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A Review on the Truck and Drone Cooperative Delivery Problem

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As an emerging delivery style in logistics, the cooperation between trucks and drones can significantly improve the efficiency of parcel delivery, especially in some typical scenes, such as mountainous areas, high buildings, or post-disaster material delivery. In recent years, the truck and drone cooperative delivery problem (TDCDP) has attracted more and more attention from logistic research and commercial sectors. This paper proposes a taxonomy for TDCDP and systematically summarizes the related research. First, the impacts of changes in customers and environments on truck and drone delivery modes are analyzed in detail. Second, by using the proposed taxonomy, the delivery modes in TDCDP are classified into four types: parallel delivery, mixed delivery, drone delivery with truck-assisting, and truck delivery with drone-assisting. The roles of trucks and drones are analyzed in different scenes. Then, for different delivery modes, this paper summarizes the TDCDP models and analyzes the common assumptions, constraints, and objective functions. This paper also combs the exact algorithms, heuristic algorithms, and hybrid algorithms used to solve different kinds of TDCDP. Finally, the current research status and future research trends are discussed, and the challenges of TDCDP are highlighted.

Keywords: Last-mile delivery; truck and drone cooperative delivery; TSP-D; VRP-D; the same day delivery.

1. Introduction

The rapid development of E-commerce [1–3] not only drives the development of the express industry, but also promotes the continuous reform of logistics delivery mode. To improve the delivery efficiency of the last mile, companies such as Amazon, DHL, and Federal Express have been testing adding drones [4–6] to parcel delivery services in recent years. Compared with traditional truck delivery, drone delivery has more advantages. First of all, the flight of drones is not limited by road networks and geographical conditions. This makes it possible to send and receive express parcels quickly in mountainous areas and disaster areas. Second, drones fly much faster than trucks, which can improve the delivery efficiency and make the delivery on the same day possible (or even within 2-h) [7, 8]. However, drones also have some shortcomings, such as small cargo capacity, limited flight range, vulnerability to weather, and ease to be disturbed. They cannot meet the needs of modern logistics alone. The use of drones and trucks to complete delivery tasks can make logistics delivery more efficient and has more obvious economic advantages. Therefore, the research on the truck and drone cooperative delivery problem (TDCDP) has important theoretical and practical significance. Figure 1 shows a mixed parcel delivery network composed of one depot, two types of customers, and multiple trucks and drones.

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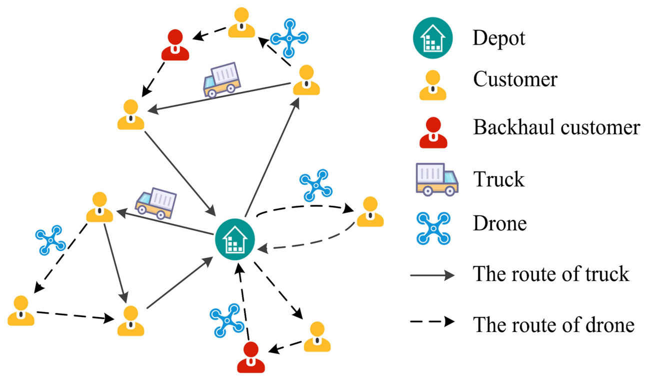


Fig. 1. Illustration of TDCDP.

Table 1. Advantages and disadvantages of truck and drone in parcel delivery.

Tool	Delivery space	Delivery speed	Parcel weight	Parcel number	Delivery range	Terrain influence	Weather influence
Truck	Ground	Slow	Heavy	Multiple	Long	Seriously	Slightly
Drone	Air	Fast	Light	Very few	Short	Slightly	Seriously

The traditional way of logistics distribution is mainly human delivery. The delivery form is that expressmen drive trucks or minivans of different sizes and endurance capacities to deliver goods or parcels. Compared with the traditional delivery modes, the truck and drone cooperative delivery mode not only brings convenience and rapidity but also saves human and material resources [23], thanks to the complementary advantages of trucks and drones in many aspects. In Table 1, the advantages and disadvantages of trucks and drones in TDCDP are summarized.

In recent years, many papers have summarized the research on the cooperation between trucks and drones, but their foci are different. Mangiaracina *et al.* [24], first, summarized the detailed delivery process of trucks and drones, and analyzed the factors in the delivery process which affect the last-mile delivery cost. Then, they studied the overall framework of last-mile delivery. Sung *et al.* [25] introduced a variety of applications for trucks and drones from multiple perspectives, and the application fields are not limited to logistics delivery. In addition, the roles, tasks, and quantities of trucks and drones cooperation were introduced, respectively. Macrina *et al.* [26], first, briefly introduced the application of drones from the perspective of civilian, environment, and defense. Then, they classified TDCDP into four categories: traveling salesman problem with drone (TSP-D), vehicle routing problem with drone (VRP-D), drone delivery problem (DDP), and carrier vehicle problem with drones (CVP-D), respectively. Boysen *et al.* [27] introduced the most widely used delivery concepts in the logistics industry at present, including human-driven delivery vans, cargo bikes, and self-service, and several most promising delivery concepts in the future, including drones, autonomous delivery robots, crowdshipping, and public transport as alternative transport options. Ding *et al.* [28] studied the cooperation relationships between unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs), and the tasks performed by UAVs and UGVs are not limited to parcel delivery, but also include navigation in GPS-challenged environments, accurate detection for targets, target tracking, surveillance, and so on. Ding *et al.* [28] also systematically analyzed the roles of UAVs and UGVs in different tasks. Starting from the delivery model of the drone, Moshref-Javadi *et al.* [29] considered the pure-play drone-based model and the synchronous or asynchronous model of drone and truck, and the synchronization points were analyzed in detail. From a two-echelon scheme perspective, Li *et al.* [30] discussed the coupling/decoupling problem between trucks and drones.

Murray *et al.* [17] first put forward the truck and drone routing problem. With the improvement of drone capabilities, this problem model has been applied in various fields, including the delivery industry. With the extensive study of TDCDP, many variants of TDCDP have emerged. An important reason for the prevalence of TDCDP is the

Table 2. The variants of TDCDP.

Property	Abbreviation	Full name
Delivery form	DDAM [9]	Drone-delivery using autonomous mobility
	TDCDP [10]	Truck-and-drone coordinated delivery problem
	HTDD [11]	Hybrid truck-drone delivery
	HVDRP [12]	Hybrid vehicle-drone routing problem
Problem attribute	HCVTSP [13]	Collaboration of heterogeneous vehicles on traveling salesman problem
	TSP-DS [14]	Traveling salesman problem with a drone station
	TSPDP [15]	Traveling salesman problem with drone and parking
	FSTSP-B [16]	Flying sidekick traveling salesman problem with backhauls
	PDSTSP [17]	Parallel drone scheduling traveling salesman problem
	TSPRD-DR [18]	Traveling salesman problem with release dates and drone resupply
	TSP-D [19, 20]	Traveling salesman problem with drone
	VRPD [21]	Vehicle routing problem with drones
	mTSPD [22]	Multi-traveling salesman problem with drone

diversity of delivery modes. The common TDCDP variants are summarized in Table 2.

In addition, Chen *et al.* [31] studied the path planning of heterogeneous robot systems for parcel delivery in an urban environment. The system is composed of UGVs and UAVs. In the system, UGVs can only run in urban environments or road networks, and UAVs are used to unload the parcels from the UGVs and deliver them to the customers. Based on the quantity of drones and trucks, Luo *et al.* [32] divided TDCDP into three categories: single-drone and single-truck problem, multi-drone and single-truck problem, and multi-drone and multi-truck problem. TDCDP could also be studied as a classical vehicle routing problem (VRP) to find the routes for drones or as a scheduling problem combined with the traveling salesman problem (TSP) in [33]. Trucks and drones cooperation can be applied to various fields such as wide-area forestry search, last-mile delivery, and ecological monitoring. Most studies of traditional TSP and VRP are to plan the routes for ground vehicles. When ground vehicles and drones cooperate to perform a series of tasks, many variants of TSP and VRP will be produced. Khoufi *et al.* [34] reviewed the variants of TSP and VRP from the perspective of changes in the quantity of trucks and drones, which are divided into one-truck and one-drone, one-truck and m-drones, n-trucks and m-drones.

In the existing studies, TDCDP was reviewed from different perspectives. However, there is still a lack of a systematic and comprehensive introduction to TDCDP from the perspective of delivery mode. The trucks and drones delivery mode is closely related to the problem model of TDCDP. Moreover, with the development of E-commerce, the emergence of new delivery modes and demands, as well as the publication of new relevant literature, TDCDP needs to be more comprehensively summarized.

This paper focuses on TDCDP and proposes a taxonomy based on the delivery mode of trucks and drones. The criteria of the taxonomy include the role of trucks, the role of drones, and whether drones can dock on trucks. The delivery modes are divided into parallel delivery, mixed delivery, drone delivery with truck-assisting, and truck delivery with drone-assisting. These four delivery modes can cover all current research about TDCDP. This taxonomy can be used to classify the studies on TDCDP, which is convenient for sorting out the delivery mode and understanding the problem model. Based on the taxonomy, we review the related literature, summarize the research trends and limitations, and highlight the challenges of TDCDP.

The main contributions and features of the paper are summarized as follows:

- A taxonomy for TDCDP is proposed, which can be used to systematically analyze delivery modes in TDCDP research. Based on the taxonomy, this paper summarizes the relevant studies of TDCDP and makes a bibliometric analysis in detail from many different perspectives. It is convenient for researchers to deeply understand the problem models and delivery modes of TDCDP.
- For different delivery modes, this paper summarizes the TDCDP models and analyzes the common assumptions, constraints, and objective functions. In addition, this paper also combs the exact algorithms, heuristic algorithms, and hybrid algorithms used to solve TDCDP with different problem models. It can help researchers gain an intuitive and comprehensive understanding of the research status, trends, and future challenges of TDCDP.
- Compared with the latest reviews, the features of this paper are as follows: Compared with Macrina *et al.* [26], we comprehensively analyze the role of trucks and drones in the delivery task and the relationship between trucks and drones. Compared with Moshref-Javadi *et al.* [29], we summarize four different kinds of common TDCDP models, the common objective functions, methods, constraints and assumptions. Moreover, these two reviews do not involve taxonomy, but this paper creatively proposes a systematic and concise taxonomy for TDCDP, which contributes to the comprehensive analysis of the TDCDP from the roles and relationships between trucks and drones.

The remainder of this paper is as follows. Section 2 introduces the essential elements of TDCDP and puts forward a taxonomy. Section 3 summarizes the models of TDCDP and analyzes the common assumptions, constraints, and objective functions. Section 4 reviews the related literature about TDCDP based on the taxonomy. Section 5 gives a bibliometric analysis and analyzes research trends and future challenges. Section 6 provides the conclusion.

2. Essential Elements

In TDCDP, the essential elements include customers, environments, trucks, and drones. Changes in customers and environments will directly affect the quantity of trucks and drones and their cooperation modes. Next, we will analyze the differences in the cooperation modes of trucks and drones about different customer distribution, customer numbers, parcel attributes, and environments. In order to facilitate the description of the problem, we unify some terms frequently used in the literature (see Table 3). These synonyms will be used interchangeably.

2.1. *Delivery tasks*

In the parcel delivery task of trucks and drones, the service object, delivery object, and delivery environment have direct impacts on the cooperation mode of the trucks and

Table 3. Synonyms description.

