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Coordinated last-mile deliveries with trucks and drones: A comparative study of operational modes

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ABSTRACT

Throughout the recent decade, drone delivery technology has been developed to address problems such as last-mile delivery and recurrent traffic jams in metropolitan regions. To resolve the relatively short travel range and limited capacity issues of drones, researchers have proposed to further enhance the utility of drones by deploying them with ground vehicles (e.g., trucks) in tandem. This new concept leads to a new transportation planning problem, i.e., coordinated delivery of trucks and drones (CDTD). In this paper, we conduct a comparative study of three representative operational models: the flying sidekick traveling salesman problem (FSTSP), the traveling salesman problem with drone (TSP-D), and the parallel drone scheduling traveling salesman problem (PDSTSP). Metrics including delivery efficiency and vehicle utilization rate are evaluated for the three models under various scenarios, to extract insights on which operational model is advantageous for which scenario. We also benchmark the algorithms for CDTD by various metrics including result quality, runtime and scalability, and conduct sensitivity analysis to assess the performance of the system under various system parameters, including drone speed, drone range and customer geographic distribution. Finally, a case study is conducted to demonstrate the superior performance of CDTD model as compared to classical TSP model based on real-world data. Experimental results demonstrate that the FSTSP and TSP-D highlight superior performance over PDSTSP and truck-only TSP when the majority of customers are out of the flight range of drone and the customer demand is clustered, as a result of the synchronization and compensation for limitations between the two types of vehicles.

1. Introduction

The rapid growth of e-commerce in China has sparked an unprecedented demand for efficient logistics and courier services. Reports reveal that the parcel delivery market in China has reached about 11,058 billion shipments and 1,056.67 billion RMB in revenue in 2022 (State Post Bureau, 2022). This surge has been further accelerated by factors such as urbanization, improved internet infrastructure, and changing consumer habits favoring online purchases. However, this surge in demand has also revealed a significant scarcity of courier services capable of handling the immense volume of packages generated by China's e-commerce boom, especially in rural areas that constitute 94% of China's landmass. This scarcity is largely attributed to the high last-mile delivery costs in rural areas, which are two to five times higher than those incurred in urban settings (People's Daily, 2022). The major reasons behind this phenomenon are extended delivery distances and shortage of warehouses, since rural areas feature dispersed residential areas and fewer logistics facilities (Yang et al., 2020).

In the recent decade, emerging technologies have been explored by logistics companies to improve operational efficiency and reduce labor intensity. The most anticipated technology among them is the use of unmanned aerial vehicles (i.e., drones) for parcel delivery. Drones are more agility and faster than urban trucks and tricycles since they can fly over congested roads without adhering to the road network. On the industry side, companys including Amazon, Meituan and SF Express have been exploring drone deliveries for a decade. The Amazon Prime Air program was launched in 2013, delivering packages with up to 5 pounds weight to customers in less than half an hour (Pierce, 2013). By the end of 2022, Meituan's unmanned aerial vehicles had accumulated over 120,000 food delivery orders, with more than 100,000 orders completed in 2022 alone (Huanqiu News, 2023).

Nevertheless, various limitations exist and affect the development of drone logistics. Mileage and capacity issues are the most serious one amongst these limitations. The majority of electric rotary-wing drones have flight range less than 30 kilometers, and the payload of small rotary-wing drones generally does not exceed 10 kilograms (DJI, 2024).

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Fig. 1. On-site experiments of coordinated delivery of trucks and drones by UPS (left) and Meituan (right).

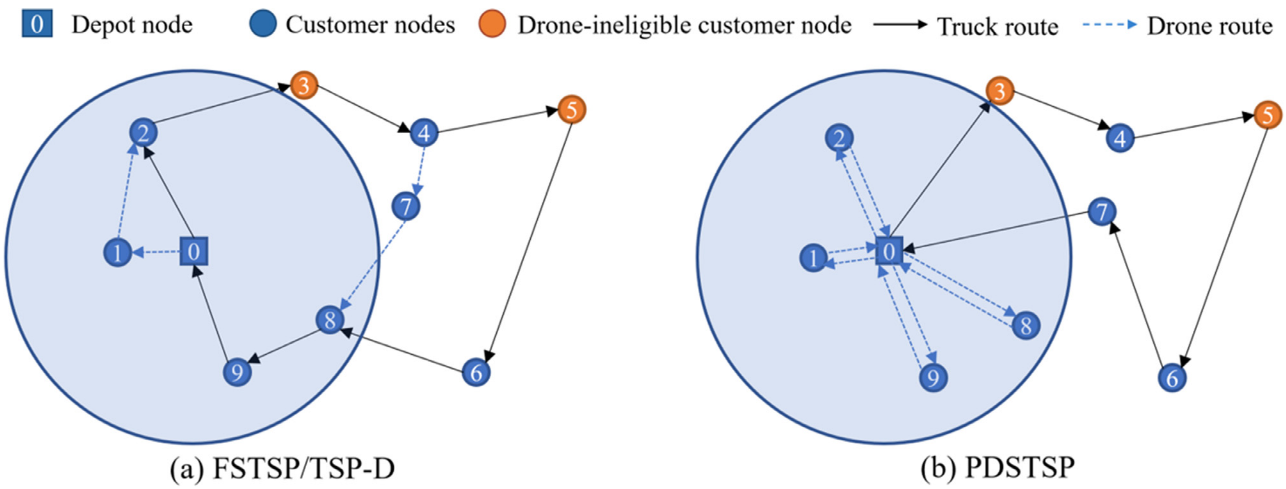

Fig. 2. Three representative operational models of CDTD problems.

