Review

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Keywords: Drones; Trucks; Vehicle routing problem; Survey

Article

A Survey of the Routing Problem for Cooperated Trucks and Drones

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Abstract: The emerging working mode of coordinated trucks and drones has demonstrated significant practical potential in various fields, including logistics and delivery, intelligence surveillance reconnaissance, area monitoring, and patrol. The seamless collaboration between trucks and drones is garnering widespread attention in academia and has emerged as a key technology for achieving efficient and secure transportation. This paper provides a comprehensive and in-depth review of the research status on the routing problem for coordinated trucks and drones, covering aspects such as application background, cooperative modes, configurations, issues have been taken into consideration, and solution methodologies.

Keywords: Drones; Trucks; Vehicle routing problem; Survey

1. Introduction

The drone market has witnessed a notable trend toward the miniaturization of Unmanned Aerial Vehicles (UAVs or drones), with smaller drones emerging as the prevalent models in commercial sectors. Nevertheless, the constraints of these drones become evident when faced with large-scale operations. This scenario unveils a fresh avenue for cooperation between drones and ground vehicles (considered trucks in this paper).

Table 1 illustrates that both the truck and the drone have their respective advantages and limitations. However, their complementary functional characteristics offer clear collaborative benefits. Firstly, the truck acts as a mobile base station for the drone, enhancing its operational scope. Owing to its excellent endurance, the truck can be equipped with mechanisms for drone launch and landing. Secondly, the truck can carry multiple spare batteries or be fitted with charging equipment, enhancing the drone's continuous operational capacity enabling swift battery replacement or recharging. Furthermore, leveraging its substantial payload capacity, the truck can serve as a mobile warehouse, and pre-load necessary materials or packages for the drone's subsequent work. Lastly, the drone's versatility, unconstrained by road conditions, enables it to swiftly and directly access challenging environments or high-risk areas.

Table 1. The comparison of the characteristics between the drone and the truck

Characteristics	Drone	Truck
Payload	Low	High
Endurance	Short	Long
Unit cost	Low	High
Route	Permitted airspace	Along road network

Acknowledging the significant advantages of cooperated trucks and drones, scholars have intensively explored this field, especially following the introduction of the Flying Sidekick Traveling Salesman Problem (*FSTSP*) by Murry and Chu in 2015 [1].

In order to carry out a comprehensive investigation, we employed the keywords "truck drone" and "route planning" on the Web of Science (WOS) platform, searching for publications from 2015 to 2024. Among the 256 articles retrieved, 225 were directly related to the routing challenges with the truck-drone cooperation. The distribution of these studies over the years is depicted in the Figure 1. As can be seen, there has been a notable surge in publications within this domain, with over 120 new papers emerging in 2022 and 2023 alone, constituting half of the total number of articles.

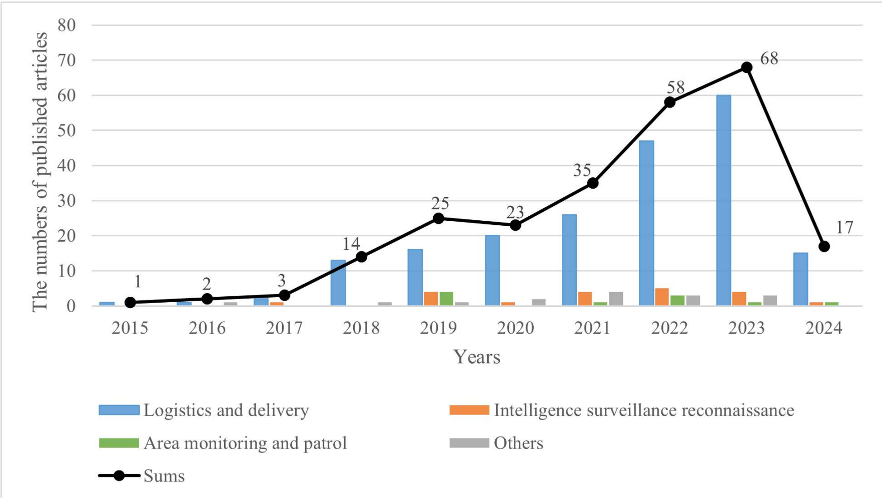

Figure 1. Papers published in the field of routing problems for cooperated trucks and drones before 2024

In this survey, we first categorize the problem context into three main application areas: logistics and delivery, intelligence surveillance and data collection, as well as area monitoring and patrol. This classification helps to clarify the various scenarios where truck-drone teamwork can be utilized.

Considering the variety of application scenarios, the functions performed by trucks and drones in these tasks differ considerably. Based on the unique roles these two vehicles play in the collaboration, the truck-drone cooperation mode can be categorized into four primary types: synchronous operation of truck and drone, independent operation of truck and drone, the truck serving as auxiliary support to the drone, and the drone serving as auxiliary support to the truck. We not only provide a detailed description of these modes, but also conduct an in-depth analysis of the challenges that such collaboration introduces to route planning in each mode.

With the growing exploration of cooperation between trucks and drones, contemporary research extends beyond the analysis of individual vehicles. To assess the impact of vehicle quantity on route planning, we further explore the complexities of route planning across diverse vehicle counts. Specifically, drawing from research conducted over the past two years, we concentrate on three situations in multiple trucks and multiple drones: multiple combinations of single truck and single drone, multiple combinations of single truck and multiple drones, and multiple trucks and multiple drones without predetermined pairings.

Furthermore, current research gives greater consideration to the optimization challenges in real-world scenarios. We therefore perform a thorough analysis of objective functions and constraints, categorizing them as time-related factors, drone performance limits, and operational constraints. By addressing these constraints, we attain a broader understanding of the issues investigated in the majority of the existing literature. Moreover, we have conducted a supplementary review that focuses on dynamic issues, which have received increased attention in the past two years. To our knowledge, this is the inaugural instance where dynamic issues have been included in such a review.

Lastly, we provide an overview of the solution methodologies employed, categorizing them into four types: the exact algorithms, the heuristic algorithms, the metaheuristic algorithms, and other algorithms. For each category, we undertake a systematic analysis and summation, contributing to a deeper understanding of the methodologies available to address these challenges.

In the context of prior research, several reviews have indeed delved into the collaboration between trucks and drones from various perspectives. Nonetheless, it bears mentioning that a substantial

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number of novel studies have surfaced in the last two years. This review provides a thorough examination of existing literature across three key aspects: cooperation modes, problem constraints, and solution methodologies. The distinctions between this review and existing reviews can be summarized as follows:

Khoufi et al. [2] examined the role of drones in assisting trucks through an extension of the *TSP-D* and *VRP-D* problems. However, as drone technology has advanced, there have been some studies highlighting drones' capability to undertake tasks independently.

Chung et al. [3] focused on the drone route planning problem, categorizing it into drone operations (*DO*) and combined drone-truck operations (*DTCO*). In this process, the challenges and constraints encountered in real-world truck-drone collaboration have not been fully explored.

Macrina et al. [4] also discussed the application and challenges of drones in the commercial field, specifically from the angle of drone assistance.

Li et al. [5] summarized the collaborative route planning between trucks and drones from a two-echelon perspective, where the truck route constitutes the first echelon and the drone route the second.

Jazemi et al. [6] focused on the scenario where unmanned devices (robots or drones) aid truck deliveries in last-mile delivery.

It is apparent that the current reviews have neglected a significant portion of research conducted over the past five years, particularly those studies from the last two years, and have not provided a comprehensive summary analysis including more than 200 articles. Furthermore, existing reviews are inadequate in terms of depth and comprehensiveness when it comes to addressing the problem constraints and challenges associated with collaborative route planning for trucks and drones.

To rectify this gap, the present paper embarks on a detailed examination of all literature on truck-drone cooperated route planning in the following sections.