The terms used in this paper	Synonyms
Truck	Vehicle
Drone	UAV
Parcel	Package, goods, cargo
Depot	Warehouse, depository
Customer	Demand point, customer point

drones. When performing the delivery task, first of all, it is necessary to clarify the service object, that is, the customer. Related attributes such as quantity, locations, and demands need to be clarified. Then, regarding the delivery object, that is, the parcel, we also need to know its basic attributes, such as quantity, weight, size, etc. Finally, it is necessary to take into account the environment where the delivery task is performed, such as cities, mountain areas, disaster areas, etc. The cooperation delivery modes between trucks and drones may vary.

2.1.1. *Customers*

In the actual delivery task, generally, there are many kinds of customers. In addition to some basic attributes of customers, we also need to comprehensively consider the relationship between customers, for example, the delivery time demands of customers and shelf life of the goods in the parcels. Specifically, the cooperation mode of trucks and drones, the delivery task allocation, and the order of task execution may be affected by the distribution of customers, customers' requirements on the urgency of parcel delivery, customers with return demand or delivery demand, and so on.

2.1.2. *Parcels*

The basic properties of parcels directly determine who can carry out the delivery task. These properties include parcel size, weight, quantity, etc. Second, the properties of the customer to whom the parcel belongs also affect the cooperation mode of trucks and drones. For example, for the delivery task in remote mountainous areas, trucks cannot directly reach the customer points due to terrain reasons, and drones may not be able to complete the delivery task independently due to their limited endurance. At this time, the relay delivery mode of trucks and drones can be adopted. The first half of each delivery task is the process from the depot to some places near customer points, and the second half is the parcel delivery process. In the first half of the delivery task, trucks load drones and parcels to go to some places near customer points. In the second half, drones will directly deliver the parcels to customers after entering mountainous areas.

2.1.3. *Environments*

Different environments will affect the driving or flight ability of trucks and drones to varying degrees. For example, in mountainous areas or disaster areas, due to narrow or blocked roads, trucks will be difficult to drive or can only move slowly. However, this environment will not affect the flight ability of drones. Second, the existence of electromagnetic areas and bad weather in the environment will have a great impact on the flight ability and speed of drones. Therefore, the cooperation mode of trucks and drones is also affected by environments. The impact of environments on the abilities of trucks and drones should be analyzed according to specific task scenarios, so as to determine the cooperation mode of trucks and drones.

2.2. *Trucks and drones*

In TDCDP, delivery tools include trucks and drones (as shown in Table 1). Drones mainly refer to small unmanned rotorcrafts. Due to their small size, drones can realize flexible take-off and landing on trucks. These characteristics of drones make the cooperative delivery mode of truck and drone more abundant. However, fixed-wing UAVs can not hover due to their curvature constraints, which makes it difficult to cooperate with trucks to achieve collaborative cargo distribution. Generally, compared with drones, trucks have a larger capacity, longer endurance time, and less cost per unit distance, but the delivery speed is slower. In a delivery scheme, when the number of trucks and drones and their combination modes change, TDCDP models may be different (we will describe it in detail later, as shown in Table 8).

Table 4 lists the matching relationships between different tasks and delivery tools. From the perspective of who is more suitable for delivery, the use of delivery tools can be divided into three categories: trucks-only represented by 1, drones-only represented by 2, and trucks or drones represented by 3 [35].

Table 4. Matching relationships between different tasks and delivery tools.

Subject	Attribute	Delivery tool
Parcel	Big, heavy, multiple	1
	Urgent	2
	Small, light, one, normal	3
Customer location	Far	1
	Restricted terrain	2
	Not-restricted terrain, near	3
Environment	Disaster-area, mountain-area, crowded road network, tall buildings	2

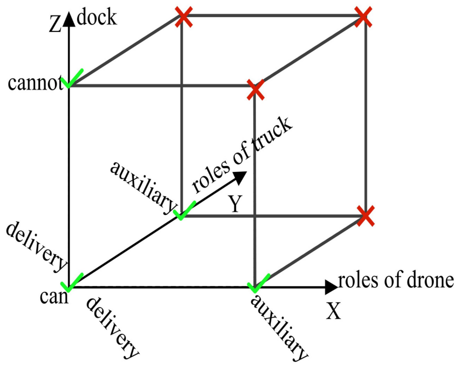


Fig. 2. Visual representation of the TDCDP taxonomy.

Based on the cooperation mode of trucks and drones, we propose a taxonomy and divide the delivery mode in TDCDP into four types, including *parallel delivery*, *mixed delivery*, *drone delivery with truck-assisting*, and *truck delivery with drone-assisting*. The taxonomy is shown in Fig. 2. The X-axis indicates the roles of drones, the Y-axis indicates the roles of trucks, and the Z-axis represents whether drones can dock on trucks. According to the taxonomy, we classify the TDCDP into four modes represented by green check marks:

- Parallel delivery: Both trucks and drones can deliver parcels, and drones cannot dock on trucks, which can be represented as $\mathrm{D}_D \| \mathrm{T}_D$[a];
- Mixed delivery: Both trucks and drones can deliver parcels, and drones can dock on trucks, which can be represented as $\mathrm{D}_D \rightarrow \mathrm{T}_D$;
- Drone delivery with truck-assisting: Drones deliver parcels with trucks as auxiliary tools, and drones can dock on trucks, which can be represented as $\mathrm{D}_D \rightarrow \mathrm{T}_A$;
- Truck delivery with drone-assisting: Trucks deliver parcels with drones as auxiliary tools, and drones can dock on trucks, which can be represented as $\mathrm{D}_A \rightarrow \mathrm{T}_D$.

As shown in Fig. 2, there are four other modes represented by red crosses: $\mathrm{D}_A \rightarrow \mathrm{T}_A$, $\mathrm{D}_A \| \mathrm{T}_A$, $\mathrm{D}_A \| \mathrm{T}_D$, and $\mathrm{D}_D \| \mathrm{T}_A$. In $\mathrm{D}_A \rightarrow \mathrm{T}_A$ and $\mathrm{D}_A \| \mathrm{T}_A$, trucks and drones both play auxiliary roles, so there are no tools for direct delivery, which is illogical, so these two modes are not feasible. In $\mathrm{D}_A \| \mathrm{T}_D$, trucks deliver parcels with drone-assisting, and drones cannot dock on trucks. When drones appear as an auxiliary tool, they must dock on trucks to replenish their parcels. So the third mode is not feasible. In $\mathrm{D}_D \| \mathrm{T}_A$, drones deliver parcels with truck-assisting, but drones cannot dock on trucks. When trucks are used as an auxiliary tool, they act as carrier tools, charging facilities, etc. If drones cannot dock on trucks, trucks cannot charge drones, replace the battery for drones, or supplement the parcels. So the fourth mode is not feasible, either.

We have summarized the applicable scenarios of the four delivery modes:

- Parallel delivery: The first delivery mode is generally used in cases where customers are densely distributed near the depots. Trucks and drones will not go to the same customer point.
- Mixed delivery: The second delivery mode is generally used in the case of large task scenarios and scattered customers. Generally, the routes of trucks and drones have intersections which are generally set on customer points.
- Drone delivery with truck-assisting: The third delivery mode is generally used in the case of restricted terrain or blocked road network. In this case, trucks carry drones and parcels to some places near customer points, when trucks are unable to pass the road due to obstructions. Then, drones will load the parcels and deliver them to the customer points.
- Truck delivery with drone-assisting: The fourth delivery mode is generally used in the same day delivery. All orders on the same day have been known in advance, but due to time constraints or products that have not been made, trucks will deliver some parcels to customers first, and then drones will supply the trucks dynamically.

For these four delivery modes, we analyzed the flow direction of parcels (as shown in Fig. 3). The parcels start

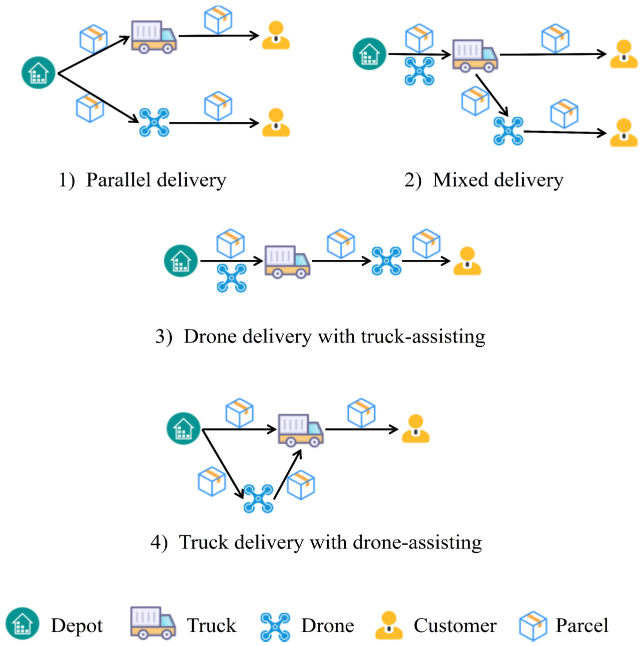


Fig. 3. The flow direction of parcels.

[a] "D" represents "drone". "T" represents "truck". In the subscript, "D" represents "delivery tool", and "A" represents "auxiliary tool". "$\|$" represents that drones cannot dock on trucks. "$\rightarrow$" represents that drones can dock on trucks.

from the depot and end at the customers. According to the requirements of the delivery tasks or the constraints of environmental factors, parcels will be delivered by trucks or drones.

3. TDCDP Models

TDCDP has a variety of models, due to the different configurations of trucks and drones, the different distribution and demands of customers, the different weights and sizes of parcels, and the different environments. Therefore, we summarize the common assumptions, constraints, and objective functions to gain insights into TDCDP.

3.1. *Assumptions*

In the research process, it is impossible to cover all factors due to the complexity of TDCDP. Therefore, different researchers make different assumptions about specific problems in different aspects or at different degrees. Next, we summarize the common assumptions in TDCDP [18].

(A1) Trucks remain to transport parcels when the drones are delivering parcels [18].
(A2) Trucks can serve drones many times.
(A3) Trucks and drones move at constant speeds.
(A4) The driving costs of trucks per unit of distance are the same [32].
(A5) In the process of drones delivery, drones can be transported to the place near the customer point by trucks [18].
(A6) Drones' charging time is negligible.
(A7) The flight path of a drone is a straight line, and the path length is expressed by Euclidean distance.
(A8) The influence of parcels' weight on drone endurance is ignored.
(A9) A drone can carry at most one parcel.
(A10) The flight costs of drones per unit of distance are the same [32].
(A11) The number of arrivals of trucks or drones to customer points is once and only once (except for depots).
(A12) Trucks or drones that arrive at the rendezvous point first must wait for the last arriving one.
(A13) The waiting cost is not considered.
(A14) There is only one parcel in the delivery task for each customer.
(A15) The capabilities of trucks are the same, and the capabilities of drones are the same, too.
(A16) The impact of the natural environment on drones is not considered.

Among them, some assumptions are applicable to most problem scenarios such as A1, A2, A4, A5, and A10–A12. However, there are still some assumptions that are only applicable to specific scenarios. Next, we analyze them in detail.