Besides, adverse weather conditions like rain, wind, and fog can impact drone operations, potentially causing delays in deliveries.

As drones continue to gain attention in the delivery industry, researchers and companies are exploring new business models to extend their effective range and capacity. One promising operating model is to allow drones to collaborate with delivery vehicles, e.g., trucks, to finish the last mile delivery. In this operating model, trucks not only serve as the transportation vehicles, but also temporary warehouses for drones. Drones can be launched and recovered while the truck is driving en-route, serving customer demands by legs of flights. The truck also enables the drones to recharge, swap batteries, or transfer packages, which could extend the drone's effective operating range and weight of parcels carried. This approach has already been tested by several companies, such as UPS and Meituan, demonstrating great potential to revolutionize the delivery industry by providing more cost-effective and sustainable delivery solutions. Fig. 1 shows two on-site experiments of coordinated delivery of trucks and drones (CDTD) by UPS (left) and Meituan (right).

The widespread interest of CDTD problems has led to a plethora of research papers. For an overview of the literature of CDTD problems, the reader is referred to several excellent surveys and reviews in this area (Chung et al., 2020; Moshref-Javadi et al., 2021; Pasha et al., 2022; Wandelt et al., 2023; Wang et al., 2024b). Various coordinated delivery modes of trucks and drones have been proposed in the literature, however, it remains unclear which operational mode is advantageous for which scenario, which is characterized by the distribution of customers and depot, the flight range and speed of drones, etc. Besides, most CDTD problems are NP-hard, leaving room for devising and tuning solution techniques, be it exact methods or heuristics (Wandelt et al., 2022; Wang et al., 2024a). Although some larger problems can be solved quite well, it is not well understood which solution approaches work best for various CDTD problems and why. It is thus necessary to conduct a benchmark comparison of various CDTD solution algorithms.

In this paper, we conduct a comparative study of three representative operational models: the flying sidekick traveling salesman problem (FSTSP), the traveling salesman problem with drone (TSP-D), and the parallel drone scheduling traveling salesman problem (PDSTSP). A schematic representation of the three operational models is visualized in Fig. 2. The rectangular node 0 represents the depot and the remaining circular nodes represent customers, in which the orange nodes are drone-ineligible. The solid black arcs represent the flow of the truck, while the dashed blue arcs represent the flight of the drone. Both of the FSTSP model and the TSP-D model consider synchronized movement of a drone and a truck, i.e., the drone can launch from the truck with a single package to deliver to a customer and then rendezvous with the truck at another location, while the truck can also deliver packages to other customers while the drone is flying. In contrast, the PDSTSP model considers independent movement of a truck and multiple drones, i.e., a single truck and a fleet of identical drones depart and return to a single depot. The drone serves customers directly from the depot in a point-to-point manner, while the truck serves the customers in a TSP route manner.

Metrics including delivery efficiency and vehicle utilization rate are evaluated for the three models under various scenarios, to extract insights on which operational model is advantageous for which scenario. These three models provide the basic structures for CDTD problems, and the majority of CDTD papers incorporate extensions on top of them. The comparative study includes various metrics such as runtime, scalability, and result quality. Through evaluating the pros and cons of different models and algorithms, this paper aims to summarize previous works. Patterns and similarities among different solution techniques would be identified and extracted, providing insights for developing new methodologies for large-scale real-world drone logistics problems. The major contribution of this study is summarized as follows:

- We conduct a comparative study of the three representative operational models for CDTD, and evaluate metrics including delivery efficiency and vehicle utilization rate under various scenarios, to extract insights on which operational model is advantageous for which scenario.
- We compare the performance of exact/heuristic algorithms for the three typical CDTD models regarding runtime, scalability, and result quality.
- We conduct sensitivity analysis to assess the performance of a drone delivery system under various system parameters, such as drone speed, drone range and customer geographic distribution.
- We conduct a case study to demonstrate the superior performance of CDTD models as compared to classical TSP model based on the city road network data of Beijing.

The remainder of this paper is as follows: Section 2 presents a comprehensive review of CDTD problem from two perspectives: the problem types and vehicle roles. Section 3 reviews models for the FSTSP, TSP-D, and PDSTSP problems with assumptions and formulations. Section 4 summarizes multiple exact and heuristic solutions for each problem. Section 5 conducts various experimental evaluations to each model, sensitivity analysis to assess the performance of the system under varying parameters, and a case study based on the city road network data of Beijing. Section 6 concludes the paper and discusses future research directions.