The paper is structured as follows: Section 2 provides a summary of the current background of the application. Section 3 presents the classification of the truck-drone cooperation mode. In Section 4, an analysis of the configurations of trucks and drones involved in the current literature is provided. Section 5 offers an analysis of the problem objectives and constraints considered so far. The algorithms and solution methodologies applied in the literature are presented in Section 6. Finally, some possible existing problems and future research directions are given in Section 7.

2. Application Background

2.1. Logistics and Delivery

As depicted in Figure 1, the field of logistics and delivery exhibits a research focus on the challenges and solutions pertaining to routing problems associated with cooperated trucks and drones. This research hotspot has emerged not only due to the exponential growth of e-commerce in recent years, but also as a response to the escalating demands for efficient, cost-effective, and environmentally friendly logistics systems [7–9]. Moreover, this emphasis is driven by the intricate and practical characteristics inherent in this collaborative mode concerning payload capacity, coordination mechanisms, and path planning. The cooperated trucks and drones in logistics and delivery mainly applied in the following scenarios:

(1) **Last-mile delivery** [10–18]: The last-mile delivery, serving as a crucial link in the logistics and delivery chain, is often hindered by traffic congestion [19–22] and inconvenient transportation in remote areas [23,24]. However, the integration of truck-drone application can effectively address the limitations faced by traditional delivery trucks at present: drones can take off from trucks and directly deliver parcels to customers, circumventing various obstacles encountered during ground transportation while enhancing timeliness and accuracy of deliveries [25].

(2) **Emergency supply delivery** [26–35]: The collaborative integration of trucks and drones demonstrates unparalleled advantages in supply delivery for natural disasters and medical emergencies. The

ground truck enables swift transportation of emergency supplies to the vicinity of disaster areas, while the drone overcomes terrain and road restrictions to accurately deliver supplies to affected regions.

(3) **Takeout and food delivery** [36–40]: With the advancement of the takeout and retail industry, there is a growing demand for timely delivery, and the utilization of cooperated trucks and drones can enhance operational efficiency, ensuring food freshness and customer satisfaction [41]. Moreover, cooperative operations facilitate expedited and accurate delivery processes that align with the pursuit of prompt service in contemporary urban lifestyles.

2.2. Intelligence Surveillance Reconnaissance and Data Collection

The coordinated utilization of trucks and drones has demonstrated advantages in intelligence surveillance, reconnaissance, and data collection. In this operational mode, the truck remains stationed in a secure and accessible area while deploying the drone to conduct reconnaissance in inaccessible or hazardous regions, thereby reducing potential risks associated with direct human exposure [42–44]. Moreover, the drone can access areas where traffic is obstructed due to natural disasters for real-time exploration [45–49]. Simultaneously, the truck serves as a mobile base station from which the drone can take off and land to extend its effective reconnaissance radius [50,51]. Additionally, the direct communication distance between the drone and truck ensures stable and efficient transmission of reconnaissance information for real-time processing and analysis.

2.3. Area Monitoring and Patrol

Compared to intelligence reconnaissance, the cooperative application in area monitoring and security patrol places greater emphasis on achieving comprehensive coverage of specific areas. Typical examples are agricultural vegetation monitoring [52,53] and pesticide spraying [54], where a drone equipped with a high-definition camera is utilized for real-time monitoring of vegetation growth and environmental changes, while a truck serves as a mobile platform for the drone to replace batteries or sensors. Another similar scenario involves fire monitoring in forest areas [55]. Through collaboration, this approach effectively ensures comprehensive coverage of mountainous forest regions and enables timely detection and mitigation of potential fire hazards.

Additionally, this mode has also been implemented for road traffic monitoring and high-voltage power line inspection. In the field of transportation [56–60], drones are immune to traffic congestion, enabling real-time transmission of road traffic conditions and providing a foundation for decision-making in traffic management departments. In the realm of high-voltage power line inspection [61], drone utilization can reduce personnel workload and security risks while ensuring the safe and stable operation of the power system.

3. Cooperative Modes of Trucks and Drones

The cooperative mode of trucks and drones not only directly impacts the operational efficiency of the system but also influences the complexity associated with solving routing problems [3]. These cooperative modes can be categorized into four types: synchronous operation of truck and drone, independent operation of truck and drone, the truck serving as auxiliary support to the drone and the drone serving as auxiliary support to the truck. Figure 2 illustrates these four modes involving one truck and one or two drones.

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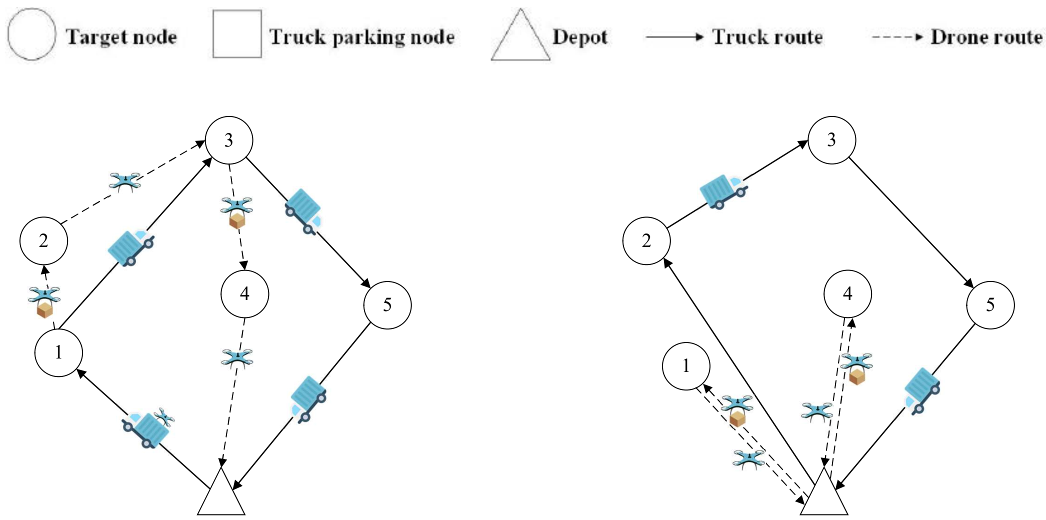
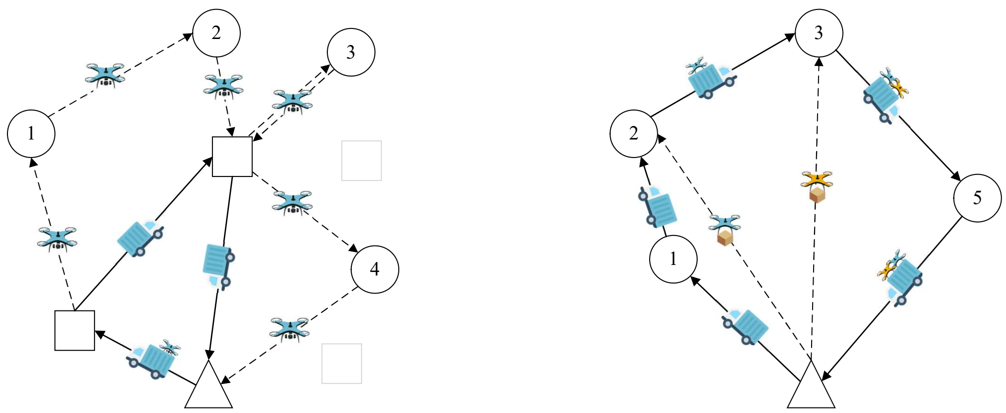


(a) Truck and drone work synchronously

(b) Truck and drone work independently



(c) Truck serving as auxiliary support to the drone

(d) Drone serving as auxiliary support to the truck

Figure 2. Four cooperative modes of trucks and drones

3.1. Synchronous Operation of Truck and Drone

The synchronous operation of truck and drone enables them to independently perform their main tasks along intersecting routes, facilitating spatio-temporal cooperation. As illustrated in Figure 2(a), the drone departs from the truck at a customer node or the depot, flies to other customer nodes, and returns to the truck for recharging or battery replacement in preparation for subsequent flights. Simultaneously, the truck serves other customer nodes synchronously but must reach intersection nodes before the battery depletes in order to retrieve the drone. Currently, only one paper [60] discusses this synchronous operational mode and considers scenarios where both truck and drone can patrol and scout target road segments while proposing an effective solution for arc routing problems encountered during truck-drone collaboration.