For (A3), nevertheless, some studies focus on the variable speed of drones and try to find a tradeoff between speed and benefit [36, 37]; For (A6), if the battery is replaced for the drone, the charging time can be ignored. However, if the charging equipment is used to charge the drone, the power of the charging equipment and the charging completion time need to be considered; For (A7), it is applicable in an open-field environment. However, when the drones perform the delivery task in the urban environment, it is obvious that the path length expressed by the Euclidean distance between two customer points is inaccurate. At this time, the impact of buildings on drone path planning should be considered; For (A8), however, some studies consider the influence of parcel weight on the endurance of drones and construct the energy function [38–42]; For (A9), currently, due to the limitations of drone technology, drones can only carry one parcel at a time. With the progress of science and technology, drones are expected to carry multiple parcels for delivery at one time; For (A13), it is applicable when the problem is to minimize the total path consumption. When the problem is to minimize the total task completion time, the waiting cost must be considered; For (A14), in actual situations, customers may have multiple parcel delivery needs. At this time, multiple parcels can be packaged into a large package. Then, it is determined who will deliver the large package; For (A15), in actual scenarios, the capabilities of trucks and drones are mostly heterogeneous; For (A16), geographical factors, weather factors, and human factors in the environment will limit the ability of trucks and drones to varying degrees and will have a great impact on the task allocation of delivery tasks. Completely disregarding environmental factors may lead to infeasible plans in actual scenarios.

Assumptions (A1)–(A4) are about trucks. Assumptions (A5)–(A10) are about drones. Assumptions (A11)–(A14) are about the delivery process. Assumptions (A15) and (A16) are about environments. From the above assumptions, it can be seen that there are many assumptions about TDCDP because of the uncertainties of delivery tasks, environments, and trucks and drones.

3.2. *Decision variables*

For convenience, the key symbols used to describe TDCDP are shown in Table 5.

Generally, TSP, VRP, and their variants can be described as combinatorial optimization problems on Graphs [43, 44]. A directed graph $\mathcal{G}$ is composed of vertex set $\mathcal{V} = (v_1, \dots, v_N)$, edge set $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$, and distance matrix

Table 5. Key symbols.

Symbol	Description
m	The indicator of trucks
h	The indicator of drones
i, j, k, n	The indicators of nodes, including customers and depots
M	The total quantity of trucks
H	The total quantity of drones
N	The total quantity of nodes
L	The total quantity of depots
P	The total quantity of customers
e_T^m	The driving range of the mth truck
e_D^h	The flight range of the hth drone
d_T^m	The driving distance of the mth truck
d_D^h	The flight distance of the hth drone
c_T	The driving cost of trucks per unit of distance
c_D	The flight cost of drones per unit of distance
d_T	The total driving distance of trucks
d_D	The total flight distance of drones
t_T^m	The task completion time of the mth truck
t_D^h	The task completion time of the hth drone
t_T	The total time consumption of trucks
t_D	The total time consumption of drones
s_i	The ith customer's satisfaction
w_i	The ith customer's waiting time
tt_i^m	The time when the mth truck arrives at the ith customer
td_j^h	The time when the hth drone arrives at the jth customer
q_T	The quantity of trucks that participate in delivery
q_D	The quantity of drones that participate in delivery
f_q	The total quantity of trucks and drones that participate in delivery
f_{dis}	The total travel distance of trucks and drones
f_{tim}	The total time consumption of trucks and drones
d_{ij}	The distance between node i and node j
$S_{\max}$	The total customers' satisfaction
T_W	The total customers' waiting time
T_M	The task completion time
$\mathcal{N} = \{0, 1, \ldots, N+1\}$	The node set
$\mathcal{N}_0 = \{0, 1, \ldots, N\}$	The node set that truck or drone leaves from
$\mathcal{N}_+ = \{1, 2, \ldots, N+1\}$	The node set that truck or drone arrives at
$\mathcal{M} = \{1, 2, \ldots, M\}$	The truck set
$\mathcal{H} = \{1, 2, \ldots, H\}$	The drone set
$\mathcal{C} = \{1, 2, \ldots, P\}$	The customer set
$\mathcal{C}_T, \mathcal{C}_D, \mathcal{T\_S}$	The sets of customers delivered by trucks, drones, and the set of transfer station, respectively
$\mathcal{G}_m$	The customer set of the mth truck
$\mathcal{G}_h$	The customer set of the hth drone
$\mathcal{T}_{\text{are}}$	The area where trucks can delivery parcels
$\mathcal{S}_{\text{are}}$	The area where drones can delivery parcels
i_{wei}	The parcel weight of the ith customer
i_{siz}	The parcel size of the ith customer

Table 5. (*Continued*)

Symbol	Description
i_{pos}	The position of the ith customer
i_{tim}	The time demand of the ith customer
m_{wei}^M	The maximum weight of the mth truck
h_{wei}^M	The maximum weight of the hth drone
m_{siz}^M	The maximum size of the mth truck
h_{siz}^M	The maximum size of the hth drone
x_{ij}^m	The mth truck visit node i then to node j
y_{ijk}^h	The hth drone takes off from node i to visit node j then land on node k
y_{ij}^h	The hth drone takes off from node i to visit node j
p_{ij}^m	It indicates whether the mth truck visits node i before node j
b_{ij}^m	The mth truck visits node i and j and $j > i$
u_i^m	It indicates whether the mth truck visits node i

$\mathcal{D} = [d_{i,j}] \in \mathbb{R}^{N\times N}$ with $i, j = 1, \ldots, N$. Customers and depots can be expressed as vertices. Edge $(v_j, v_i) \in \mathcal{E}$ indicates that trucks or drones go from customer v_i to customer v_j. Distance matrix $\mathcal{D} = [d_{i,j}] \in \mathbb{R}^{N\times N}$ represents the distances between vertices $\mathcal{V} = \{v_1, \ldots, v_N\}$.

Remark. The vertices in the graph include depots and customer points. The edges in the graph include the connection relationships between the depots and customers or among customers. When the same edge is traveled by trucks or drones, the costs may be different. The distance between two points where the drone flies can be approximated by the Euclidean distance, but the route of the truck from one point to another is constrained by the road network and the environment. Moreover, in drone delivery with truck-assisting delivery mode, the stop point of the truck can be defined as a transfer station that is different from the customer points. It is a temporary stop selected by trucks due to environmental constraints. In addition, the transfer stations are also the vertices in the graph.

The common decision variables of TDCDP models are shown below. Decision variables (1)–(4) determine the nodes that the mth truck visits and visiting sequence. Decision variable (5) or (6) determines the nodes that the hth drone visits.

$$x_{ij}^m = \begin{cases} 1 & \text{if the } m\text{th truck goes from node } i \text{ to node } j \\ & \forall i \in \mathcal{N}_0,\ j \in \mathcal{N}_+,\ i \neq j,\ m \in \mathcal{M}, \\ 0 & \text{otherwise}, \end{cases} \tag{1}$$

$$p_{ij}^m = \begin{cases} 1 & \text{if the } m\text{th truck visits node } i \text{ before node } j \\ & \forall i \in \mathcal{N}_0,\ j \in \mathcal{N}_+,\ i \neq j,\ m \in \mathcal{M}, \\ 0 & \text{otherwise}, \end{cases} \tag{2}$$

$$b_{ij}^m = \begin{cases} 1 & \text{if the } m\text{th truck visits nodes } i \text{ and } j \text{ and } j, (j > i) \\ & \forall i \in \mathcal{N}_0,\ j \in \mathcal{N}_+,\ i \neq j,\ m \in \mathcal{M}, \\ 0 & \text{otherwise}, \end{cases} \tag{3}$$

$$u_i^m = \begin{cases} 1 & \text{if node } i \text{ is in the path of the } m\text{th truck} \\ & \forall i \in \mathcal{N},\ m \in \mathcal{M}, \\ 0 & \text{otherwise}, \end{cases} \tag{4}$$

$$y_{ijk}^h = \begin{cases} 1 & \text{if the } h\text{th drone takes off from node } i \text{ to} \\ & \text{visit node } j \text{ and land on node } k, \quad \forall i \in \mathcal{N}_0, \\ & j \in \mathcal{N}_0,\ k \in \mathcal{N}_+,\ i \neq j,\ j \neq k,\ h \in \mathcal{H}, \\ 0 & \text{otherwise}, \end{cases} \tag{5}$$

$$y_{ij}^h = \begin{cases} 1 & \text{if the } h\text{th drone flies from node } i \text{ to node } j, \\ & \forall i \in \mathcal{N}_0,\ j \in \mathcal{N}_+,\ i \neq j,\ h \in \mathcal{H}, \\ 0 & \text{otherwise}. \end{cases} \tag{6}$$

3.3. *Constraints*

This section summarizes the common constraints in TDCDP. Generally speaking, constraints can be divided into three categories: truck and drone constraints, delivery task constraints, and environment constraints [45].

3.3.1. *Truck and drone constraints*

The main constraints of trucks and drones include the maximum driving or flight distance, the maximum load, the number of parcels that trucks and drones can carry, and the impact of parcels' weight on the endurance of trucks and drones [38, 46]. Moreover, whether drones can deliver them is also affected by the size of parcels.

3.3.2. *Delivery task constraints*

The constraints of the delivery task mainly include time constraints and intersection constraints. To be specific, customers require parcels to be delivered at the specified time [47]. In mixed delivery mode and drone delivery with truck-assisting mode, trucks need to arrive at the intersection customer points first and wait for the drones [7].

3.3.3. *Environment constraints*

The environment constraints in TDCDP are mainly the impact of terrains, such as high-rise buildings [48], road network [49], and mountain areas, which will restrict the delivery of trucks.

Next, we will introduce the formulaic representation of various constraints in detail.

- Truck and drone constraints [47]:

$$d_T^m = \sum_{i \in \mathcal{N}_0} \sum_{j \in \mathcal{N}_+,\ i \neq j} x_{ij}^m d_{ij}, d_T^m < e_T^m, \quad \forall m \in \mathcal{M}, \tag{7}$$

$$d_D^h = \sum_{i \in \mathcal{N}_0,\ j \in \mathcal{N}_+,\ i \neq j} \sum_{k \in \mathcal{N}_+,\ j \neq k} y_{ijk}^h (d_{ij} + d_{jk}), \quad d_D^h < e_D^h, \quad \forall h \in \mathcal{H}. \tag{8}$$

Constraint (7) denotes the truck driving distance. Constraint (8) denotes the drone flight distance.

$$\sum_{i \in \mathcal{N}_+} x_{0i}^m = 1, \quad \forall m \in \mathcal{M}, \tag{9}$$

$$\sum_{i \in \mathcal{N}_0,\ j \in \mathcal{N}_+,\ i \neq j} x_{i,j}^m = 1, \quad \forall m \in \mathcal{M}, \tag{10}$$

$$\sum_{j \in \mathcal{N}_0} x_{j,N}^m = 1, \quad \forall m \in \mathcal{M}, \tag{11}$$

$$\sum_{i \in \mathcal{N}_+} y_{0i}^h = 1, \quad \forall h \in \mathcal{H}, \tag{12}$$

$$\sum_{i \in \mathcal{N}_0,\ j \in \mathcal{N}_+,\ i \neq j} y_{i,j}^h = 1, \quad \forall h \in \mathcal{H}, \tag{13}$$

$$\sum_{j \in \mathcal{N}_0} y_{j,N}^h = 1, \quad \forall h \in \mathcal{H}. \tag{14}$$

Constraints (9)–(14) ensure that trucks and drones can only enter and leave the assigned customer points once in the delivery process.