2. Literature review

In this section, we review the literature on CDTD problems by two perspectives: the problem types and vehicle roles. Regarding the classification of problem types, we review two categories including routing and scheduling, and area coverage. We classify the literature based on problem types instead of application areas, since a particular problem type, e.g., routing and scheduling, can be used for multiple application areas, e.g., logistics, security, and entertainment. Regarding the classification of vehicle roles, we review two major scenarios, i.e., synchronized working units of both types of vehicles, and independent working units of both type of vehicles. Both research streams are closely related to our comparative study of operational models of CDTD. The FSTSP model and the TSP-D model belongs to the former scenario, while the PDSTSP model is the typical model of the latter scenario.

2.1. CDTD research based on problem types

The majority of CDTD research problems are highly relevant to the optimization of routing and scheduling for both types of vehicles, namely trucks and drones. Routing and scheduling play pivotal roles in orchestrating the seamless collaboration between these two distinct yet complementary modes of transportation. This synergy finds its most frequent and practical applications in the domain of transportation and logistics, particularly in the efficient and timely delivery of goods and items (Agatz et al., 2018; Dell'Amico et al., 2020; Kim & Moon, 2018; Rave et al., 2023; Wang et al., 2017; Wang & Sheu, 2019; Yang et al., 2023; Yurek & Ozmutlu, 2018). In the parcel delivery context, drones usually serve one customer per sortie while trucks have unlimited load capacity of items. Some common assumptions of CDTD delivery problems include 1) synchronized working of drone and truck, 2) unit capacity of a drone, 3) limited flying range of a drone, and 4) unlimited capacity of a truck (Jeong et al., 2019; Murray & Chu, 2015; Murray & Raj, 2020; Schermer et al., 2019). In the routing and scheduling problem of CDTD research, there are also other research papers that consider disaster management and security (Fikar et al., 2016; Garone et al., 2011; 2010), media and entertainment (Phan & Liu, 2008), and other general applications (Luo et al., 2017; Mathew et al., 2013; Savuran & Karakaya, 2016)

Another popular problem type in CDTD literature is the area coverage operation, which has wide application in surveillance and data/image collection (Mathew et al., 2013; Sujit et al., 2009; Tokekar et al., 2016). Area coverage operations can employ either a drone or a truck as the primary vehicle. In both cases, the operational efficiency and effectiveness benefit from the support of the complementary vehicle. When a drone is designated as the primary vehicle, ground vehicles can play essential roles in multiple functions, including providing battery recharging services, performing drone maintenance, and aiding in transportation to optimize energy consumption and extend the drone's flight range. For example, drones are designated as the primary vehicles for tasks like continuous surveillance along specified routes, while unmanned ground vehicles take on responsibilities such as recharging the drones (Mathew et al., 2013). A drone can act as the primary vehicle for acquiring aerial images for soil classification, while an unmanned ground vehicle can be utilized to transport the drone, thus conserving its energy. Conversely, if a truck takes on the primary role, a drone can assist by directing the truck's path and collecting data from it. In a study conducted by Sujit et al. (2009), autonomous underwater vehicles explore the depths of the ocean, with drones serving the role of collecting data from these underwater vehicles and aiding in their navigation.

2.2. CDTD research based on vehicle roles

The majority of CDTD literature considers synchronized working units of both type of vehicles to jointly optimize the routing and scheduling for both type of vehicles (Jeong et al., 2019; Murray & Chu, 2015; Murray & Raj, 2020; Schermer et al., 2019). In synchronized working (SW) units, drones and trucks typically have equally important roles. This arrangement is commonly used in logistics delivery operations, where a drone departs from a truck to deliver an item to a customer, returns to the truck to recharge or replace its battery, and prepares for the next mission (Chung et al., 2020). Meanwhile, the truck continues to deliver items to customers while also traveling to the next location where both vehicles can meet. Murray and Chu (2015) are the first to propose flying sidekick traveling salesman problem (FSTSP) that pairs traditional delivery trucks with drones. The resulting problem describes a variant of the classical traveling salesman problem where the drone is launched from the truck, goes to deliver goods to a customer and then rendezvouses with the truck in a third customer location. Agatz et al. (2018) have put forward two heuristics based on local search and dynamic programming, which prioritize the route and clusters subsequently, to tackle a TSP-D closely resembling the FSTSP. While the FSTSP assumes that a drone cannot rendezvouse with the truck at the node of its release, the TSP-D accounts for this possibility and also considers the drone to be faster than the truck. Bouman et al. (2018a) introduce an exact dynamic programming method to solve the TSP-D. Their study indicates that their algorithm outperforms direct MILP solution. Due to the enormous computational times required by the models of Murray and Chu (2015) and Agatz et al. (2018), Yurek and Ozmutlu (2018) suggest an iterative approach that decomposes the problem into two stages and solves a MILP model in the second stage. They present an optimization-based heuristic and introduce a new set of instances for the problem.