3.2. Independent Operation of Truck and Drone

The drone, although more flexible, has limitations in terms of endurance and payload capacity, which makes it challenging to cover all service areas. On the contrary, trucks have a stronger capacity but lower delivery efficiency. By combining these two vehicles, overall efficiency can be improved when working independently.

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As depicted in Figure 2(b), the truck and the drone commence their missions from the base station, independently visiting customer nodes without intersecting each other's routes. Subsequent studies extend this scenario to encompass parallel deliveries involving multiple trucks and drones [62–64]. Furthermore, some researchers suggest utilizing drones for supplementary delivery in specific scenarios where trucks face limitations. Lee et al. [41] propose a strategy wherein the truck delivers ordinary food while the drone simultaneously delivers perishable items to ensure high delivery efficiency. Besides, drones are also utilized for prompt response to dynamic customer demands, providing instant delivery services [35,38,65,66]. Additionally, Momeni et al. utilize drones to access different levels of tall buildings in order to reduce delivery time [67].

3.3. The Truck Serving as Auxiliary Support to the Drone

The limited capacity and endurance often hinder drones from independently completing tasks in long distances or complex environments in practical applications. To address this issue, some studies propose utilizing trucks as mobile base stations for drone takeoff and landing.

Figure 2(c) illustrates the target nodes that need to be visited by the drone and the parking nodes designated for the truck. On one hand, the drone is capable of accessing road-free areas or reaching high elevations of tall buildings [17,22,52,53,68]. On the other hand, by transporting the drone in close proximity to the target node, the truck can minimize its energy consumption during flight and extend its operational range [47,69]. Additionally, serving as a mobile base station, the truck can also replenish packages for the drone [30,54].

Besides, the payload of the drone usually remains fixed during reconnaissance and patrol missions. As a result, many studies allow the drone to visit multiple target nodes or arcs within a single flight route [50,61,70]. Moreover, in scenarios where parking nodes are limited, some researchers propose that the truck can wait while the drone performs its tasks [45,50,71–74]. Alternatively, certain strategies explore the possibility of multiple take-offs and landings at a single node by the drone [73,75].

3.4. The Drone Serving as Auxiliary Support to the Truck

The truck is deemed to be assisted by drones in two primary scenarios. The first scenario involves utilizing drones to provide replenishment support for the truck. As depicted in Figure 2(d), considering potential delays in customer deliveries [76] or the limited payload capacity of the truck [77], the truck can proactively deliver packages to certain customer nodes using drones. Similarly, Dayarian et al. address emerging customer demands during truck deliveries by utilizing drones for timely replenishment [39]. Another situation arises when the truck must adhere to a predetermined route and is considered as the primary vehicle due to its high priority [15,78]. In such cases, drones are utilized to visit customer nodes located outside of the fixed route.

4. Configurations of Trucks and Drones

The configurations of trucks and drones can be categorized into five types, as illustrated in Figure 3. For the sake of clarity, we denote the truck as T and the drone as D. These five types are: single truck and single drone (*1T1D*), single truck and multiple drones (*1TmD*), multiple combinations of single truck and single drone ($m\times$(*1T1D*)), multiple combinations of single truck and multiple drones ($n\times$(*1TmD*)), and finally, multiple trucks with multiple drones (*mTnD*).

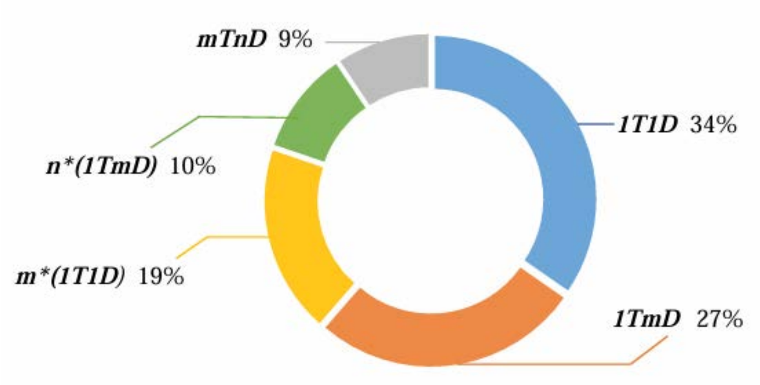

Figure 3. The distribution diagram of the configurations of trucks and drones

4.1. Single Truck and Single Drone

The current research in the field of routing problem for cooperated trucks and drones primarily focuses on the single truck and single drone mode, which is considered as the basic scenario. Some researchers attempt to extend this routing problem from the traditional Traveling Salesman Problem (*TSP*). In line with the cooperative mode of trucks and drones, Murray and Chu propose a variant called the Flying Sidekick Traveling Salesman Problem (*FSTSP*), where one truck carries one drone starting from and returning to the depot after serving all customers [1]. The drone has flexibility to detach from the truck at any truck node, but it must return to another designated truck node after serving each customer. The optimization objective of *FSTSP* aims to minimize the total time required for serving all customers.

Meanwhile, Aagatz et al. introduce the Traveling Salesman Problem with Drone (*TSP-D*) [79]. Unlike the *FSTSP* problem, *TSP-D* emphasizes the auxiliary role of the drone: it is not allowed to make independent deliveries without utilizing the truck. Additionally, in *TSP-D* problem, the truck remains stationary and waits while the drone carries out deliveries. Building upon the assumptions of *FSTSP* problem, researchers define a variant of *TSP-D* problem aiming to minimize the operational cost of the entire delivery system and name it min-cost Traveling Salesman Problem with a drone (min-cost *TSP-D*) [80].

In addition to the challenges arising from the *TSP* problem, there are certain issues that stem from the specific characteristics of truck-drone mode routing. In this mode, the primary routing is established for trucks in the first stage, while secondary routing is assigned to drones in the second stage [45,70,81,82]. This type of problem is referred to as a two-stage routing problem.

Besides, considering the potential complexities in practical applications, researchers expand the *1T1D* mode by taking into account various possibilities. For instance, they address challenges such as the multi-stage delivery problem [83] and inventory allocation problem [84], examine the impact of wind direction on drone energy consumption [85], explore strategies for supplying drones to trucks [76,77], investigate methods for automated retrieval of drones by trucks during travel [86], consider uncertainties in truck travel time due to urban traffic congestion [20], study electric vehicle recharging requirements along routes [87,88], and analyze options for charging drones on trucks [89].

4.2. Single Truck and Multiple Drones

The Parallel Drone Scheduling Traveling Salesman Problem (*PDSTSP*) is initially proposed by Murray et al. [1]. In this problem, a truck and multiple drones depart from the same delivery center and return to it after completing their respective delivery tasks. The two types of heterogeneous vehicles only cooperate at the task allocation level, with no overlapping nodes on their routes. To ensure the safe operation of drones, several studies impose constraints such as allowing drones to perform tasks only when the truck is stationary and preventing the truck from traveling to other nodes until all drones are retrieved at the current node [11,14,36,50,51,72,90–93].

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The drones are required to land at an adjacent node after taking off from a truck node, which creates a similar situation [94]. However, the spatial cooperation between the truck and drones is compromised due to the restriction of taking off and landing at the same node. Nevertheless, this approach can still reduce delivery time compared to traditional ground vehicle methods [95].