$$i \in \begin{cases} \mathcal{G}_m & \text{if } i_{\text{wei}} < m_{\text{wei}}^M \quad \forall i \in \mathcal{C},\ m \in \mathcal{M}, \\ \mathcal{G}_h & \text{if } i_{\text{wei}} < h_{\text{wei}}^M \quad \forall i \in \mathcal{C},\ h \in \mathcal{H}. \end{cases} \tag{15}$$

$$i \in \begin{cases} \mathcal{G}_m & \text{if } i_{\text{siz}} < m_{\text{siz}}^M \quad \forall i \in \mathcal{C},\ m \in \mathcal{M}, \\ \mathcal{G}_h & \text{if } i_{\text{siz}} < h_{\text{siz}}^M \quad \forall i \in \mathcal{C},\ h \in \mathcal{H}. \end{cases} \tag{16}$$

Constraints (15) and (16) ensure that parcels delivered by trucks or drones need to meet their maximum load and size requirements.

$$\sum_{i \in \mathcal{N}_0,\ j \in \mathcal{N}_+,\ i \neq j} \sum_{k \in \mathcal{N}_+ j \neq k} y_{ijk}^h \leq u_i^m, \quad \forall m \in \mathcal{M},\ h \in \mathcal{H}, \tag{17}$$

$$\sum_{i \in \mathcal{N}_0,\ j \in \mathcal{N}_+,\ i \neq j} \sum_{k \in \mathcal{N}_+ j \neq k} y_{ijk}^h \leq u_k^m, \quad \forall m \in \mathcal{M},\ h \in \mathcal{H}. \tag{18}$$

Constraints (17) and (18) ensure that the starting node i and the landing node k of a drone flight must be visited by trucks.

$$p_{ij}^m + p_{ji}^m = b_{ij}^m \quad \forall i,j \in \mathcal{N},\ j > i,\ m \in \mathcal{M}, \tag{19}$$

$$u_i^m \leq b_{ij}^m, \quad \forall i,j \in \mathcal{N},\ j > i,\ m \in \mathcal{M}, \tag{20}$$

$$u_j^m \leq b_{ij}^m, \quad \forall i,j \in \mathcal{N},\ j > i,\ m \in \mathcal{M}, \tag{21}$$

$$u_i^m + u_j^m \leq 1 + b_{ij}^m, \quad \forall i,j \in \mathcal{N},\ j > i,\ m \in \mathcal{M}, \tag{22}$$

$$p_{0,i}^m = u_i^m, \quad \forall i \in \mathcal{N},\ m \in \mathcal{M}, \tag{23}$$

$$p_{i,N+1}^m = u_i^m, \quad \forall i \in \mathcal{N},\ m \in \mathcal{M}. \tag{24}$$

Constraints (19)–(24) ensure the rationality of the order of customer points visited by trucks.

- Delivery task constraints [47]:

$$\sum_{i \in \mathcal{N}_0,\, j \in \mathcal{N}_+,\, i \neq j} x_{ij}^m + \sum_{i \in \mathcal{N}_0} \sum_{k,\, j \in \mathcal{N}_+, i \neq j,\, j \neq k} y_{ijk}^h = 1,$$
$$\forall m \in \mathcal{M}, h \in \mathcal{H}. \tag{25}$$

Constraint (25) requires customer points to be visited only once by either a truck or a drone.

$$\sum_{i \in \mathcal{N}_0,\, j \in \mathcal{N}_+,\, i \neq j} x_{ij}^m = \sum_{k \in \mathcal{N}_+, j \neq k} x_{jk}^m, \quad \forall m \in \mathcal{M}, \tag{26}$$

$$\sum_{i \in \mathcal{N}_0,\, j \in \mathcal{N}_+,\, i \neq j} y_{ij}^h = \sum_{k \in \mathcal{N}_+,\, j \neq k} y_{jk}^h, \quad \forall h \in \mathcal{H}. \tag{27}$$

Constraints (26) and (27) require trucks and drones to leave the customer that they have visited.

$$y_{0ij}^h \leq \sum_{h \in \mathcal{N}_0, j \in \mathcal{N}_+} x_{hj}^m \quad \forall i \in \mathcal{N}_0,\ m \in \mathcal{M},\ h \in \mathcal{H}. \tag{28}$$

Constraint (28) requires that if a drone starts to fly from the depot to visit a customer point, then the truck must visit the landing customer point of drone too.

$$\sum_{i,j \in \mathcal{N}_0,\, j \neq i} \sum_{k \in \mathcal{N}_+,\, j \neq k} x_{ijk}^m \leq 1, \quad \forall m \in \mathcal{M}, \tag{29}$$

$$\sum_{i,j \in \mathcal{N}_0,\, j \neq i} \sum_{k \in \mathcal{N}_+,\, j \neq k} y_{ijk}^h \leq 1, \quad \forall h \in \mathcal{H}. \tag{30}$$

Constraints (29) and (30) require trucks and drones to leave any customer points including the depot only once.

$$u_i^m - u_j^m + 1 \leq (N+2)(1 - x_{ij}^m),$$
$$\forall i \in \mathcal{N},\ j \in \mathcal{N}_+,\ j \neq i. \tag{31}$$

Constraint (31) eliminates the truck subtour.

$$tt_i^m \leq i_{\text{tim}}, \quad \forall i,j \in \mathcal{N},\ j > i,\ m \in \mathcal{M}. \tag{32}$$

$$td_i^h \leq i_{\text{tim}}, \quad \forall i,j \in \mathcal{N},\ j > i,\ h \in \mathcal{H}. \tag{33}$$

Constraints (32) and (33) ensure that the time when the trucks or drones arrive at the customer point cannot be later than the time requirement of the customer point.

- Environment constraints [47]:

$$i \in \begin{cases} \mathcal{G}_m & \text{if } i_{\text{pos}} \in \mathcal{T}_{\text{are}}, \quad \forall i \in \mathcal{C},\ m \in \mathcal{M}, \\ \mathcal{G}_h & \text{if } i_{\text{pos}} \in \mathcal{D}_{\text{are}}, \quad \forall i \in \mathcal{C},\ h \in \mathcal{H}. \end{cases} \tag{34}$$

Constraint (34) ensures that trucks and drones can reach the location where customers are.

3.4. *Objective functions*

In TDCDP, different objective functions can be constructed according to different task scenarios or different preferences of decision-makers. In Table 6, we summarize several common objective functions. It should be noted that the objective function of different task scenarios may have different expressions.

3.4.1. *Cost*

This kind of objectives is to reduce various consumption. Generally, it includes the total path length consumption of trucks and drones, the total time consumption of trucks and drones, and the makespan. Generally, when the objective is to minimize the cost in TDCDP, all customer demands must be satisfied. That is to reduce resource consumption on the premise of completing the task.

From the customer's perspective, customers have requirements regarding the delivery time. If the drones or trucks fail to deliver parcels at the scheduled time, the customers have to wait at the customer points. The waiting time is a consumption of resources. The longer the waiting time, the greater the consumption is. In [51], the sum of the waiting time of customers is minimized by presenting a mathematical formulation and a heuristic solution approach for the optimal planning of delivery routes in a multi-modal system combining trucks and drones operations.

3.4.2. *Customer satisfaction*

This kind of objectives is to maximize customer satisfaction. That is to complete the task to the greatest extent. Generally, the quantity of trucks and drones is limited or the capacity is limited, so decision-makers wish to complete as many tasks as possible [32].

3.4.3. *Multi-objective optimization*

A multi-objective optimization model in TDCDP is developed with multiple conflictive objectives [53], such as minimizing the path costs and maximizing the customer service level in terms of timely deliveries [54]. In [39], the objective function is based on three different objectives: the minimization of the path length of trucks and drones, the number of drones, and the number of batteries used.

Table 6. Typical optimization objectives in TDCDP.

No.	Objectives	Functions	Description	Reference
1	Maximum satisfaction	$S_{\max} = \sum_{i=1}^{P} s_i$	Total satisfaction of customers	[32]
2	Minimum path cost	$f_{\text{dis}} = c_T d_T + c_D d_D$	Total distance cost of trucks and drones	[19, 50]
3	Minimum time cost	$f_{\text{tim}} = t_T + t_D$	Total time consumption	[10]
4	Minimum waiting time	$T_W = \sum_{i=1}^{P} w_i$	Total waiting time of customers	[51]
5	Minimum number	$f_q = q_T + q_D$	Total number of trucks and drones that participate in delivery	[48]
6	Minimum makespan	$T_M = \min\{\max\{t_T^m, t_T^h\}\} m \in \mathcal{M},\ h \in \mathcal{H}$	Task completion time	[15, 17, 52]

3.5. *Common models in TDCDP*

In different delivery modes, the basic problem models mainly include VRP and VRP-D. In this section, we will detailedly introduce several VRP and VRP-D models in TDCDP shown in Table 7. A complete problem model includes objective function, decision variables, constraints, and a series of assumptions. Specific constraints and assumptions need to be determined according to specific task requirements.

In *parallel delivery* mode, one or multiple trucks and one or multiple drones deliver parcels independently from one depot. The routes of trucks and drones do not intersect. If the objective is to minimize the time cost (see Table 6), the VRP model can be described in Table 7. If the drone can only deliver one parcel at a time, there are two combinations of the values of y_{ij}^h is $(i = 0, j \in \mathcal{C}_\mathcal{D})$ and $(i \in \mathcal{C}_\mathcal{D}, j = 0)$.

In *mixed delivery* mode, multiple trucks carry one or multiple drones from one depot for delivery. Usually, the makespan is optimized. This delivery problem can be modeled as VRP-D (Case 1) shown in Table 7.

In *drone delivery with truck-assisting* mode, the starting points of the drones and the routing points of the trucks are the transfer stations. Each transfer station has a certain correspondence with the customer points around it. If the drone can only deliver one parcel at a time, there are two combinations of the values of y_{ij}^h is $(i \in \mathcal{T\_S}, j \in \mathcal{C}_\mathcal{D})$ and $(i \in \mathcal{C}_\mathcal{D}, j \in \mathcal{T\_S})$. If the total path cost is optimized, this delivery problem can be modeled as VRP-D (Case 2) shown in Table 7.

In *truck delivery with drone-assisting* mode, there are two combinations of the values of y_{ij}^h is $(i = 0, j \in \mathcal{C}_\mathcal{D})$ and $(i \in \mathcal{C}_\mathcal{D}, j = 0)$. Meanwhile, the customer points in $j \in \mathcal{C}_\mathcal{D}$ are the customer points where the drones supply the trucks. If the total path cost is optimized, this delivery problem can be modeled as VRP-D (Case 3) shown in Table 7.

When there are multiple depots in the task scenario, the above problem models VRP, VRP-D (Case 1), VRP-D (Case 2), and VRP-D (Case 3) can be extended to m-depot VRP, m-depot VRP-D (Case 1), m-depot VRP-D (Case 2), and m-depot VRP-D (Case 3). Multiple trucks with multiple drones depart from multiple depots for delivery. When it is specified that trucks and drones must return to the depot which they started from, first, it is necessary to determine the corresponding relationship between depots and trucks and drones.

We summarize the number of depots, trucks, and drones in various delivery modes and analyse the problem models in Table 8. For four delivery modes, the combinations of the different quantity of depots, trucks, and drones are sorted out. It can be found that the problem models of $\mathrm{D}_D \to \mathrm{T}_D$ and $\mathrm{D}_D \to \mathrm{T}_A$ are the same in three different number combinations of the depot, truck, and drone.