In contrast to the literature concerning synchronized working units of both type of vehicles, another stream of literature considers independent working units of both type of vehicles. The parallel drone scheduling traveling salesman problem (PDSTSP) proposed by Murray and Chu (2015) allows for the use of a single truck or a fleet of identical drones to serve customers. The goal is to minimize the makespan, which is the time taken for the truck to return to the depot. As drones and the truck do not work together in this version, they are not synchronized. Drones begin and end their routes at the depot, serving one customer at a time and can make multiple trips, leaving the depot more than once. A heuristic is proposed by the authors to solve this problem, which involves constructing an initial solution where drones serve all eligible customers and applying local search heuristics to improve the solution. Mbiadou Saleu et al. (2018) address the PDSTSP and suggest a two-step heuristic as an iterative solution. They consider the PDSTSP as a bilevel problem, where the first level determines how the customers are split between trucks and drones, and the second level optimizes the routing. In contrast, Dell'Amico et al. (2020) propose a simplified MILP model and various matheuristics for the PDSTSP, primarily based on the traditional Lin-Kernighan algorithm for the TSP, along with local search procedures and MILP resolution. Dayarian et al. (2020) propose a dynamic variant in which drones have a non-conventional role; they do not deliver packages but resupply trucks that are making deliveries. The drones can resupply trucks anywhere as long as the truck is stopped, making the system efficient for dynamic deliveries at low cost. The authors formally define the problem as a VRP-D and describe its main features and constraints. They focus on the single-drone, single-truck variant and develop different algorithms to solve the problem and compare their performance. They also quantify the potential benefits of using drone resupply, such as increasing the number of orders served and reducing service time.

3. Problem formulations

This section starts with a brief review of three typical CDTD problems and their formulations; the goal of this section is to set the notation and terminology for the remainder of this study. The following problems are formalized as defined in the literature: FSTSP in Section 3.1, TSP-D in Section 3.2 and PDSTSP in Section 3.3.

3.1. Flying sidekick traveling salesman problem (FSTSP)

As a variant of the classical Traveling Salesman Problem (TSP), the flying sidekick traveling salesman problem (FSTSP) considers a delivery system operated by a truck and a drone, in which the drone can be launched from the truck to deliver a single package and then rendezvous with the truck at another location node, while the truck can also make deliveries simultaneously (Murray & Chu, 2015). The objective is to minimize the makespan to visit all the customers. The basic routing components of the drone in FSTSP are defined as *sorties*, which consisting of three location nodes, i.e., a launch node, a flying node and a rendezvous node. The sets, parameters and decision variables of the FSTSP model are tabulated in Table 1. It is assumed that drones have restricted capacity, so they are capable of serving only one customer during each sortie. The mathematical model of the FSTSP proposed by Murray and Chu (2015) is as follows:

$$\min \quad t_{c+1} \tag{1}$$

$$\text{s.t.} \quad \sum_{\substack{i\in N_0\\ i\neq j}} x_{ij} + \sum_{\substack{i\in N_0\\ i\neq j}} \sum_{\substack{k\in N_+\\ \langle i,j,k\rangle\in P}} y_{ijk} = 1 \quad \forall j\in C \tag{2}$$

$$\sum_{j\in N_+} x_{0j} = 1 \tag{3}$$

$$\sum_{i\in N_0} x_{i,c+1} = 1 \tag{4}$$

$$u_i - u_j + 1 \leqslant (c+2)\left(1 - x_{ij}\right) \quad \forall i\in C, j\in \left\{N_+ : j\neq i\right\} \tag{5}$$

$$\sum_{\substack{i\in N_0\\ i\neq j}} x_{ij} = \sum_{\substack{k\in N_+\\ k\neq j}} x_{jk} \quad \forall j\in C \tag{6}$$

$$\sum_{\substack{j\in C\\ j\neq i}} \sum_{\substack{k\in N_+\\ \langle i,j,k\rangle\in P}} y_{ijk} \leqslant 1 \quad \forall i\in N_0 \tag{7}$$

$$\sum_{\substack{i\in N_0\\ i\neq k}} \sum_{\substack{j\in C\\ \langle i,j,k\rangle\in P}} y_{ijk} \leqslant 1 \quad \forall k\in N_+ \tag{8}$$

$$2y_{ijk} \leqslant \sum_{\substack{h\in N_0\\ h\neq i}} x_{hi} + \sum_{\substack{l\in C\\ l\neq k}} x_{lk} \quad \forall i\in C, j\in \{C : j\neq i\}, k\in \left\{N_+ : \langle i,j,k\rangle\in P\right\} \tag{9}$$

$$y_{0jk} \leqslant \sum_{\substack{h\in N_0\\ h\neq k}} x_{hk} \quad \forall j\in C, k\in \left\{N_+ : \langle 0,j,k\rangle\in P\right\} \tag{10}$$

$$u_k - u_i \geqslant 1 - (c+2)\left(1 - \sum_{\substack{j\in C\\ \langle i,j,k\rangle\in P}} y_{ijk}\right) \quad \forall i\in C, k\in \left\{N_+ : k\neq i\right\} \tag{11}$$

$$t'_i \geqslant t_i - M\left(1 - \sum_{\substack{j\in C\\ j\neq i}} \sum_{\substack{k\in N_+\\ \langle i,j,k\rangle\in P}} y_{ijk}\right) \forall i\in C \tag{12}$$

Table 1
Sets, parameters and decision variables of the FSTSP model.