Additionally, a limited number of studies involve fixed base stations for drones [96–99] or lockers in the delivery system [100]. In the initial stage, the truck visits all the base stations and provides packages that need to be delivered. In the subsequent stage, drones depart from their respective base stations to carry out delivery tasks before returning to their original locations.

Moshref et al. are the first to propose a mode in which multiple drones can take off and land interleaved on a single truck route, presenting a corresponding mixed integer linear programming model [101]. Besides, Murray and Raj focus on the scheduling problem of operation sequence when multiple drones take off and land at the same node, extending the original *FSTSP* problem to the Multiple Flying Sidekick Traveling Salesman Problem (*mFSTSP*) [102]. Subsequently, researchers consider various realistic factors impacting this problem, such as whether to allow drones to land and wait [103], multiple visits by drones [104], variable flight speed of drones [105], and replenishment capability for trucks by drones [106]. Similarly, some researchers extend the *TSP-D* problem to the Traveling salesman problem with multiple Drones (*TSP-mD*).

To fully leverage the potential of drones, several studies propose incorporating additional parking nodes [107–110] or enabling drones to take off from the truck en route [15,54,103,111]. Through theoretical analysis of the *TSP-mD* problem, Morandi et al. [112] demonstrate that allowing the truck to visit certain nodes repeatedly yields significant benefits in reducing overall delivery time.

4.3. Multiple Combinations of Single Truck and Single Drone

Through early exploration and verification of the truck-drone mode, researchers have begun to apply this mode on a larger scale scenario to consider the overall planning and optimization of multiple *1T1D* systems. However, due to limitations in drone technology intelligence level and the need for operational stability, many researchers still focus on single drone carried by a single truck combination, primarily discussing task allocations and routing problems within these *1T1D* systems. This problem is considered as the Vehicle Routing Problem with Drone (*VRP-D*). The *VRP-D* not only focuses on collaborative route optimization between trucks and drones within a system but also optimizes task allocation between different systems from an overall perspective.

The current research has already incorporated multiple truck and drone cooperative systems to collaboratively accomplish delivery or pick-up and delivery tasks [29,37,113–121]. Additionally, one study explores the cooperative delivery with multiple depots [122].

In addition, when the *1T1D* mode fails to meet all customer requirements, effectively utilizing the $m\times$*(1T1D)* mode for delivery has become a focal point of research [68,123–130]. Puglia et al. propose that drones can deposit packages at secure locations specified by customers during delivery to bypass time window constraints [12] . Furthermore, certain studies also consider time-varying factors such as varying truck speeds due to ground traffic congestion [26,131,132], or drone flight speed limitations imposed by weather conditions [133].

In the investigation of the $m\times$*(1T1D)* mode, an increase in the quantity of trucks and drones can result in elevated maintenance and costs. Some studies concentrate on minimizing the overall operational cost, encompassing transportation cost, truck-use cost, parking cost, and other expenses [134], while others aim to optimize both the overall operational cost and completion time concurrently [68,125,135].

4.4. Multiple Combinations of Single Truck and Multiple Drones

The application scenario of the combinations of a single truck and multiple drones, denoted as $n\times$*(1TmD)*, has been explored by some researchers. Considering time windows, several studies

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impose restrictions on the truck to remain stationary while drones perform tasks [136,137], or constrain drones to take off and land at the same node [42,138].

4.5. Multiple Trucks and Multiple Drones

The multiple trucks and drones (*mTnD*) mode described in this section refers to the scenario where $m \neq n$ is allowed, which can be categorized into the following four scenarios:

The first scenario involves the extension of the *PDSTSP* problem, where multiple trucks and drones are concurrently executing tasks in parallel [34,35,40,62–67]. Essentially, this problem pertains to heterogeneous vehicle route planning with a focus on coordinating task allocation among different trucks or drones.

In the second scenario, the interdependence between trucks and drones is disregarded as the drone can opt for landing on other nearby trucks [139–143].

The third scenario encompasses a hybrid setting involving three delivery modes: independent truck, independent drone, and cooperative truck-drone combination [48,117,144,145]. This mode allows either the truck or drone in the cooperative combination to operate autonomously.

The final situation entails utilizing one type of vehicle to support another; for instance utilizing drones to assist in truck deliveries [41] or incorporating drone base stations [146], which enables multiple visits by trucks to provide packages required for drones.

5. The Issues Have been Taken into Consideration

5.1. Objectives

The optimization objectives of the routing problem for cooperated trucks and drones can be primarily categorized into two domains, namely time-related and cost-related objectives, as illustrated in Figure 4.

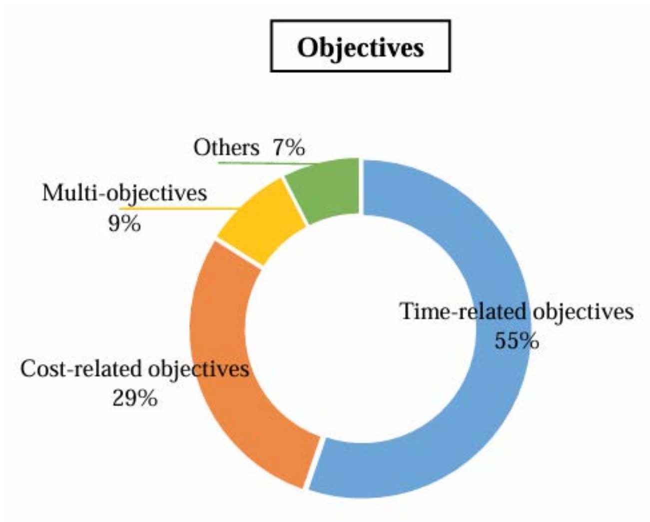

Figure 4. The distribution diagram of objectives

5.1.1. Time-Related Objectives

In the process of collaborative operation between trucks and drones, the drone can perform tasks simultaneously with the truck to reduce the overall completion time. Murray and Chu is the first to propose the *FSTSP* problem to minimize total completion time [1]. Subsequent discussions on routing problems involving one truck and one or more drones also prioritize completion time as the optimization objective. These discussions include the *FSTSP* problem [147–153], the *TSP-D* problem [79,89,154–162], the *mFSTSP* problem [102,105,163–165] and the *TSP-mD* problem [104,108,166,167], etc.

Furthermore, in the context of multiple truck-drone cooperative systems, many studies opt to optimize the longest working time (or makespan) among all vehicles[114,133,168,169]. Additionally, some studies consider the completion time as the sum of working times for all truck-drone systems [125]. Moreover, certain studies designate the departure time of the truck as *T0* and aim to minimize customers' waiting time by reducing the duration from package delivery initiation until all customers receive their packages [92,101].

5.1.2. Cost-Related Objectives

The cost primarily encompasses transportation expenses, fixed truck costs, and operating costs. Specifically, the transportation cost of a truck is typically associated with the distance traveled, while the flight cost of a drone can be calculated based on its flight distance [23,170], flight time (including waiting time)[80], or energy consumption [82,171]. Additionally, some studies consider personnel costs in relation to the working time of truck-drone collaboration from an operational perspective [123]. Furthermore, certain studies treat personnel and maintenance costs as fixed expenses within the truck-drone cooperative system [123,128].

Furthermore, in order to enhance the collaboration between trucks and drones, researchers also incorporate a penalty cost for waiting time to incentivize personnel to work more efficiently and reduce overall costs [80,128,136]. Some studies consider other types of expenses. For instance, Zang et al. propose incorporating parking costs for trucks by allowing them to wait in designated parking lots [134]. Zou et al. introduce lockers into the problem and consider factors such as their location and operating costs [100]. Najy et al., on the other hand, combine the truck-drone mode with inventory routing problems and include warehouse storage costs [84].