4. Methods for TDCDP

In this section, we summarize the current methods to solve TDCDP with different delivery modes.

Table 7. Typical problem models in TDCDP.

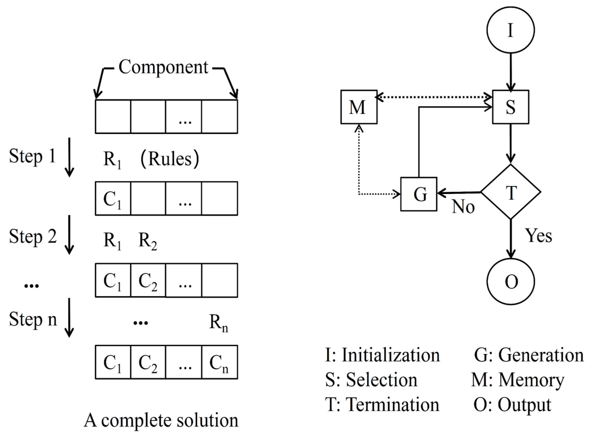
Problem model	Assumptions	Constraints	Decision variables	Objectives functions
VRP	(A1), (A3)–(A4), (A7)–(A11), (A14)–(A16)	(7)–(16), (19)–(27), (29)–(34)	(1)–(4), (6), $\mathcal{C}_\mathcal{T} \bigcup \mathcal{C}_\mathcal{D} = \mathcal{C}$	(3)
VRP-D (case1)	(A1)–(A16)	(7)–(34)	(1)–(5), $\mathcal{C}_\mathcal{T} \bigcup \mathcal{C}_\mathcal{D} = \mathcal{C}$	(6)
VRP-D (case2)	(A2)–(A12), (A14)–(A16)	(7)–(16), (19)–(24), (26)–(27), (29)–(34)	(1)–(4), (6), $\mathcal{C}_\mathcal{D} = \mathcal{C}$	(2)
VRP-D (case3)	(A3)–(A4), (A7)–(A12), (A14)–(A16)	(7)–(16), (19)–(24), (26)–(27), (29)–(34)	(1)–(4), (6), $\mathcal{C}_\mathcal{T} = \mathcal{C}$	(2)

Table 8. The model differences in different delivery modes.

Delivery mode	Depot number	Truck number	Drone number	Problem model
$D_D \| T_D$	1	1/Multiple	1/Multiple	VRP
	Multiple	Multiple	Multiple	m-depot VRP
	1	1	1/Multiple	TSP-D [55]
$D_D \rightarrow T_D$	1	Multiple	1/Multiple	VRP-D (case1) [11]
	Multiple	Multiple	Multiple	m-depot TSP-D [37], m-depot VRP-D (case1) [41], m-depot TSP-D + m-depot VRP-D (case1)
	1	1	1/Multiple	TSP-D [32]
$D_D \rightarrow T_A$	1	Multiple	Multiple	VRP-D (case2) [48]
	Multiple	Multiple	Multiple	m-depot TSP-D, m-depot VRP-D (case2) [14], m-depot TSP-D + m-depot VRP-D (case2)
$D_A \rightarrow T_D$	1	1	1/Multiple	TSP-D [7]
	Multiple	Multiple	Multiple	m-depot VRP-D (case3)

Next, we will introduce three kinds of methods to solve TDCDP: exact algorithms, heuristic algorithms, and hybrid algorithms [56, 57]. Among them, exact algorithms can find the optimal solution to the problem. When the scale of the problem is small, the exact algorithms can find the optimal solution in an acceptable time. When the scale of the problem is large, the performance of the exact algorithms decreases significantly. Exact algorithms mainly include branch-and-cut algorithm, dynamic programming method, brute-force search, and so on. Heuristic algorithms are a kind of method to solve problems through inductive reasoning of past experience and experimental analysis. The heuristic algorithms obtain the suboptimal solution or the optimal solution of the problem with a certain probability with the help of some intuitive judgment or trial. Heuristic algorithms can be divided into traditional heuristic algorithms and meta-heuristic algorithms. Traditional heuristic algorithms include the constructive method, local search algorithm, solution space compression method, and so on. Meta-heuristic algorithms include tabu search algorithm, genetic algorithm, ant colony optimization algorithm, and so on. Hybrid algorithms can be generated according to different hybridization strategies [58]. From the parent relationship, hybridization strategies include collaboration, embedding, and assistance. From the hybridization level, hybridization strategies include population level, subpopulation level, individual level, and component level. From operating order, hybridization strategies include sequential order, parallel order, and no order, and so on.

There are mainly two strategies in the process of finding the optimal solution, one is constructive heuristic strategy, and the other is iterative search strategy. The framework of the constructive heuristic algorithm and iterative search algorithm is shown in Fig. 4. No matter which algorithm is applied, the most important part includes the design of the generation operator and selection operator. In the design process of one solution, the constructive heuristic algorithm will first define the components of one solution, then design the generation rules for each part, and finally construct the solution step by step according to the designed rules. In the iterative search algorithm, some solutions are generated by initialization first, and then the selection operation is performed according to the selection operator, followed by the judgment of whether the termination condition is reached. Generation operators are used to generate new solutions, and then the selection is performed, and the operation is repeated until the termination condition of the algorithm is reached. In general, during the selection process, an external archive can be set to store the so-far-best solutions to guide the generation and selection of new solutions.



(a) Constructive heuristic algorithm (b) Iterative search algorithm

Fig. 4. Algorithm framework.

4.1. *Methods for $D_D \| T_D$*

In this delivery mode, trucks and drones deliver parcels in parallel, and their routes do not intersect. In general, drones

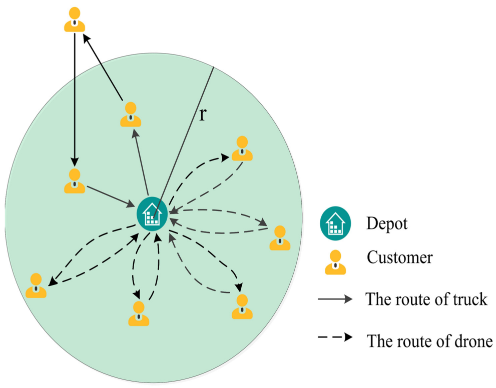


Fig. 5. Parallel delivery.

can only deliver one parcel at a time. Taking the depot as the center, the customers within the circle with half of the maximum flight range of the drone as the radius can be delivered parcels by drones. The TDCDP of this delivery mode can be attributed to the VRP with heterogeneous vehicles. If there are multiple depots, TDCDP models can be attributed to m-VRP. The schematic diagram of $\mathrm{D}_D \| \mathrm{T}_D$ is shown in Fig. 5. Drones only can serve the customers within the circle with radius r.

4.1.1. *Exact methods*

In [59], an exact method based on a dynamic programming approach was proposed to solve the TSP-D problem in large instances. The method consists of three steps. First, it enumerates the shortest paths for the truck for every start node, end node, and set of truck nodes covered by the path. Then, it combines these truck paths with drone nodes to obtain efficient operations, that is, operations that represent the least costly way to cover a set of nodes with an operation. Finally, it computes the optimal sequence of these operations such that all locations are covered and the sequence start and ends at the depot.

4.1.2. *Heuristic methods*

In [19], a fast routing heuristic algorithm based on local search and dynamic programming approach was proposed to solve the TSP-D problem. A greedy heuristic strategy was proposed to partition the truck tour into a subtour for the drone and a subtour for the truck. In addition, the differences between truck delivery only and truck-drone cooperative delivery are compared and analyzed in depth.

4.1.3. *Hybrid methods*

In [60], an extension of the VRP-D called the VRP-Ds and en route operations was modeled with the objective of minimizing the makespan. To solve this problem, an algorithm based on the concepts of variable neighborhood search and tabu search was proposed. In the variable neighborhood search algorithm, the local search method is used to identify the local optima. Tabu search algorithm is used to identify certain moves as forbidden such as to prevent cycling.

In [50], a hybrid genetic search algorithm based on dynamic population management and a split algorithm with adaptive diversity control was proposed to solve TDCDP with the parallel delivery mode. In addition, problem-tailored crossover and local search operators were designed to advance the convergence of the hybrid genetic search algorithm. The objective is to minimize the cost and time spent by trucks and drones to complete the delivery tasks.

4.2. *Methods for* $\mathrm{D}_D \rightarrow \mathrm{T}_D$

In this delivery mode, both trucks and drones can deliver parcels and drones can dock on trucks. This saves the capacity consumption of drones. When drones dock on trucks, drones can be charged or the battery can be replaced. In this way, the delivery range of drones is expanded. In the actual shopping process, customers have demands for parcel delivery and parcel backhaul. The various needs of customers can be divided into two types: (1) only delivery (see Fig. 6), (2) both delivery and backhaul (see Fig. 7). In the backhaul situation, a drone carries a parcel for delivery first and then goes to another customer to pick up a backhaul parcel. Due to the limitation of drone capacity, only one parcel can be carried at a time. In essence, the backhaul situation only imposes a constraint on visiting orders of customers.

4.2.1. *Exact methods*

In [61], a Benders-type decomposition algorithm was proposed, aiming at decomposing the TSP-D into two natural decision stages: selecting and sequencing a subset

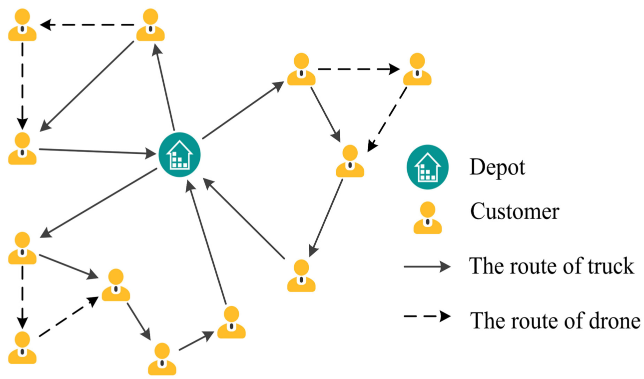


Fig. 6. Mixed delivery without backhaul.

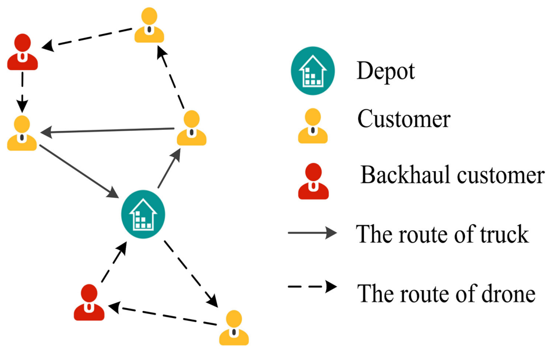


Fig. 7. Mixed delivery with backhaul.

of customers served by one truck, and planning where the drones would take off from the truck to the remaining customer points.

In [62], a new mixed integer linear programming (MILP) model and branch-and-cut algorithm were developed for the VRP-D with two different time-oriented objective functions. In the branch-and-cut algorithm, several lower bounds and problem-specific valid inequalities were introduced and proved their validity. A relaxation of the VRP-D was presented and it is capable of producing good lower bounds in distinctly reduced run times.

In [15], a MILP formulation and a greedy randomized algorithm were proposed to solve truck and DDPs, which aimed to minimize the makespan of serving all the customers. In the experimental example, the number of drones was 0/1/3/5, the number of trucks was 2, and the number of customers is 10/15/30. A similar problem was solved in [47], too. However, its objective is to minimize the comprehensive transportation cost of trucks and drones.