Sets	
C	set of all customers, $C = \{1,2,\ldots,c\}$
C'	set of drone-eligible customers, $C' \subseteq C$
N	set of all nodes, where the first node and the last node are the depot node, $N = \{0,1,\ldots,c+1\}$
N_0	set of nodes that the truck may depart from, $N_0 = \{0,1,\ldots,c\}$
N_+	set of nodes that the truck may arrive at, $N_+ = \{1,2,\ldots,c+1\}$
P	set of all feasible drone sorties
Parameters	
$\tau_{i,j}$	the travel time from node $i\in N$ to node $j\in N$ for the truck
$\tau'_{i,j}$	the travel time from node $i\in N$ to node $j\in N$ for the drone
s_L, s_R, e	the launch time, rendezvous time and flight endurance for the drone
Decision variables	
x_{ij}	1 if the truck travels from $i\in N_0$ to $j\in N_+$ with $i\neq j$, and 0 otherwise
y_{ijk}	1 if the drone travels from $i\in N_0$ to $j\in C'$ and back to $k\in C_+$
t_j	the time at which the truck arrives at node $j\in N$
t'_j	the time at which the drone arrives at node $j\in N_+$
P_{ij}	1 if customer $i\in C$ is visited before customer $j\in \{C : j\neq i\}$ in the truck route
u_i	the position of node $i\in N_+$ in the truck's path

$$t'_i \leqslant t_i + M\left(1 - \sum_{\substack{j\in C\\ j\neq i}} \sum_{\substack{k\in N_+\\ \langle i,j,k\rangle\in P}} y_{ijk}\right) \quad \forall i \in C \tag{13}$$

$$t'_k \geqslant t_k - M\left(1 - \sum_{\substack{i\in N_0\\ i\neq k}} \sum_{\substack{j\in C,C\\ \langle i,j,k\rangle\in P}} y_{ijk}\right) \quad \forall k \in N_+ \tag{14}$$

$$t'_k \leqslant t_k + M\left(1 - \sum_{\substack{i\in N_0\\ i\neq k}} \sum_{\substack{j\in C\\ \langle i,j,k\rangle\in P}} y_{ijk}\right) \quad \forall k \in N_+ \tag{15}$$

$$t_k \geq t_h + \tau_{hk} + s_L\left(\sum_{\substack{l\in C\\ l\neq k}} \sum_{\substack{m\in N_+\\ \langle k,l,m\rangle\in P}} y_{klm}\right) + s_R\left(\sum_{\substack{i\in N_0\\ i\neq k}} \sum_{\substack{j\in C\\ \langle i,j,k\rangle\in P}} y_{ijk}\right) - M(1 - x_{hk}) \tag{16}$$

$\forall h \in N_0, k \in \{N_+ : k \neq h\}$

$$t'_j \geq t'_i + \tau'_{ij} - M\left(1 - \sum_{\substack{k\in N_+\\ \langle i,j,k\rangle\in P}} y_{ijk}\right) \quad \forall j \in C', i \in \{N_0 : i \neq j\} \tag{17}$$

$$t'_k \geq t'_j + \tau'_{jk} + s_R - M\left(1 - \sum_{\substack{i\in N_0\\ \langle i,j,k\rangle\in P}} y_{ijk}\right) \quad \forall j \in C', k \in \{N_+ : k \neq j\} \tag{18}$$

$$t'_k - (t'_j - \tau'_{ij}) \leq e + M(1 - y_{ijk}) \tag{19}$$

$\forall k \in N_+, j \in \{C : j \neq k\}, i \in \{N_0 : \langle i,j,k\rangle \in P\}$

$$u_i - u_j \geq 1 - (c+2)p_{ij} \quad \forall i \in C, j \in \{C : j \neq i\} \tag{20}$$

$$u_i - u_j \leq -1 + (c+2)(1 - p_{ij}) \quad \forall i \in C, j \in \{C : j \neq i\} \tag{21}$$

$$p_{ij} + p_{ji} = 1 \quad \forall i \in C, j \in \{C : i \neq j\} \tag{22}$$

$$t'_l \geq t'_k - M\left(3 - \sum_{\substack{j\in C\\ \langle i,j,k\rangle\in P\\ j\neq l}} y_{ijk} - \sum_{\substack{m\in C\\ m\notin\{i,j,k\}}} \sum_{\substack{n\in\{N_+ : n\neq i, n\neq j\}\\ \langle l,m,n\rangle\in P}} y_{lmn} - p_{il}\right) \tag{23}$$