5.1.3. Multiple Objectives

During the task execution process, bi-objective optimization problems have started to incorporate task efficiency and cost considerations [55,172–174]. Building upon this, Zhang et al. decompose the cost into completion time, energy consumption of trucks and drones, and operating cost determined by working time [175].

Besides, customer satisfaction is a crucial evaluation metric in the context of delivery. Several studies focus on enhancing customer satisfaction by minimizing waiting time for customers [124,176,177] or maximizing the coverage of served customers [29]. In the green routing problem, optimizing carbon emissions from trucks plays a significant role. Some researchers propose reducing truck utilization or increasing drone utilization to mitigate carbon emissions [8,9,135,178–180].

5.1.4. Other Objectives

In the field of logistics and delivery, researchers primarily focus on maximizing customer node revenue [15,74,181]. Conversely, research in reconnaissance backgrounds tends to prioritize maximizing coverage rates [48] or the information value of target nodes [46]. Similarly, when utilizing cooperated trucks and drones for traffic patrol purposes, minimizing accident probabilities is taken into consideration [57].

Besides, Van et al. consider both the total amount of supplies delivered and the number of nodes visited [34], while Lu et al. aim to balance supply delivery by minimizing the difference in satisfaction rates among demand nodes [133]. When conducting combat missions, Yan et al. opt to minimize equipment damage costs and penalties for unperformed tasks to mitigate vehicle risk [49], whereas Cheng et al. propose maximizing drone retrieval probability in a similar scenario [182].

5.2. Constraints

The constraints associated with time windows in customer nodes, drone performance, and operations are illustrated in Figure 5.

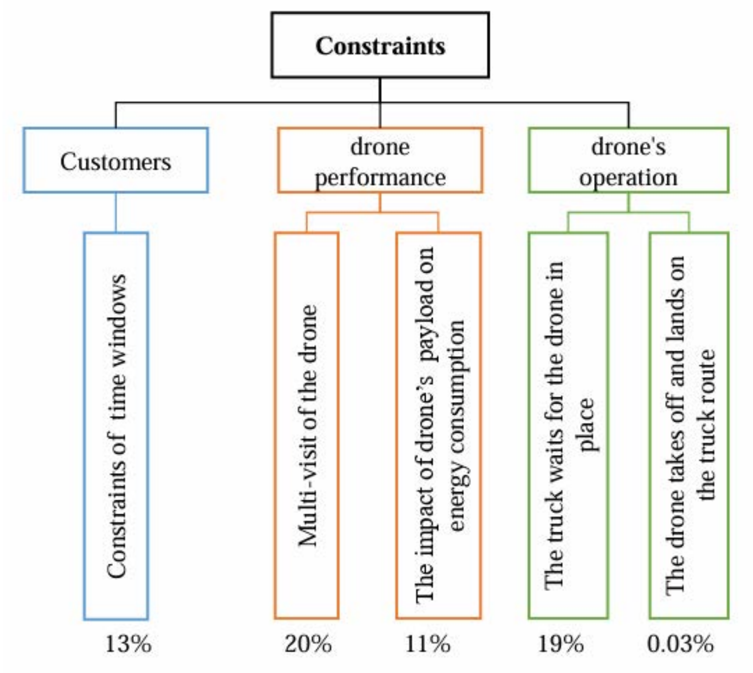

Figure 5. Constraints involved in the literature

5.2.1. Constraint of Time Windows in Customer Nodes

(1) Consideration of time windows when truck and drone are working independently

Based on the *PDSTSP* problem, Ham is the first to propose the routing problem for pick-up and delivery with considering the time windows in customer nodes [65]. Subsequently, Sawadsitang et al. and Van et al. investigate uncertainty factors in the delivery process under the independent operation mode of trucks and drones [34,66].

(2) Consideration of time windows in two-stage delivery

The truck is often required to remain stationary while the drone operates, leading to a collaborative routing problem known as two-stage delivery [136,145,181,183]. Additionally, Chen et al. propose using delivery robots as an alternative to drones [137], where multiple robots can be deployed for simultaneous deliveries once the truck has stopped and can only resume travel after these robots have completed their tasks and returned. Furthermore, Cao et al. introduce the concept of a drone base station [176], where the truck drops off packages along its route for parallel delivery by the drone. It should be noted that the timing of the truck's visit to the drone base station must ensure that the drone can provide services within the customer-specified time window.

(3) Consideration of soft time windows when truck and drone are working synchronously

The time window constraints in the current *VRPTW* problem can be categorized into two types: soft time windows and hard time windows. In problems related to soft time windows, customers are allowed a certain degree of deviation from their desired service time window, but they usually incur corresponding penalty costs. Researchers typically determine the penalty function coefficient based on the priority of different customers. Das et al. construct a *MILP* model for this problem and apply *NSGA-II* to solve the counterpart Multi-objective optimization problem [124].

(4) Consideration of hard time windows when truck and drone are working synchronously

During the synchronous movement, not only should we consider the spatio-temporal cooperation of the two vehicles, but also take into account the additional requirements imposed by hard time windows on route planning from a temporal perspective. This further increases the complexity and difficulty of solving the problem. Some studies relax the constraint of hard time windows. For instance, Puglia et al. propose that packages can be placed in a designated safe location during drone delivery, allowing us to ignore time windows on drone routes [12]. To enable contact-free delivery during

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epidemic periods, Zhang and Li suggest that customers can collect their packages from lockers, thus loosening the service time constraint [130]. Moreover, some studies adjust the mode of truck-drone collaboration, for example, Luo et al. propose that drones can land and wait without considering energy consumption while waiting [177,184]. Additionally, to ensure safe operation of drones, researchers restrict drones to be retrieved at the next truck node after leaving their current truck node [42,126,185]. Furthermore, Xing et al. not only consider time windows but also analyze how travel times in different periods affect delivery efficiency [132]. Kim et al. present a flexible collaborative strategy where drones can land on other trucks for more efficient delivery [143]. It is worth noting that most previous studies assume that drones carry at most one package per flight. However, a small number of researches consider scenarios where drones visit multiple nodes in a single flight [127,129,186]. For example, The study conducted by Amine et al. overlooks the pairing relationship between the drone and truck, yet permits the drone to land on other nearby trucks subsequent to completing the delivery [141].

5.2.2. Constraints of Drone Performance

(1) Multi-visit of the drone

In the reconnaissance mission, research in this field primarily focuses on the multiple visits of the drone, as its payload remains constant throughout the flight [46,48,69,70]. In the domain of logistics and delivery, considering the drone's ability to support multiple customer nodes in a single flight due to its payload capacity and endurance, achieving multiple visits by drones is anticipated for enhancing overall delivery efficiency while leveraging their advantages in terms of operational cost and delivery speed.

