the drone-truck tandem operational activities. Synchronization between the two types of vehicles will become challenging. Considering the package delivery operation, once the drone is launched to deliver, it moves to the predetermined location to meet the truck. In the meantime, negative factors that occur on the airway or road will prevent these vehicles from reaching the predetermined locations and will negatively affect the optimization process. During the drone-truck rendezvous, it is likely that the truck will wait for the drone in case of disruptions caused in the airway, or the drone will wait for the truck longer than expected in case of disruptions caused in the roadway. This uncertainty has not been sufficiently investigated in the reviewed literature. It is thought that the research will be examined in more depth in the near future. The application of powerful optimization techniques in addition to artificial intelligence and data mining to handle uncertainties will eliminate these uncertainties in drone-truck collaborative operations.

4.2. Modeling and development of solution methods

Drone-truck routing problems, which are known to be NP-hard, are usually formulated with ILP, MIP or MILP. As the problem complexity increases, the optimization process of that problem becomes more challenging. As a result of the review, it is seen that although small-dimensional drone-truck cooperative routing problems can be solved with exact solution methods, large-sized problems cannot be solved successfully. It is essential to develop heuristic, metaheuristic, or learning based methods, especially for large-sized instances. Murray and Chu formulated the FSTSP and provided optimization with a heuristic algorithm [10]. Although many heuristic, metaheuristic, or learning based algorithms have been developed since then, there is still much opportunity for new, efficient algorithms to be introduced to the literature to respond to the changing world problems.

There is a need for more research on metaheuristic solution approaches with high stability and fast search in high-dimensional search space for current drone-truck collaborative problems with high complexity. Therefore, new methods related to the design of metaheuristic optimization algorithms are applied. New mutation operators and new guidance mechanisms are introduced to improve the performance of metaheuristic algorithms [162–166]. In addition to metaheuristic optimization algorithms, learning-based approaches have been used to solve drone-truck collaborative routing problems. Learning-based solution approaches can be an effective method for solving drone-truck collaborative routing problems. However, in order for these approaches to be effective, sufficient amount and quality of data is needed. Therefore, investigating the data requirements of different learning-based algorithms for these problems could be a research topic. This research could reveal which learning-based algorithms require less data for certain routing problems.

Although there are combinations of different numbers of drones and trucks in the publications reviewed, the number of studies with a single drone and a single truck is higher than the others. Considering real-world standards, it is predicted that studies with multiple drones and multiple trucks will be more necessary. Using simulation studies to determine the appropriate number of drone and truck combinations for real-world scenarios can be an effective research direction. Thus, studies can be conducted by comparing the results of different combinations in a shorter period of time with the simulations.

Technological advances, such as improved computing capacity, big data analytics, artificial intelligence and machine learning, allow multi-objective optimization problems to be solved more efficiently. Research conducted on multi-objective routing optimization problems indicates that progress in this field is rapidly continuing. The pareto approach, which is widely used in multi-objective optimization problems, is one of the most frequently studied topics in recent years [53, 149, 167, 168]. It is seen as a research direction that the studies on the pareto approach are carried out on drone-truck collaborative routing problems. Thus, this points to its potential contribution to solving multi-objective route optimization problems more efficiently.

Table 2 shows that although drone-truck collaborative routing is mostly used in transportation and logistics for package delivery to customers, in recent years it has also been applied in agriculture for routing in spraying, fertilization and paving operations. As described in Section 3.2.5 Agriculture, in the agriculture application area, there is a complex routing problem. To overcome this complexity, the application of the solution approaches mentioned above to this application area is an important research topic for researchers.

4.3. Dynamic truck-drone collaboration

The concept of dynamic truck-drone collaboration represents an emerging trend in logistics, offering the potential to significantly increase operational efficiency. In traditional truck-drone routing problems, routes are planned in advance, and the roles of trucks and drones are well defined. However, dynamic systems introduce real-time adaptability, where trucks and drones continuously interact to adapt to changing conditions and customer demands.

Dynamic Resupply Systems: One of the most innovative developments in this area is the use of drones for resupplying trucks, allowing for dynamic, mid-operation resource management. In these systems, trucks typically deliver parcels to customers, while drones either deliver smaller packages or assist in resupplying trucks from a central depot. This structure allows the trucks to remain in the field longer, as they are not required to return to the depot for refueling, loading, or unloading. This model is particularly useful for high-density urban areas where traffic congestion can cause delays. Remote or rural regions where distances between customers are large, and frequent depot returns would reduce efficiency.

Dynamic integration of new customers: Unlike static delivery systems, where customer locations are predetermined, dynamic truck-drone collaboration allows for adaptive routing where new customer requests are integrated during the operation. This is possible by real-time data collection and route optimization algorithms that continuously update the delivery routes based on incoming customer orders. The drone and truck can communicate their location and availability to ensure optimal scheduling of tasks.

The benefits of dynamic customer integration are: (i) Trucks no longer need to follow fixed routes, but can deviate to serve new customers, improving response time and resource utilisation. (ii) Drones can perform last-mile delivery while trucks continue to deliver to other customers, making it possible to serve more customers in a single operation. (iii) Because drones can perform short-distance deliveries from trucks to customers, the need for additional truck mileage is reduced, saving fuel and labour costs.

Real-Time Decision-Making: Dynamic systems rely on real-time decision-making powered by artificial intelligence and machine learning algorithms. These systems process data on-the-go, analyzing. Machine learning algorithms help continuously optimize routes, suggesting the best path for the truck and deciding when and where the drone should rendezvous with the truck or deliver to the customer. These decisions are made in real time to ensure the most efficient use of resources.