$\forall i \in N_0, k \in \{N_+ : k \neq i\}, l \in \{C : l \neq i, l \neq k\}$

$$t_0 = 0 \tag{24}$$

$$t'_0 = 0 \tag{25}$$

$$p_{0j} = 1 \quad \forall j \in C \tag{26}$$

$$x_{ij} \in \{0,1\} \quad \forall i \in N_0, j \in \{N_+ : j \neq i\} \tag{27}$$

$$y_{ijk} \in \{0,1\} \quad \forall i \in N_0, j \in \{C : j \neq i\}, k \in \{N_+ : (i,j,k) \in P\} \tag{28}$$

$$1 \leq u_i \leq c+2 \quad \forall i \in N_+ \tag{29}$$

$$t_i \geq 0 \quad \forall i \in N \tag{30}$$

$$t'_i \geq 0 \quad \forall i \in N \tag{31}$$

$$p_{ij} \in \{0,1\} \quad \forall i \in N_0, j \in \{C : j \neq i\} \tag{32}$$

The objective function (1) minimizes the latest return time for the truck or drone to the depot. Constraint (2) ensures each customer is served once by either the drone or truck. Constraints (3) and (4) ensure the truck departs and arrives at the depot once. Subtour elimination is governed by Constraint (5). Truck visiting and departure are detailed in Constraint (6). Drone launch and rendezvous restrictions are imposed by Constraints (7) and (8). Constraints (9) to (18) ensure truck-drone assignment and synchronization. Arrival times are determined considering travel and service times. Maximum drone flight time is regulated by Constraint (19). Variables are defined in Constraints (27) to (32).

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

The goal of the Traveling Salesman Problem with Drone (TSP-D) is to determine the most time-efficient route that visits all customer locations, utilizing either the truck or the drone. The TSP-D is very similar to the FSTSP, and the primary difference lies in their assumptions and formulation. The TSP-D uses the concept of *operations* as the basic routing component, considering both the routing of the drone and the truck as a unified component, thus leading to synchronization issue for both types of vehicles. Fig. 3 illustrates four operational patterns in the TSP-D model. The first involves the truck carrying the drone directly from start node s to end node e while the drone remains inactive. In the second pattern, the truck travels from s to e while the drone visits node d, with synchronization at e. The third pattern includes truck visits to intermediary node(s) t between s and e, while the drone reaches node d, representing the typical TSP-D operation. Lastly, in the fourth pattern, the truck remains stationary at node s while the drone visits node d. The sets, parameters and decision variables of the TSP-D are tabulated in Table 2. The integer programming model of the TSP-D is formulated as follows:

$$\min \quad \sum_{o\in O} t_o \alpha_o \tag{33}$$

$$\text{s.t.} \quad \sum_{o\in O(i)} \alpha_o \geq 1 \quad \forall i \in N \tag{34}$$

$$\sum_{o\in O^+(i)} \alpha_o \leq c \cdot \beta_i \quad \forall i \in N \tag{35}$$

$$\sum_{o\in O^+(i)} \alpha_o = \sum_{o\in O^-(i)} \alpha_o \quad \forall i \in N \tag{36}$$

$$\sum_{o\in O^+(S)} \alpha_o \geq \beta_i \quad \forall S \subset C, i \in S \tag{37}$$

$$\sum_{o\in O^+(0)} \alpha_o \geq 1 \tag{38}$$

$$\beta_0 = 1 \tag{39}$$

$$\alpha_o \in \{0,1\} \quad \forall o \in O \tag{40}$$

$$\beta_i \in \{0,1\} \quad \forall i \in N \tag{41}$$

Objective function (33) minimizes tour cost, the sum of chosen operations' costs. Constraint (34) ensures all nodes are covered by at least one operation. Constraint (35) sets y_v to 1 if any operation starting at node v is chosen. Constraints (36) and (37) ensure a Eulerian graph representation of selected operations, facilitating feasible truck-and-drone tours. Constraints (38) ensure graph connectivity. Constraint (39) mandates tour start and end at the depot. Constraints (40) and (41) enforce binary variables.

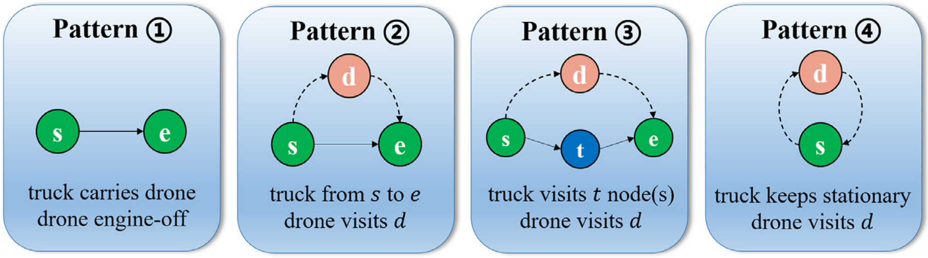

Fig. 3. Four possible patterns of *operation* in the TSP-D model.

Table 2
Sets, parameters and decision variables of the TSP-D model.

Sets	
O	set of operations, $o \in O$
$O^-(i)$	subset of operations with start node $i \in N$
$O^+(i)$	subset of operations with end node $i \in N$
$O(i)$	subset of operations that contain node $i \in N$
$O^-(S)$	subset of all operations with the start node in S and the end node in $N \backslash S$, for each set of nodes $S \subset N$
$O^+(S)$	subset of all operations with the end node in S and the start node in $N \backslash S$, for each set of nodes $S \subset N$
Parameters	
t_o	the travelling time for the truck and drone to take operation $o \in O$ in a synchronized manner
Dec. var.	
α_o	1 if the operation $o \in O$ is chosen in the solution, and 0 otherwise
β_i	1 if node $i \in N$ is chosen as a start node in at least one operation, and 0 otherwise

Table 3
Sets, parameters and decision variables of the PDSTSP model.