(2) The impact of drone's payload on energy consumption

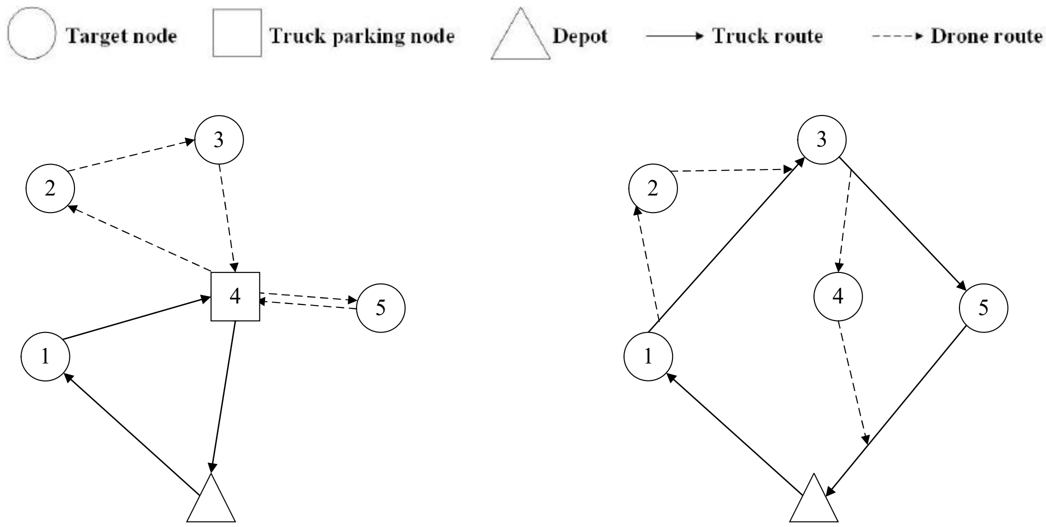
In an actual delivery scenario, the drone is typically fully loaded before departure and empty-loaded upon completion of the delivery when returning to the truck. It is generally assumed that the energy consumption of the drone positively correlates with both flight time and payload during a single visit by the drone [15,71,89,187]. The energy consumption of the drone during a flight can be divided into two stages: firstly, when flying to the customer node while providing delivery service under maximum payload conditions, and secondly, when returning to the landing node without any load and waiting for retrieval by the truck. Building upon this assumption, Raj and Murray extend their analysis on how drone speed impacts energy consumption [105], while Pugliese et al. consider weather factors' influence on drone energy consumption [13].

5.2.3. Constraints of Drone's Operation

To ensure efficient collaboration between vehicles, numerous studies impose restrictions on trucks, requiring them to depart from the current node and maintain synchronization with the drone after releasing it. Additionally, some propose that the truck should wait for the drone at a designated location or allow for automatic takeoff and landing of the drone while the truck is in transit.

(1) The truck waits for the drone in place

As depicted in Figure 6(a), the drone's ability to fly from node 4 to node 5 and return to the base station may be compromised if it is required to take off and land at the same node. In such cases, arranging for a truck to serve node 5 becomes necessary, leading to potential increases in delivery time and cost. Consequently, some researchers propose a mode where the truck remains stationary during the drone's delivery [71,134,188,189]..



(a) The truck stays in place while the drone flies

(b) The drone takes off and lands on truck route

Figure 6. Illustrations of two operations of the drone

Moreover, Moshref et al. propose three distinct operational modes: stationary truck with flying drone, moving truck with flying drone, and a hybrid mode that combines both aforementioned modes [101]. The experimental results demonstrate that the hybrid mode exhibits the highest delivery efficiency and can reduce customer waiting time by over 60% compared to traditional truck delivery methods. Additionally, Coindreau et al. [123] impose a constraint on not allowing the truck to launch and retrieve multiple drones at the same location, while some researchers permit multi-trip capabilities for drones at a single node [97,115].

(2) The drone takes off and lands on the truck route

As illustrated in Figure 6(b), during the truck's traversal of the road network, the drone can autonomously navigate to residential areas for package deliveries [33,103]. This collaborative mode not only expands the drone's service coverage [15,86], but also enhances operational efficiency between vehicles [186]. Researchers design various strategies to achieve this efficient collaborative delivery approach. For instance, Schermer et al. propose a two-stage strategy where the truck route is initially constructed and subsequently synchronized with drone routes [114]. Masone et al. discretize the road network to establish collaborative routes between these vehicle types [190] . Additionally, Thomas et al. first cluster customer nodes and then construct collaborative routes within each cluster [191].

5.3. Dynamic Issues

More and more researchers begin to consider the routing challenges associated with truck-drone systems in dynamic environments. For instance, Sawadsitang et al. present a framework called Joint Ground and Aerial Delivery Service Optimization and Planning (*GADOP*), which formulates the problem as a three-stage stochastic integer programming model that accounts for uncertainty in drone package delivery [66]. Yan et al. propose incorporating task abortion when routes of trucks and drone clusters are subjected to random attacks, aiming to minimize the expected total cost of unvisited targets considering potential destruction of trucks and drones [49]. Long et al. introduce a dynamic truck-drone collaboration strategy for efficient and resilient urban emergency response, with the objective of minimizing total service delay and response completion time [32]. Additionally, Liu et al. consider the impact of traffic congestion or adverse weather conditions on truck speed, extending the *FSTSP* problem by formulating it into a Markov Decision Process (*MDP*) [20].

In addition, Ramos et al. analyze the utilization of drones for medicine delivery and formulate the problem as the Dynamic Parallel Drone Scheduling Vehicle Routing Problem with Lead-Time

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[35]. Chen et al. investigate same-day delivery using trucks and drones, proposing a deep Q-learning approach to determine whether a new customer should be assigned to drones or trucks, or if no service should be offered at all [38]. Dayarian et al. introduce a same-day home delivery system where trucks are replenished by drones whenever they remain stationary and allow drone landing [39].

6. Solution Methodologies

The methodologies to solve the routing problems of cooperated trucks and drones can be primarily classified into four categories: the exact algorithms, the heuristic algorithms, the metaheuristic algorithms, and other algorithms. The distribution of each methodology used in current research is illustrated in Figure 7.

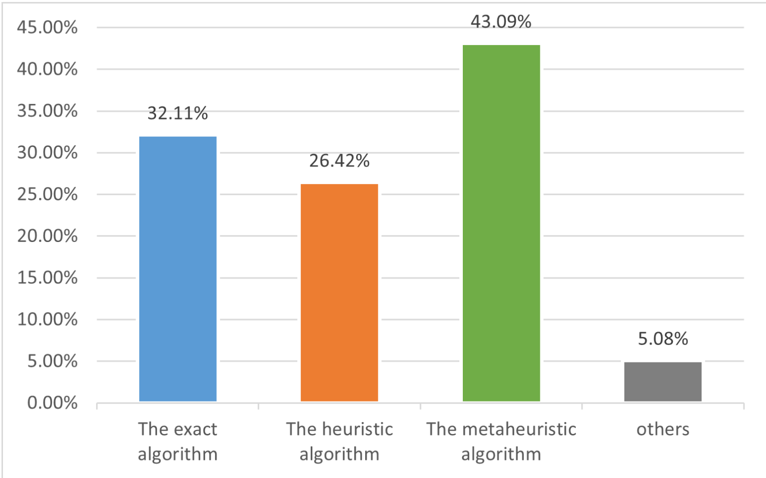

Figure 7. The proportions of methodologies used in the current researches

6.1. The Exact Algorithms

The common modeling approaches for routing problems involving cooperated trucks and drones include Mixed Integer Linear Programming (*MILP*), Mixed Integer Programming (*MIP*), Integer Programming (*IP*) and other models. Figure 8 illustrates the utilization of these different models.

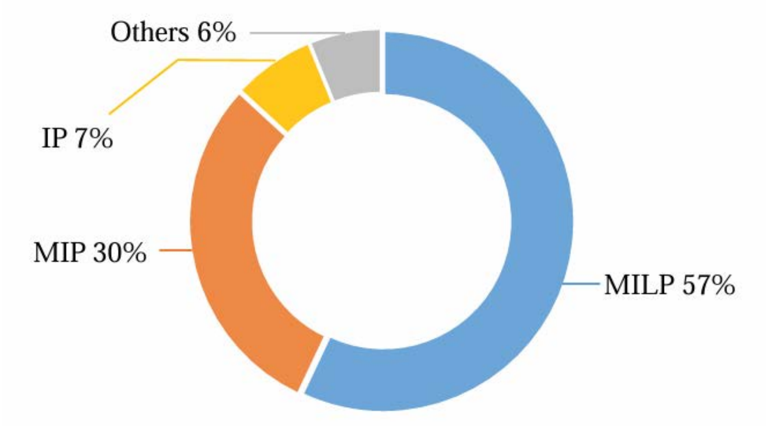

Figure 8. The utilization distribution diagram of the mathematical models

The majority of *MILP* models typically utilize binary decision variables to represent the visitation status of nodes and edges, as well as the mode of visitation. On the other hand, constant decision variables are utilized to depict variations in time, energy consumption, payload, and other unchanging states along the route. The typical problems include the *FSTSP* problem [163,192,193,193,194], the *mFSTSP* problem [102], the *TSP-D* problem [80,160,195], the *TSP-mD*problem[99,104,167,196], the *VRP-*

D problem [114,123,129], the *VRP-mD* problem [125,137,168,197,198], the *PDSTSP* problem [62–64,199], etc., and the aforementioned problems can all be effectively solved by model solvers such as CPLEX and Gurobi. In order to enhance solving efficiency, various branch strategies have been proposed by researchers. such as the branch and cut algorithm [125,163,167,193–196,200,201], the branch and bound algorithm [156], the branch and price algorithm [202], the branch and price and cut algorithm [129,171,203,204], etc. Besides, the dynamic programming algorithm is also applied to solve these problems [77,154,160,205].