Daniel *et al.* [60] studied the TSP-D problem early. In the problem, there are a set of customers and a truck that is equipped with a single drone. The TSP-D demands that all customers are served exactly once and the minimal delivery time is obtained by the branch-and-cut algorithm in [63].

In [52], two waiting strategies were designed between drones and customers for the flying sidekick traveling salesman problem (FSTSP). One is that drones could wait for customers, and the other is that drones could only wait for customers in flight mode. For FSTSP, the authors proposed three-indexed and two-indexed formulations and a set of inequalities that can be realized in the branch-and-cut algorithm to test the two strategies, and the accuracy of the algorithm was significantly improved.

In [64], the case of return demand in drone parcel delivery problem was also studied. In addition, trucks also participate in the task of picking up parcels. The cases of one depot and multiple depots were studied, respectively. A constraint programming approach was proposed to solve TDCDP with the mixed delivery mode.

4.2.2. *Heuristic methods*

An efficient three-phased heuristic algorithm was proposed in [37] to solve a truck and multiple drones mixed delivery problem. The objective is to minimize the makespan. In the proposed algorithm, the three phases include first planning a loop for the truck, then determining the number of drones, and finally arranging the scheduling time.

In [38], for FSTSP, the influence of parcels' weight on endurance capabilities on drones was considered by using MILP model. The existence of prohibited flight area is also considered, which would have an impact on the path planning of drones. Then, a two-phase constructive and search heuristic algorithm was proposed to solve the real-world problems.

An adjacent distance-based assignment (ADA) heuristic algorithm was proposed in [16] for TSP-D. The heuristic rules include the order-first split-second heuristic and the clustering-based heuristic. Experiments showed that the ADA heuristic algorithm could provide high-quality solutions with short computation time. Since the algorithm can solve instances with up to 100 customer points, it could be applied to tackle large-size problems in the real world.

In [13], the mixed delivery problem of drones and trucks was abstracted as the collaboration of heterogeneous vehicles on traveling salesman problem (HCVTSP). The authors proposed a heuristic algorithm named heterogeneous collaboration vehicles iterative local search (HCVILS) and a perturbation based on destruction and construction to avoid local optima. The objective is to minimize the latest time at which trucks or drones return to the depot.

In most studies, the place where the drone stops at the truck can only be the customer point. In this case, due to the different distances between the customers, the speeds of trucks and drones are also different, so it would cause the situation that one arrives at the customer point first and the other has not arrived yet, and the waiting would also cause the consumption of resources and time. Different from other studies, the drone could dock on the truck at any time in [65]. A greedy heuristic algorithm was used to solve the problem, which greatly improves the performance of the delivery process and reduces energy consumption.

In most research, drones will return to the trucks from which they take off. However, when multiple trucks are involved in the delivery problem, the drone may start from one truck and return to another, and the resource consumption will be less than that of the drone returning to the taking-off truck. In addition, an adaptive insertion heuristic algorithm was proposed to solve the multi-traveling salesman problem with drone in [22]. The objective is to minimize the total task completion time.

In [46], a drone can carry multiple parcels. The authors modeled the mixed delivery problem as a two-stage routing model and proposed a two-stage route-based modeling approach to solve the problem. It is necessary to plan both the routing sequence of the truck and the routing sequence of the drone. The objective is to minimize the total cost of trucks and drones.

4.2.3. *Meta-heuristic methods*

In [66], a multi-start tabu search (MSTS) algorithm based on a special neighborhood structure and a two-stage solution evaluation strategy were proposed to solve the mixed delivery problem. The objective is to minimize the makespan. The experimental results demonstrate the accuracy and efficiency of the proposed algorithm on small-scale instances.

Moshref-Javadi *et al.* solved the mixed delivery problem using an adaptive tabu search-simulated annealing (ATSA) algorithm proposed in [67] and the truck and drone routing algorithm proposed in [51], respectively, and optimized the customers' waiting time.

In a new case, the drone is placed on the roof of the truck to assist the truck in parcel delivery. An iterative optimization algorithm based on decomposition was proposed, which solved the delivery problem of 20 customers and optimized the delivery completion time in [20].

4.2.4. *Hybrid methods*

In [32], a hybrid multi-objective genetic optimization approach incorporated with a Pareto local search algorithm was proposed to solve the TDCDP. Particularly, the authors also developed a greedy heuristic method to create initial solutions and introduced a problem-specific solution representation, genetic operations, as well as six heuristic neighborhood strategies for the hybrid algorithm. The objectives are to minimize the transportation cost and maximize the customer satisfaction.

In [11], a more efficient truck-drone parcel delivery system was constructed including employing trucks, truck-carried drones, and independent drones. Efficient heuristic algorithms were proposed to solve the mixed delivery problem in three steps. First, multiple routes of trucks are constructed according to the payload limit of trucks. Second, the density-based spatial clustering of applications with noise (DBSCAN) algorithm is used to cluster customers and build flight segments to improve the delivery capability of drones. Third, in order to obtain the optimal global paths, an improved iterative local search (ILS) algorithm is used to search the neighborhood of the initial solution. The objective is to minimize the total energy consumption of trucks, truck-carried drones, and independent drones.

A new variant of VRP called VRP with drones (VRPD) was formulated in [68] according to the need of routing a heterogeneous fleet of drones and trucks from large areas. In VRPD, trucks and drones can deliver parcels independently or cooperatively. In the case of dependent delivery, at a given point (customer or depot) the drone takes off from a truck to serve a customer and then return to the same truck, as long as the capacity and endurance constraints for a drone are satisfied. In the other case, each type of truck travels independently from the others. A hybrid genetic algorithm was proposed to solve VRPD problem. The objective is to minimize the total travel time of trucks and drones. In addition, there are some other studies about the mixed delivery mode [21, 54, 55, 69], which can be referred by interested readers. The problem of parcel delivery for large-scale customers with a quantity of about 200 was solved in [69].

4.3. Methods for $D_D \rightarrow T_A$

Because the terrain [48] or traffic network [49] will limit the traffic capacity of trucks, the traffic ranges of trucks are greatly constrained. Therefore, on the road where trucks are not allowed to pass, the parcel delivery must be carried out by drones. In this case, trucks act as carrier tools for drones and parcels. Therefore, temporary stops need to be selected for trucks in the delivery process.

In this delivery mode, drones deliver parcels with trucks as auxiliary tools and drones can dock on trucks. Among them, trucks may have three roles: carrier tools, charging tools, and mobile depots.

- Trucks acting as carrier tools

Trucks send drones and parcels to some places near customer points and then drones directly deliver parcels to customers. When there is only one truck, this delivery problem model is essentially TSP for the truck. When there are multiple trucks, this delivery problem model is essentially VRP for trucks. If one drone can serve multiple customers at one time, the first layer of this delivery problem model is TSP or VRP for trucks, and the second layer is TSP for each drone.

- Trucks acting as charging tools

Trucks are used as a charging tool for drones. Here, charging tools generally refer to replacing the battery for drones, and the time consumption of the battery replacement process is ignored in most studies. The schematic diagram of one truck acting as a charging tool for drones in TDCDP is shown in Fig. 8. One truck starts from the depot and goes to the center of the circle shown in Fig. 8. This circular area covers most of the customer points. Then, drones take the center of the circle where the truck is as the temporary depot to carry out the delivery task. If necessary, drones will go to the location of the truck for charging.

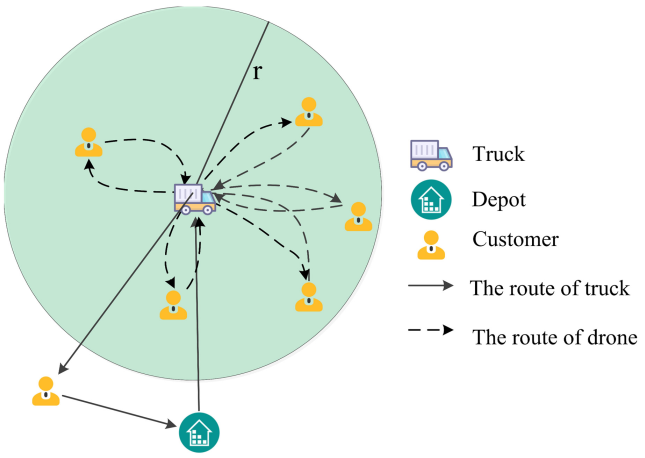


Fig. 8. The truck acts as a charging device.

- Trucks acting as mobile depots

Trucks act as a mobile depot for drones. Here, the route points are selected for trucks according to the distribution of customers. It should be ensured that most customer points are distributed around the route points. These route points are not necessarily customer points. When the truck arrives at a selected route point, the drone relays the delivery to customers near the route point. The schematic diagram of trucks acting as mobile depots for drones in TDCDP is shown in Fig. 9. One truck starts from the depot and goes to customer 1. When the truck arrives at customer 1 or the location near customer 1, one drone takes off from the truck and delivers the parcel to the customer in the tall building.

4.3.1. *Exact methods*

In [70], the use of public transport as the carrier for drones greatly reduces energy consumption. This method obviously improves the delivery range of drones. An exact solution algorithm was proposed to find the optimal round-trip path, and it is extended to adapt to the randomness of the path. The basic idea of the exact solution algorithm is label setting, that is, constantly updating the labels of nodes

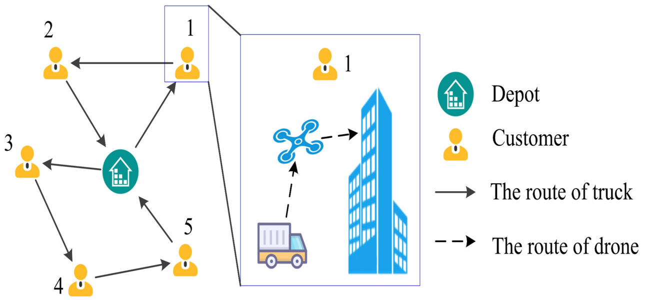


Fig. 9. The truck acts as a mobile depot.

that represent the truck stops until the path is found. There are two key technologies. The first is a recursive formula to guide the label setting operation. The second method is to adjust the labels of some nodes to facilitate the construction of reverse travel.

4.3.2. *Heuristic methods*

In [14], the TSP-DS was developed based on mixed-integer programming. Fundamental features of the TSP-DS were analyzed and route distortion was defined. The objective is to minimize the delivery time of a truck and drones. The authors extended the classic Clarke and Wright algorithm to divide TSP-DS into an independent traveling salesman problem and parallel identical machine scheduling problems.

A novel solution methodology was developed in [12] which extended the classic Clarke and Wright algorithm to solve the HVDRP. The objective is to minimize the total operation cost for trucks and drones.

Similar to the task in [12], drones need to traverse the task points to perform corresponding tasks, and trucks appear as a mobile charging device [71]. The application scenario is post-disaster auxiliary search and rescue in [71]. The problem in [71] is essentially a two-level VRP. The first layer is the drone routing problem, and the second layer is the mobile charging truck routing problem. The two-layer VRP problem is constrained and the two layers are coupled with each other. A construct-and-adjust heuristic method was proposed to minimize the normalized weighted sum of the total number of trucks and drones and the cost of drones.