Sets	
D	set of identical drones, $d \in D$
C'	subset of customers that may receive delivery of their parcel via a drone, i.e., these customers are drone-eligible, $C' \subseteq C$
C''	subset of drone-eligible customers that are also within the drone's range from the depot, i.e., customer $i \in C'$ is in set C'' if $\tau'_{0,i} + \tau'_{i,c+1} \le e$
Dec. var.	
$\hat{x}_{i,j}$	1 if the truck travels from node $i \in N_0$ to node $j \in \{N_+ : j \neq i\}$, and 0 otherwise
$\hat{y}_{i,d}$	1 if customer $i \in C''$ is served by drone $d \in D$, and 0 otherwise
$\hat{u}_i$	the position of node $i \in N_+$ in the truck's path, $1 \le \hat{u}_i \le c+2$

3.3. Parallel drone scheduling traveling salesman problem (PDSTSP)

The parallel drone scheduling traveling salesman problem (PDSTSP) involves the optimal routing of a delivery truck and multiple delivery drones to serve a set of customers in an independent manner (Murray & Chu, 2015). Regarding the application scenario, the FSTSP and TSP-D mainly consider the case in which the depot is relatively far from the customer locations and the drone is operating in tandem with the truck. In contrast, the PDSTSP primarily deals with the case in which a significant proportion of customers are located within the flight range of drone from the depot. In the PDSTSP, a single truck and a fleet of identical drones depart and return to a single depot. The drone serves customers directly from the depot in a point-to-point manner, while the truck serves the customers in a TSP route manner, so that the synchronization effect between both types of vehicles is not considered. The objective is to minimize the latest time that a vehicle returns to the depot, such that each customer is served exactly once. The sets, parameters and decision variables of the PDSTSP are tabulated in Table 3. The mixed integer linear programming formulation of the PDSTSP is formulated as follows:

$$\min \quad z \tag{42}$$

$$\text{s.t.} \quad z \ge \sum_{i \in N_0} \sum_{\substack{j \in N_+ \\ j \neq i}} \tau_{i,j} \hat{x}_{i,j} \tag{43}$$

$$z \ge \sum_{i \in C''} \left(\tau'_{0,i} + \tau'_{i,c+1} \right) \hat{y}_{i,d} \quad \forall d \in D \tag{44}$$

$$\sum_{\substack{i \in N_0 \\ i \neq j}} \hat{x}_{i,j} + \sum_{\substack{d \in D \\ j \in C''}} \hat{y}_{j,d} = 1 \quad \forall j \in C \tag{45}$$

$$\sum_{j \in N_+} \hat{x}_{0,j} = 1 \tag{46}$$

$$\sum_{i \in N_0} \hat{x}_{i,c+1} = 1 \tag{47}$$

$$\sum_{\substack{i \in N_0 \\ i \neq j}} \hat{x}_{i,j} = \sum_{\substack{k \in N_+ \\ k \neq j}} \hat{x}_{j,k} \quad \forall j \in C \tag{48}$$

$$\hat{u}_i - \hat{u}_j + 1 \le (c+2)\left(1 - \hat{x}_{i,j}\right) \quad \forall i \in C, j \in \left\{N_+ : j \neq i\right\} \tag{49}$$

$$1 \le \hat{u}_i \le c+2 \quad \forall i \in N_+ \tag{50}$$

$$\hat{x}_{i,j} \in \{0,1\} \quad \forall i \in N_0, j \in \left\{N_+ : j \neq i\right\} \tag{51}$$

$$\hat{y}_{i,d} \in \{0,1\} \quad \forall i \in C'', d \in D \tag{52}$$

The objective function (42) seeks to minimize the latest return time for both vehicle types to reach the depot. Constraints (43) and (44) establish lower bounds on z by incorporating the routing decisions of both vehicles. Constraint (45) ensures each customer is served once by either a truck or a drone. Constraints (46) and (47) mandate the truck's departure and return to the depot exactly once. Constraint (48) maintains flow balance for the truck at any customer node, while Constraint (49) serves as a standard subtour elimination constraint. Constraints (50) to (52) define decision variables.

4. Solution techniques

4.1. Solution techniques for FSTSP

The MILP model for the FSTSP can be directly solved by standard optimization solvers such as CPLEX and Gurobi. Although the optimal solution is guaranteed, they take extensive amount of runtime which is unaffordable in practical application. Therefore, various heuristic methods are proposed in the literature to obtain a near-optimal feasible solution in reasonable time, which presents a trade-off between runtime and result quality. In this section, three heuristic methods adopted in this benchmark are introduced.

4.1.1. Greedy randomized adaptive search procedure

The greedy randomized adaptive search procedure (GRASP), proposed by Ha et al. (2018), is a metaheuristic aiming for near-optimal solutions by continuously generating and refining candidate solutions. Initialization sets the best objective value to infinity and the iteration counter to zero. The algorithm iterates until reaching the maximum iterations. Each iteration generates a candidate solution by solving the TSP problem for the given customers using various algorithms. An auxiliary graph is constructed from the candidate solution, extracting the FSTSP solution. If the new tour improves upon the current best solution, the algorithm updates the best solution and objective value. This process repeats until reaching the maximum iterations or meeting a stopping criterion.