When adding additional constraints, such as the multi-visit of the drone [10,54,55,206,207], the impact of the drone's payload on energy consumption [71,187,208], the takeoff and landing of the drone on truck route [33,53,103] or the customer time windows [126,132,186], several studies formulate the *MIP* model. For example, Dukkanci et al. [71] utilize second-order conic programming to linearize a nonlinear model. Additionally, some researchers utilize valid inequalities [159] or the cutting plane algorithm [84,171] to reduce solution space for finding optimal solutions. Moreover, Benders decomposition algorithm is adopted by Kang et al. and Vasquez et al. to decompose problems into main and subproblems in advance [93,161], while Mbiadou et al. decompose the problems into multiple stages using dynamic programming method [62].

The current *IP* model mainly encompasses two scenarios: firstly, the drone's route is simplified as a sequence of truck nodes for takeoff, intermediate drone nodes, and a truck node for landing when the drone is restricted to visiting only one node in a single flight [1,15,28,79,150]. Secondly, the feasibility of the drone route is determined by its flight distance, with the route being limited by the longest flight time of the drone [70]. Moreover, these situations require binary decision variables exclusively in their models. To solve this model, researchers utilize methodologies such as branch and price algorithm [140] and column generation method [150].

Additionally, a limited number of studies explore the Set Covering/Packing model. Among them, Yang et al. utilize the branch and price method to address this problem [108,183,197]. Liu et al. develop a mathematical model based on route sets and designed a branch-based enumeration algorithm for it [82]. Similarly, Mara et al. consider drone routes as sets and construct a subset-based mathematical programming model [164].

6.2. The Heuristic Algorithms

The first type of heuristic algorithm is based on the principle of "the truck before the drone". It begins by constructing an initial truck route to visit all target nodes, and then applies rule-based strategies, such as the maxSavings strategy [1,61,80,148] and the greedy strategy [79,139] to replace some truck nodes with drone nodes. These strategies also encompass exact solutions for subproblems including the dynamic programming method [28,79], branch and bound method [152] and labeling algorithm [46]. Additionally, researchers utilize search algorithms [117,190] to optimize subproblem solutions which have been successfully applied in solving the *VRP-D* problems as well [10,143].

The second type of heuristic algorithm is based on the principle of "the drone before the truck" [52,61,70,81,108]. A route for the drone to visit all target nodes is initially constructed and then incorporates takeoff and landing truck nodes based on endurance and payload constraints. For instance, Kundu et al. utilize the Shortest Path Problem (*SPP*) to determine the placement of takeoff and landing nodes [153]. Furthermore, a similar concept is applied in solving two-stage routing problems [91,97,134]: multiple drone routes covering all target nodes are first established considering optional truck parking nodes, followed by the construction of the truck route according to selected landing and takeoff locations for drones in order to determine their corresponding sequence.

The third type of heuristic algorithm focuses on the strategy of "truck-drone cooperation" and constructs the truck route for visiting a subset of nodes in the initial stage. During this stage, certain papers identify nodes that can only be accessed by the truck based on constraints such as drone payload, and establish the shortest route for the truck to cover these nodes. The remaining nodes are then inserted into either the truck route or drone routes [12,50]. Moreover, some studies approach decision-

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making regarding visiting modes for target nodes from a task allocation perspective, subsequently constructing drone routes based on partial construction of the truck route [102,105,155,168,209,210]. Additionally, iterative solution methods are utilized by some researchers to optimize the problem in stages [31,152,155,211].

6.3. The Metaheuristic Algorithms

The metaheuristic algorithm can be classified into five distinct categories, namely neighborhood search, evolution, swarm intelligence, physics, and human behavior. Figure 9 illustrates the distribution of the categories and the algorithms associated with each category.

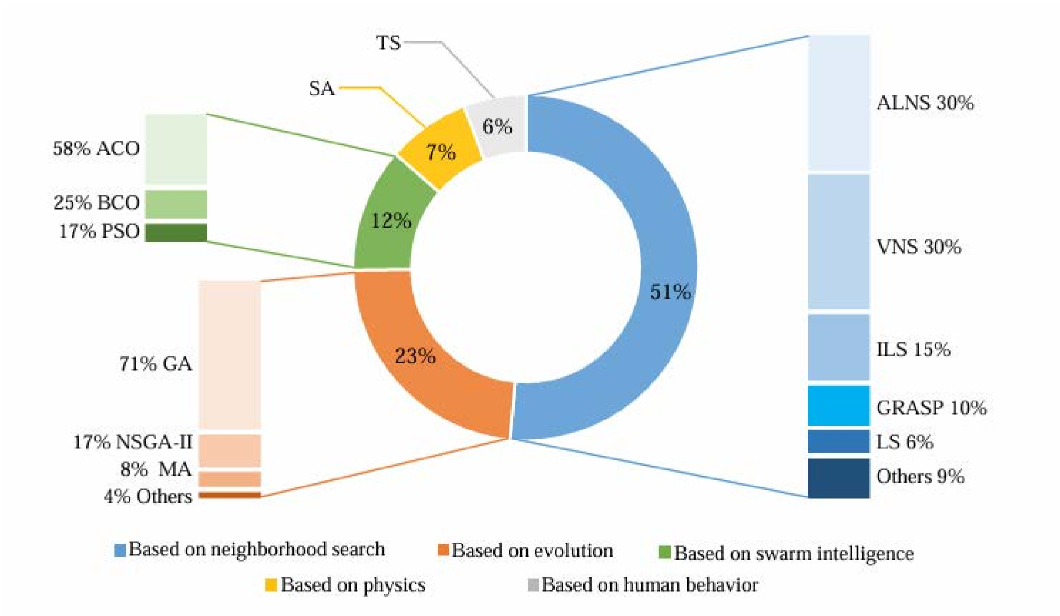

Figure 9. Map of the distribution diagram of the types of metaheuristic algorithms in the literature

(1) Metaheuristic algorithm based on neighborhood search

The Adaptive Large Neighborhood Search (*ALNS*) algorithm and the Variable Neighborhood Search (*VNS*) algorithm are the two most extensively utilized among neighborhood search algorithms.

By utilizing the *VNS* algorithm, the solution space is dynamically explored through the adaptive selection of diverse destroy and repair algorithms, while adjusting the selection probability of operators based on search process outcomes. The destroy and repair operators encompass random deletion, worst deletion, route deletion, greedy insertion, regret insertion and nearest insertion are commonly utilized [19,24,42,43,113,120,137,142,144,164,186,212]. Furthermore, some researchers integrate *GA* into the adaptive framework of *ALNS* to comprehensively explore the solution space [213].