Moreover, in [36], trucks not only act as carrier tools but also charging tools. A flexible heuristic solution was proposed to minimize the total route completion time. In addition, this paper focuses on the impact of parcels with different weights on the endurance abilities of quadrocopter and octocopter when they fly at different speeds.

In [9], autonomous vehicles and drones are used for parcels delivery solving the traffic congestion problem in the traditional last-mile delivery problem. The objective is to minimize the flight distance of drones.

4.3.3. *Meta-heuristic methods*

In [48], the authors investigated a multi-objective VRP with time window and drone transportation constraints. An improved artificial bee colony (ABC) algorithm was designed to optimize the total energy consumption of trucks, the total energy consumption of drones, and the total number of trucks. Similarly, based on the traffic network, the anchor points are selected for trucks, and the drones go deep into the city for parcel delivery [49].

In [10], a novel truck and drone coordinated delivery system was proposed, aiming at reducing direct human contact during the delivery process. Based on reinforcement learning, the total duration of the delivery was optimized to obtain the minimum value. All final deliveries are completed by the drones while trucks act as movable charging stations and carriers so that the contagion risks are reduced.

4.3.4. *Hybrid methods*

A novel hybrid genetic algorithm was proposed in [49] to solve TDCDP by minimizing the total time consumption. The proposed algorithm consists of a pipeline of several modules: population management, heuristic population initialization, and population education. The performance evaluation results show that the proposed algorithm has significant efficiency over existing algorithms.

4.4. *Methods for $D_A \rightarrow T_D$*

In this delivery mode, trucks deliver parcels with drones as auxiliary tools, and drones can dock on trucks. There are two main situations in truck parcel delivery with drone-assisting. One is that due to the limited parcel capacity of the truck, it is unable to meet the cargo needs of all customers at one time. The other situation is when a new order appears. A drone will dynamically replenish the truck when a new order appears. Moreover, the time or economic consumption caused by trucks picking up goods from the depot will be very large. Therefore, the drone can supply goods for the truck according to the needs of the truck. Because of the emergence of new orders and the dynamic replenishment of drones, the problem model in $D_A \rightarrow T_D$ is a variant of dynamic TSP or VRP, which is more complex.

The schematic diagram of trucks delivery with drone-assisting in TDCDP is shown in Fig. 10. One truck starts from the depot to provide delivery services for 9 customers, and the drone starts from the depot to replenish the truck at customer 2 and customer 5, respectively. The existing research is relatively few in this delivery mode, so we do not specifically classify the methods.

In [18], an MILP and a solution approach were developed for large instances by decomposing the problem into the truck routing and the drone-resupply decisions. The objective is to minimize the total delivery time to serve all customers.

For truck delivery, due to the emergence of new orders, the parcel is replenished by drone. Dayarian *et al.* proposed an algorithm based on two strategies of route generation and order release to optimize the path cost of trucks and drones [7] with the objective to minimize total cost.

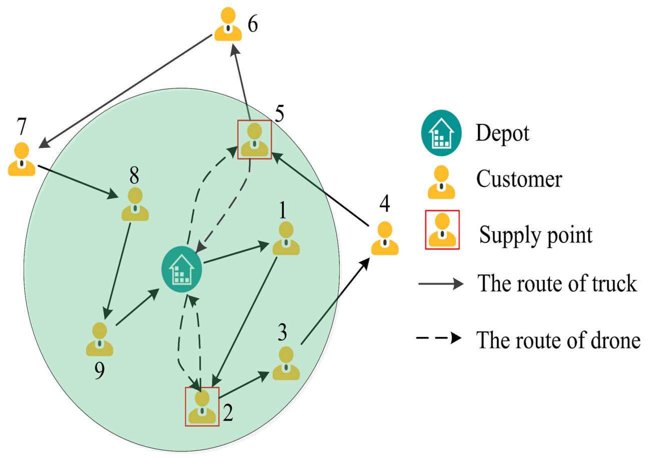


Fig. 10. A truck delivers parcels with drone-assisting.

In addition, Dayarian *et al.* also considered a highly dynamic and stochastic same-day delivery environment in which online orders, as well as in-store customers willing to make deliveries, arrive throughout the day [8]. The objective is to maximize the profit.

5. Bibliometric Analysis and Challenges

We summarize the development trend of TDCDP in recent years in Fig. 11. First, we conduct retrieval based on a topic search. In the logistics field, the topics include last mile, city logistics, home delivery, trucks and drones/UAVs, and urban logistics. From the essence of the problem, the topics include TSP-D, VRP-D, and so on. The literature data is retrieved from Web of Science closely related to TDCDP.

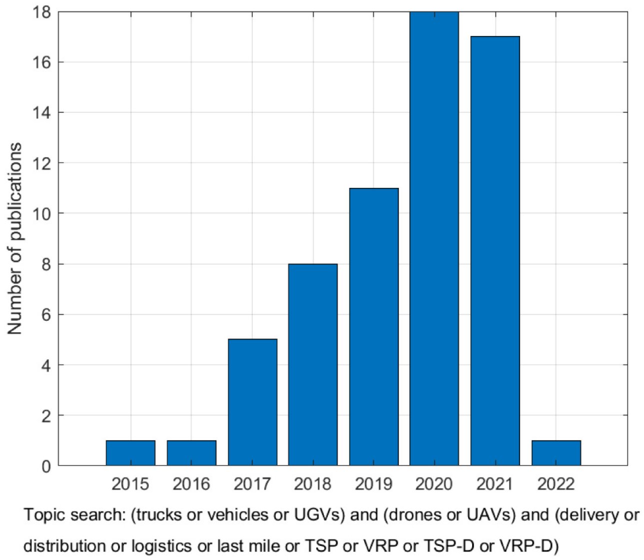


Fig. 11. The general trend.

5.1. *Research status*

In Table 9 (attached at the end of the paper), we make a comprehensive summary of the literature investigated. The tables include the references, the symbols, the number of depots, trucks, drones, and customers, problem models, optimization objectives, and methods. For the number of customers, we have simply divided them into small scale below 50 and large scale above 50. When some parameters are not specified in the literature, we use '—' to express them.

In Fig. 12, we analyze TDCDP from six different perspectives, including trucks and drones delivery mode, the number of objectives, the number of customers, the kind of the objective, problem models, and methods. Next, we will summarize the research status of TDCDP from six aspects according to the observation results.

(1) Due to drone delivery appearing in the logistics industry in recent years, most studies focus on $\mathrm{D}_D \rightarrow \mathrm{T}_D$ in TDCDP. The trucks and drones mixed delivery can make the logistics distribution more efficient and make up for the shortage of independent delivery.
(2) Most studies model TDCDP as a single-objective optimization problem. Usually, we want to use fewer resources to complete more tasks more efficiently. Therefore, there are many conflictive objectives in TDCDP that need to be optimized. In order to simplify the problem model, researchers usually convert some objectives into constraints or optimize the main objective.
(3) Most of the existing TDCDP studies are about large-scale customers. With the rapid development of e-commerce, more and more customers need parcel delivery.
(4) Most studies are devoted to the total delivery cost, total delivery time, or makespan. Some studies have also optimized the number of trucks and drones, profit, customer satisfaction, and customer waiting time.
(5) Most studies modeled TDCDP as variants of TSP or VRP, and there are more variants of TSP. In most studies, there is only one depot, so the number of customers is relatively small. However, there are also some studies that try to solve TDCDP with multiple depots.
(6) The majority of existing studies use exact algorithms or heuristic algorithms. Most of the existing studies only involve small-scale instances, and exact algorithms can solve TDCDP accurately. When the problem scale of TDCDP increases, corresponding heuristic rules can be constructed according to the knowledge contained in the problem, and TDCDP can also be well solved.

5.2. *Research trends*

5.2.1. *Delivery modes*

It can be seen from the results of literature research that in previous years, most of the research is about the mixed delivery of trucks and drones. Both trucks and drones have the function of delivering parcels. In recent years, with the development of the logistics industry and the increasing complexity of customer needs, trucks and drones have some other functions. For example, trucks can be used as charging devices, carrier vehicles, etc. to assist drones. Besides, drones can supply parcels for trucks. The auxiliary mode has attracted more and more attention.

5.2.2. *Large number of customers*

It can be seen from the results of literature research that the number of customers is gradually expanding, from several to dozens or even hundreds. For large-scale cases, some clustering methods can be used to transform the problem according to the characteristics of the actual problem to reduce the difficulties of problem-solving.

5.2.3. *Multi-objective optimization*

Most of the optimization objectives are to minimize the delivery time, the delivery cost, the time to complete the last task or maximize customer satisfaction. These problems are modeled as single-objective optimization problems. In recent years, with the wide application of multi-objective optimization algorithms, TDCDP is more and more frequently modeled as a multi-objective optimization problem.

5.2.4. *More realistic scenes*

Now most papers did not consider the impact of environments on truck and drone cooperative delivery but simply use the Euclidean distance between customers to represent the actual distance. Recently, some papers begin to consider the impact of the actual environments and traffic conditions on delivery modes. Some papers also consider the impact of load on the endurance of drones.

5.2.5. *Large delivery scenario*

Fixed-wing UAV has potential application in large-scale disaster relief missions because of their strong endurance, high speed, and large capacity. However, the fixed-wing UAV cannot hover due to its curvature constraint. So, the fixed-wing UAV and truck may not cooperate, which will change the problem properties of TDCDP.

Table 9. The model differences in different delivery modes.

References	Symbol	Depot number	Truck number	Drone number	Customer number	Problem model	Objective	Method
[7]	$D_A \rightarrow T_D$	10/40	1	1	1	TSP-D	Minimize total cost	Two strategies: Route generation and order release
[8]	—	1	—	—	—	—	Maximize profit	A sample-scenario planning method
[9]	$D_D \rightarrow T_A$	2	5	5	5	VRP-D	Minimize the drone flying distance	—
[10]	$D_D \rightarrow T_A$	1	1	1	50/200	TSP-D	Minimize the total duration of the delivery	Reinforcement learning
[11]	$D_D \rightarrow T_D$	1	5	6	100/200/300/400/500	VRP-D	Minimize the completion time	Hybrid truck-drone delivery algorithm
[12]	$D_D \rightarrow T_A$	1	—	—	6/8/50/100	TSP-D	Minimize the total operation cost	Extends the classic Clarke and Wright algorithm
[13]	$D_D \rightarrow T_D$	1/Multiple	—	—	50/75/100/125/150	—	Minimize the mission completion time	HCVILS
[14]	$D_D \rightarrow T_A$	3/8/15/24	—	1/2/3	50/100	VRP-D	Minimizes the total operation cost	Extended the classic Clarke and Wright algorithm
[15]	$D_D \Vert T_D$	1	0/1//3/5	2	10/15/30	TSP-D	Minimize the makespan	Greedy randomized algorithm and a mixed linear integer programming formulation
[16]	$D_D \rightarrow T_D$	1	1	1	7/8/9/20/50/100	TSP-D	Minimize the cost	An ADA heuristic
[18]	$D_A \rightarrow T_D$	1/2	1	1/2	10/20/30/40/50	TSP-D	Minimize the total delivery time	MILP by CPLEX
[17]	$D_D \Vert T_D$	1	1	1	9	TSP-D	Minimize the latest time	MILP formulations
[19]	$D_D \Vert T_D$	1	1	1	6/10/12	TSP-D	Minimize the cost of the tour	Fast route first-cluster second heuristics based on local search and dynamic programming
[20]	$D_D \rightarrow T_D$	1	1	1	10/11/12/13/20	TSP-D	Minimize the delivery completion time	An iterative algorithm that is based on a decomposition approach
[21]	$D_D \rightarrow T_D$	1	1	2	8	VRP-D	Minimize the completion time	Worst-case analysis
[22]	$D_D \rightarrow T_D$	1	1/2/3/4	—	[10, 100]	TSP-D	Minimize the total task completion time	A new algorithm based on insertion heuristics
[32]	$D_D \rightarrow T_D$	1/Multiple	1	Multiple	20/40/60/80	TSP-D	Minimize the transportation cost and maximize the customer satisfaction	A hybrid multi-objective optimization approach