Dynamic Truck-Drone Collaboration in Agriculture: In precision agriculture, dynamic truck-drone collaboration could revolutionize operations. Drones could monitor fields in real time, delivering data back to a truck acting as a mobile base. The truck could carry the necessary equipment or pesticides for the drone, while the drone performs aerial spraying and returns for refueling or refilling.

Real-time adaptation in agriculture can be achieved by: (i) As drones survey a field, they may detect sections that require more intensive treatment. The truck can adjust its location dynamically, allowing the drone to make multiple refills without traveling long distances. (ii) Instead of refueling and refilling at fixed points, dynamic systems would adjust truck locations based on drone usage patterns, reducing downtime and maximizing efficiency.

The dynamic truck-drone collaboration model provides flexible and scalable solutions across various industries. Whether in logistics, agriculture or emergency response, its capacity to adjust routes, incorporate real-time data, and facilitate mutual resupply operations enhances its adaptability and effectiveness. However, the success of such systems depends on the development of advanced synchronization algorithms and decision-making models to address challenges such as real-time coordination and adaptability in rapidly changing environments.

Future research should broaden the focus of dynamic systems by exploring their application in a wider range of sectors. This will not only demonstrate the versatility of these models, but also offer valuable insight for industries aiming to enhance efficiency through real-time decision-making and optimization strategies.

4.4. Others

The number of drones is very important when conducting drone-truck cooperative operations. In studies involving a fleet of drones, whether the characteristics of the drones (carrying capacity and flight distance, etc.) are the same or not has a significant impact on the optimization process. When considering the spraying of a truck-assisted drone fleet in agriculture, the different characteristics of the drones will cause the amount of pesticide to be carried by the drones and the flight endurance to be different [4]. When drone-truck cooperation for delivery in logistics, health or military is considered, it is necessary to distribute parcels according to the payload capacity of the drones. Thus, it will ensure the effective usage of existing drones [62, 82, 89, 98].

As a result of the review of publications, constraints such as drone battery constraints and payload capacity were mostly considered when developing models. Very few studies have considered the drones to pick up parcels from customers [35, 56, 60, 94, 103]. Presenting studies that meet real-world expectations to a greater extent in the future will be highly effective.

Operational decisions can be effective in reducing transportation costs, transportation time, the greenhouse effect and improving the environment [169–172]. From the reviewed publications, it is seen that sustainable objectives are not addressed except for the reduction of energy consumed or CO2 emissions. Although the inclusion of drones in routing operations is more environmentally friendly than traditional methods, there is still room for future research in utilizing them for sustainable objectives such as controlling environmental conditions or collecting waste and debris from the surroundings.

The cooperation between drones and trucks in agriculture will prevent irregular spraying. It is important to carry out appropriate spraying after identifying diseased sub-fields in agricultural fields. Thus, both unnecessary pesticides are not applied to the environment and crop productivity is quite high. For these reasons, it is foreseen that truck-assisted drones will be frequently studied on spraying operations in the future.

5. Conclusions

This paper presents a review of the characteristics, research trends and recent developments related to routing problems using drones and trucks. For this purpose, 108 recent publications in the literature are reviewed in detail. The two basic models TSP-D and VRPD used in the publications are given in detail in 3.1 Base Models and extended with different constraints. The relevant publications reviewed in this paper are classified based on the optimization objective function, the constraints used, the solution method of the problem, the inclusion or exclusion of the mathematical model, and application area in the literature, as given in Table 2. A review of drone-truck collaboration studies is presented in Section 3 under subsections. These are:

(1) *Scope of applications*: The application areas of the problems are transportation and logistics, where parcel delivery is provided to customer locations, healthcare, military and emergency operations and agriculture, where operations such as spraying, fertilization and monitoring are carried out. In this section, it is explained in detail that operations in the agricultural area are more complex than in other areas.
(2) *Number of drone-truck*: The number of drones and trucks are among the parameters that cause different difficulties in solving the problem. While examining the studies, 4 different classifications were introduced according to the number of drones and trucks used. Thus, it is seen that the optimization process of operational activities with multiple drones and multiple trucks is more challenging than the others.
(3) *Objective functions*: The main objectives of optimization of problems are time and cost. In addition to these, there are also different objective functions. The use of single objective functions and multi-objective functions was also examined in the studies. The objective functions considered in the reviewed publications are presented in Table 2. In addition, the difference of the studies involving multi-objective optimizations from single objective functions is discussed in depth in Section 3.4.2 Multi-objective optimization. Figure 6 shows the approaches used by multi-objective optimizations.
(4) *Drone-truck capacities*: The drone and truck capacities are included in the optimization algorithm as constraint functions. The most commonly used constraints in the studies are the battery energy, the payload capacity, and the flight time of the drone. These are presented in Table 2 and explained in detail in Section 3.5 Drone-truck capacities.
(5) *Solution approaches*: Different solution methods including exact, heuristic, metaheuristic and learning based approaches were used to address the problems. The distribution of the problems in the reviewed publications according to the solution method is given in Figure 7a. The metaheuristics and exact solution methods used in the problems are presented in Figures 7b and 7c, respectively. The comparison of solution approaches in optimization problems according to certain characteristics is presented in Table 3. Table 3 serves as a guideline for researchers trying to optimize drone-truck collaborative problems.

Drones carrying out operational activities together with trucks is very important for increasing efficiency. The development of drone-truck collaborative operations is still in its early stages. Drone-truck collaborative operations are expected to be widely used in many fields, especially in transportation and logistics, healthcare, military, emergency and smart agriculture applications.

In conclusion, strengthening studies with real-world data will make a valuable contribution to industry and academia. In this respect, this paper is seen as an important reference for new studies to be put forward by researchers in the future.

Conflicts of interest

The authors declare no conflict of interest.

Data availability statement

The research data associated with this article are included in the article.

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