By utilizing the Variable Neighborhood Search (*VNS*) algorithm, an improved solution can be obtained by applying a predefined set of neighborhood operations in different local search spaces around the current solution. The neighborhood operations including 2-opt, two-swap and relocation are commonly utilized[73,147,149,169,214–216]. Due to its effectiveness in finding local optima solutions, some researchers have combined *VNS* with the simulated annealing algorithm to escape from local optima by accepting suboptimal solutions based on certain acceptance criteria within the simulated annealing framework [60,109].

Besides, some researchers utilize the Local Search (*LS*) and the Iterative Local Search (*ILS*) based on heuristic algorithms. In studies considering *ILS* [61,67,69], an initial solution is generated using a constructed heuristic algorithm. Furthermore, the neighborhoods of the current solution are explored to enhance solution quality, while a disturbance factor is incorporated into the *ILS* algorithm to escape local optima during the search process [31,44,62,99,118,131,197,207]. Additionally, some researchers apply *ILS* algorithm to multi-objective problems and design a Pareto neighborhood search algorithm [177].

The Greedy Randomized Adaptive Search Procedure (*GRASP*) algorithm, unlike the *ILS* algorithm, is capable of generating a new feasible solution at the initial stage of each neighborhood search and exploring the current solution's neighborhood by using the *LS* algorithm [80,107,145,217,218].

Furthermore, some studies consider alternative local search algorithms such as large neighborhood search [10,59], destroy and reconstruct methods [63], and set-based neighborhood search algorithms following clustering [219]. These heuristic algorithms based on search criterion enable efficient exploration within the solution space from various perspectives to obtain higher quality solutions quickly.

(2) Metaheuristic algorithm based on evolution

The metaheuristic algorithm based on evolution emulates the biological process of natural selection, generating offspring solutions through genetic and mutation operations on the basis of parent solutions, and selecting superior solutions as parents for subsequent iterations.

The Genetic Algorithm (*GA*) is widely recognized as the most commonly utilized evolutionary algorithm in various domains, including optimization problems related to truck-drone collaboration [8,41,100,103,165,220,221]. In *GA* applications, researchers typically adopt a specific encoding scheme to represent solutions and utilize genetic operations such as selection, crossover, and mutation to explore the solution space. To account for the presence of two types of routes involved in truck-drone collaboration scenarios, some studies incorporate route segments of drones carried by trucks into the coding of drone routes. This approach enables recording multiple take-offs and landings as part of a complete route [133,158]. Furthermore, apart from traditional chromosome encoding methods, matrix-based encodings have also been utilized in certain investigations [184].

For multi-objective optimization problems, the Non-dominated Sorting Genetic Algorithm-II (*NSGA-II*) [130,135,173,175] is commonly utilized. The *NSGA-II* algorithm incorporates crowding-distance calculation and non-dominated sorting mechanisms based on *GA* to achieve a smoother Pareto front during the search process. To further enhance the local search capability of evolutionary algorithms, some studies utilize the Memetic Algorithm (*MA*) [88,110], which combines crossover operators with local search to diversify solutions and improve algorithm's ability for local optimization. Additionally, Blanco et al. propose a multi-agent-based evolutionary algorithm where multiple solutions undergo mutation and genetic operations simultaneously from different directions, leading to an integrated information approach that yields superior solutions [106] .

(3) Metaheuristic algorithms based on swarm intelligence

The principle of the metaheuristic algorithm based on swarm intelligence is to explore for optimal solutions by emulating the behavioral strategies observed in natural swarms. Currently, three main swarm intelligence algorithms are widely applied. Firstly, the Ant Colony Optimization (*ACO*) algorithm simulates ants' path selection and pheromone updating mechanisms during foraging. It marks and transmits high-quality paths as pheromones to guide subsequent search processes towards better directions [27,36,37,115,122,124]. Secondly, the Particle Swarm Optimization (*PSO*) algorithm learns from birds' foraging behavior: a group of evenly distributed particles initializes within the solution space, and their velocities and positions are updated based on individual and group best positions in history to achieve comprehensive exploration and local fine search within the solution space [103,111]. Lastly, the Artificial Bee Colony (*ABC*) algorithm simulates bees' division of labor, cooperation, and information-sharing mechanisms during honey collection [68,116,176].

(4) Metaheuristic algorithm based on physics

The Simulated Annealing (*SA*) algorithm is currently the most widely used physics-based metaheuristic algorithm in solving optimization problems [82,101,141,179,192,222]. By simulating the physical annealing process, this algorithm effectively escapes local optima and discovers global optimal solutions. Furthermore, some studies incorporate the Metropolis criterion into simulated annealing to enhance search diversity [30,109,113].

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(5) Metaheuristic algorithms based on human behavior

The Tabu Search (*TS*) algorithm is rooted in human behavior, utilizing a tabu list to prevent revisiting previously explored solutions. By maintaining and updating this list, it effectively avoids redundant searches and enhances search efficiency [30,32,45,50,92,104]. Similar to the *SA* algorithm, the *TS* algorithm has also been integrated into other algorithms to create more efficient and accurate hybrid approaches [114,162].

6.4. Other Algorithms

Numerous studies have utilized approximate estimation algorithms and machine learning algorithms to address the routing problem for cooperative trucks and drones. For instance, Carlsson and Song demonstrate, through theoretical analysis, that delivery efficiency is directly proportional to the square root of the speed ratio between trucks and drones [223]. Canca et al. utilize a continuous approximation method to tackle the delivery problem in large areas involving cooperated trucks and drones [224]. In recent years, there has been an increasing focus on machine learning algorithms. Liu et al. consider the impact of road traffic congestion on delivery efficiency and utilize a deep reinforcement learning algorithm to predict traffic conditions within the road network [20]. Chen et al. utilize a reinforcement learning algorithm to determine optimal service modes for new customer nodes, enabling rapid response to customer needs [38].

For two-stage delivery problems, some studies apply K-means clustering algorithm for customer node clustering while utilizing reinforcement learning methods separately for constructing truck and drone routes [14,225]. Additionally, certain studies design graph network models based on machine learning techniques by encoding truck-drone cooperative routes into highly connected graph structures, leveraging the topological structure of graphs for solution optimization in complex environments (Wang et al., 2023; Bogyrbayeva et al., 2023; Kong et al., 2023).

7. Conclusions

This paper systematically analyzes and reviews over 200 research articles pertaining to the routing problem involving collaborated trucks and drones from 2015 to 2024. We categorize the application background, specify four categories for the truck-drone collaboration modes, summarize the existing configurations of trucks and drones utilized in current literature, classify the involved problems and provide a summary of existing solution methodologies.

Despite progress, there are still some limitations: firstly, existing research insufficiently addresses customer time window and truck-drone collaboration constraints, hindering practical application. Secondly, overlooking drone performance constraints complicates real-world implementation. Lastly, advancing research necessitates more precise models and algorithms for effective solutions in complex scenarios.

Additionally, we propose several potential directions for further research: Firstly, from the perspective of model construction and algorithm design, developing flexible and practical mathematical models is crucial for improving and innovating existing algorithms, thus enhancing the coordination efficiency between trucks and drones in complex environments. Meanwhile, considering multiple optimization objectives such as truck and drone routing distance, energy consumption, and task completion time, finding the optimal solution can be achieved through multi-objective optimization algorithms. Furthermore, future research should focus on exploring realistic solutions under time window constraints, as time windows are critical factors in delivery services. Besides, researchers can delve into the actual performance limitations of drones and develop more feasible methods, such as considering multiple visiting nodes and the impact of payload on energy consumption during delivery. Secondly, attention should be given to dynamic environment adaptability, studying how to achieve efficient collaborative route planning in dynamic environments. This includes developing algorithms that can update routes in real-time to respond to dynamic obstacles and unforeseen events in the environment, as well as researching adaptive planning strategies that allow trucks and drones to dynamically adjust their routes based on environmental changes. Lastly, from an environmental perspective, future research can expand the collaboration modes between drones and engine-fueled vehicles, including electric vehicles, to reduce pollution emissions.

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