Table 9. (*Continued*)

References	Symbol	Depot number	Truck number	Drone number	Customer number	Problem model	Objective	Method
[35]	$D_D \rightarrow T_D$	1	1	—	Small 5/6/7/8/9 large 20/50/75/100/175/200	TSP-D	Minimize the total travel time	An iterated greedy heuristic based on the iterative process of destruction and reconstruction of solutions
[55]	$D_D \rightarrow T_D$	1	1	4	8/10/25/50/100	TSP-D	Minimize the total completion time of whole operation	A greedy timing algorithm and a stochastic partition local search
[37]	$D_D \rightarrow T_D$	1	1	3	10/25/50/100	TSP-D	Minimize the makespan	An efficient three-phased heuristic algorithm
[41]	$D_D \rightarrow T_D$	Multiple	Multiple	Multiple	6/7/8/125/500	VRP-D	Minimize the overall delivery time and the total cost	A simulated annealing heuristic algorithm
[48]	$D_D \rightarrow T_A$	1	25	25	100	VRP-D	Minimize the total energy and the total number of trucks and drones	Improved ABC algorithm
[36]	$D_D \rightarrow T_A$	1	1	1–8	12	TSP-D	Minimize the total route completion time	A flexible heuristic solution
[38]	$D_D \rightarrow T_D$	2	1	1	10/20/30/40/50	TSP-D	Influence of parcels' weight on drones	MILP by CPLEX
[42]	$D_D \rightarrow T_D$	Multiple	Multiple	Multiple	10–50	VRP-D	Minimize an overall transportation cost	Branch-and-cut
[46]	$D_D \rightarrow T_D$	1	1	1	20/40/100	TSP-D	Minimize the drone cost/ truck cost/total cost	A two-stage route-based modeling approach
[47]	$D_D \rightarrow T_D$	1	1	1	8	TSP-D	Minimize the comprehensive transportation cost of trucks and drones	Two-phase method
[49]	$D_D \rightarrow T_A$	—	1	5	150–450	TSP-D	Minimize the time/distance cost	A novel hybrid genetic algorithm
[51]	$D_D \rightarrow T_D$	1	1	3	4–20	TSP-D	Minimize the sum of customer waiting time and the total transportation cost	MILP model
[54]	$D_D \rightarrow T_D$	1	2/4/6	2/4/6	50	TSP-D	Minimize the travel cost and maximize the customer service level	A novel collaborative pareto ant colony optimization algorithm
[50]	$D_D \Vert T_D$	1	1	1	8–10	TSP	Minimize the cost and time	Hybrid genetic search
[52]	$D_D \rightarrow T_D$	1	1	1	10	TSP-D	Minimize the completion time	Branch-and-cut

Table 9. (*Continued*)

References	Symbol	Depot number	Truck number	Drone number	Customer number	Problem model	Objective	Method
[59]	$D_D \| T_D$	1/2	1/2/3/4	1/2/3/4	—	TSP-D	Minimize the cost of the tour	Exact solution approaches based on dynamic programming
[60]	$D_D \| T_D$	1	3	3	20/50	TSP-D	Minimize the makespan	An algorithm based on VNS and Tabu
[61]	$D_D \rightarrow T_D$	1	1	1/2/3	10/11/12/13/14/15/ 16/17/18/19/20	TSP-D	Minimize the total truck travel time plus its total delay	A Benders-type decomposition algorithm
[62]	$D_D \rightarrow T_D$	—	Multiple	1/2	20/30	VRP-D	Minimize the maximum completion time of all vehicles	Branch-and-cut
[63]	$D_D \| T_D$	1	1	1	10/19	TSP-D	Minimize total time	Branch-and-cut algorithm
[64]	$D_D \rightarrow T_D$	1/2	1/2	1/2	20/50/100	TSP-D	Minimize the makespan	A constraint programming approach
[65]	$D_D \rightarrow T_D$	1	1	1	30	TSP-D	Minimize the delivery time	A greedy heuristic algorithm
[66]	$D_D \rightarrow T_D$	1	1	2	20/50/100	TSP-D	Minimize the makespan	A MSTS algorithm
[67]	$D_D \rightarrow T_D$	1	1	1/2/3/4/5/6	10/20/50/100	TSP-D	Minimize the sum of waiting time	An efficient hybrid Tabu search-simulated annealing algorithm
[68]	$D_D \rightarrow T_D$	1	5/10/20/ 30/40	1/2/3/4	6/10/12/20/50/ 100/150/200	VRP-D	Minimize the total traveling time	Hybrid genetic algorithm
[69]	$D_D \rightarrow T_D$	1	1/2/3	1/2/3	5/6/7/8/9/10/11/12/ 50/100/150/200	VRP-D	Minimize the operational cost	An adaptive large neighborhood search metaheuristic
[70]	$D_D \rightarrow T_A$	—	—	—	—	—	Minimize the total distance cost	An exact solution algorithm
[71]	$D_D \rightarrow T_A$	1	—	1	157	—	Minimize the normalized weighted sum of the total number of trucks and drones and the cost of the drones	Construct-and-adjust heuristic method

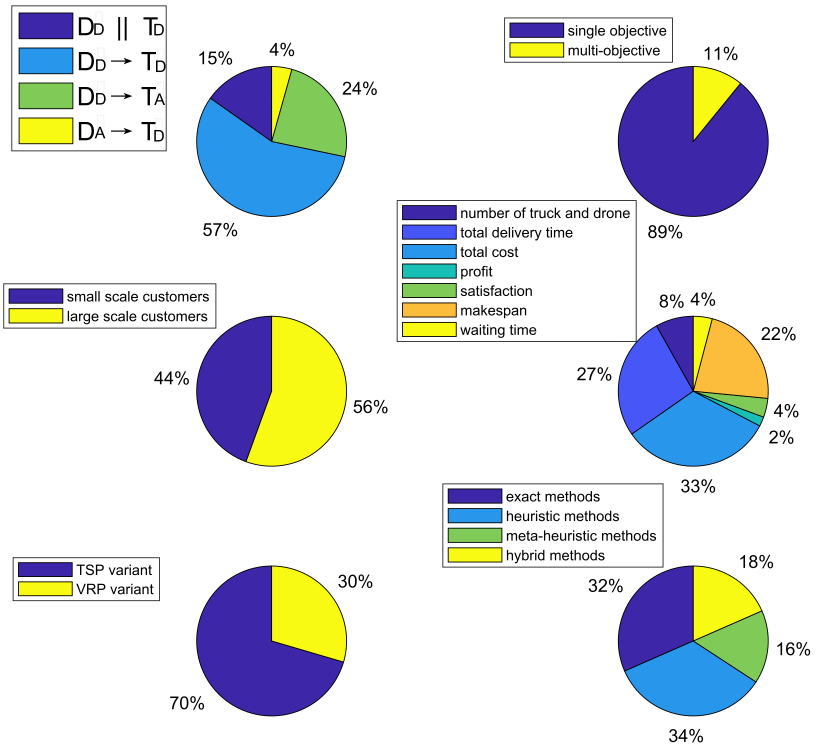


Fig. 12. Literature distribution from different perspectives.

5.2.6. *Artificial intelligence*

With the rapid development of artificial intelligence technology, unmanned driving and other technologies are maturing. By tracking the traffic information in real-time and adjusting the transportation path in time, the delivery time can become more accurate. The delivery robot can automatically generate a reasonable distribution route, and avoid vehicles, speed bumps, and obstacles on the way.

5.3. *Challenges*

5.3.1. *Complex constraints*

TDCDP faces multiple constraints. In addition to the regular delivery and return of parcels, customers' requirements for time should also be considered, such as immediate delivery or delivery at an agreed time. Environments also have different constraints on the mobility and flight capacity of trucks and drones, which directly affect the results of delivery task planning. Multiple complex constraints make the design of encoding and decoding and solving process more difficult in the process of algorithm design.

5.3.2. *Uncertainties*

In TDCDP modeling process, there are various uncertainties, such as the time and location demand of customers, the emergence of new orders, and the cancellation of existing orders. Changes in some environmental factors will also bring uncertainties to TDCDP, such as changes in the weather and road conditions. The existence of uncertainty makes the TDCDP more difficult to solve. First, modeling uncertainties is a complex process. Second, the existence of uncertainties makes the evaluation of solutions more difficult.

5.3.3. *Dynamic factors*

With the rapid development of the logistics industry, the number of orders is gradually increasing. Especially for the same-day delivery problem, the dynamic update of orders directly affects the delivery task planning. There are also many dynamic factors in the environment, such as dynamic obstacles and dynamic changes in road conditions. These factors not only affect the quality of the delivery scheme but may directly lead to the infeasibility of the delivery scheme. For dynamic factors, it is necessary to predict them and adjust the original scheme in time to control the cost within a reasonable range.

5.3.4. *Multi-objective TDCDP*

At present, TDCDP involving multiple objectives is still challenging. In practical problems, the objective is usually not a single one but a combination of multiple objectives such as delivery efficiency, customer satisfaction, path distance consumption, time consumption,makespan, etc. Different decision-makers may focus on different objectives. Therefore, the design of optimization methods and the construction of the decision-making process will become more difficult to meet different objectives.

5.3.5. *Large-scale TDCDP*

In the future, the number of customers, trucks, and drones in TDCDP will gradually increase, and the cooperation mode of trucks and drones will also show diversity. The increase in problem scale will lead to an increase in computational complexity. Some traditional exact algorithms will become unsuitable. It is necessary to mine the problem-specific knowledge according to the characteristics of TDCDP and incorporate the knowledge into algorithms.

In real scenarios, the above factors generally do not appear alone, but in a certain combination, such as multiple constraints with multiple objectives, and multiple objectives with uncertainties, which will increase the difficulty of TDCDP to a greater extent.

6. Conclusion

Trucks and drones cooperative delivery has been attracting more and more attention. This paper focuses on TDCDP and proposes a taxonomy based on the delivery modes of trucks and drones. The criteria of this taxonomy include the role of trucks, the role of drones, and whether drones can dock on trucks. The delivery modes are divided into parallel delivery, mixed delivery, drone delivery with truck-assisting, and truck delivery with drone-assisting. These four delivery modes can cover all current research about TDCDP. This taxonomy can be used to classify the studies on TDCDP, which is convenient for sorting out the delivery modes and understanding the problem models. Based on the taxonomy, this paper systematically reviews the advances in TDCDP and performs a comprehensive investigation and analysis of the recent research. For different delivery modes, this paper summarizes the TDCDP models and analyzes the common assumptions, constraints, and objective functions. In addition, this paper also combs the exact algorithms, heuristic algorithms, and hybrid algorithms used to solve different kinds of TDCDP. Finally, this paper summarizes the research status, research trends, and limitations, and highlights the challenges of TDCDP.

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