4.1.2. Dynamic customer relocation algorithm

The dynamic customer relocation algorithm (DCRA), proposed by Murray and Chu (2015), combines TSP and relocation techniques. Each iteration calculates potential cost savings by redistributing customers for drone delivery and selects the scheme with the largest savings to enhance the solution. Key functions include *calcSavings, relocateAsTruck*, and *relocateAsUAV*. *calcSavings* computes cost reductions from removing a customer from the truck's route. *relocateAsTruck* reassigns customers to the truck's route, while *relocateAsUAV* does so for the drone's route.

4.1.3. Greedy partitioning heuristic

The greedy partitioning (GP) heuristic, proposed by Agatz et al. (2018), addresses the FSTSP problem. It first generates TSP routes and categorizes customers based on attributes (drone-visited or truck-visited), as shown in Fig. 4. The heuristic comprises three operators: *MakeFly, PushLeft*, and *PushRight*. At each step, it modifies the solution using one of these operators, selecting the one that saves the most delivery time. Node labels indicate drone, truck, or dual service. The FSTSP solution is obtained once all nodes have appropriate labels. The algorithm terminates after a set number of iterations, with a time complexity of $O(N \log N)$ using suitable data structures. It relies heavily on the initial TSP solution and may employ multiple local search heuristics for modification.

4.2. Solution techniques for TSP-D

The mathematical model for the TSP-D problem is essentially a linear integer programming problem, which can be solved using commercial optimization software such as CPLEX and Gurobi. However, such mathematical programming solvers often have relatively low computational efficiency and may not meet the requirements for solving large-scale problems. Therefore, it is necessary to design efficient exact solution algorithms to improve solving efficiency. Compared to large-scale heuristic algorithms for solving the FSTSP, exact solution algorithms can ensure that the returned solution is globally optimal when the algorithm terminates and can be rigorously proven theoretically. In this section, two exact solution approaches adopted in this benchmark are introduced.

4.2.1. Three-pass dynamic programming

The three-pass dynamic programming method (3PDP), introduced by Bouman et al. (2018a), tackles the TSP-D, drawing inspiration from the Bellman-Held-Karp dynamic programming algorithm for the TSP (Bellman, 1962). In the first pass, it adapts the dynamic programming algorithm for the regular TSP to find the shortest truck path for each start node, end node, and covered truck node set. The second pass combines truck paths from the first pass with drone nodes to generate *operations*, representing the least costly coverage of node sets for given start and end nodes. In the third pass, it computes the optimal sequence of operations covering all locations, starting and ending at the depot. Authors achieve this by iteratively solving *subproblems* to find the best operation sequence from the depot, covering specific nodes, and ending at a specific node.

4.2.2. A* search with MST-based heuristic

The algorithm in Section 4.2.1 has a drawback: it solves many irrelevant subproblems, adding to a table of exponential size even

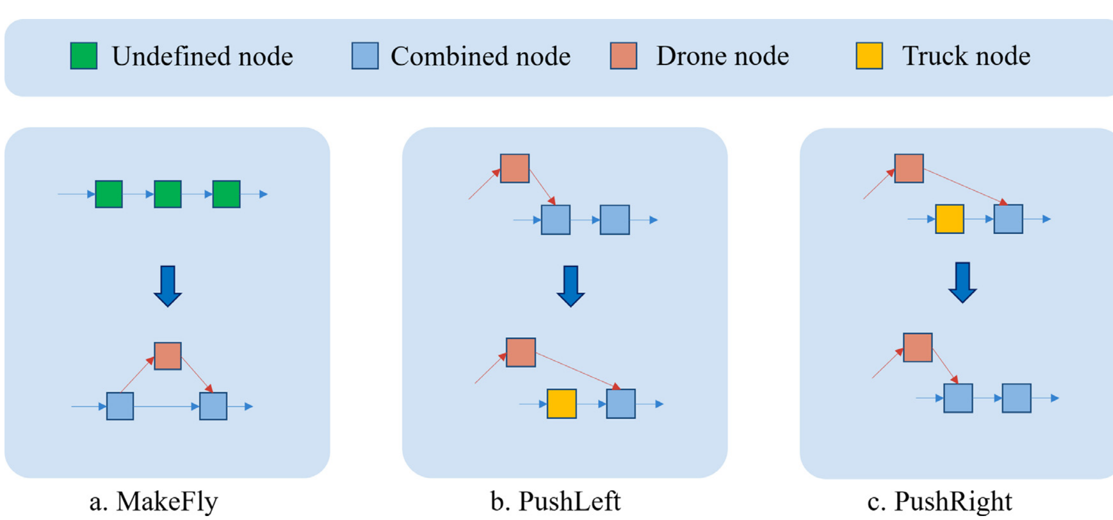

Fig. 4. Three operators in the greedy partitioning heuristic.

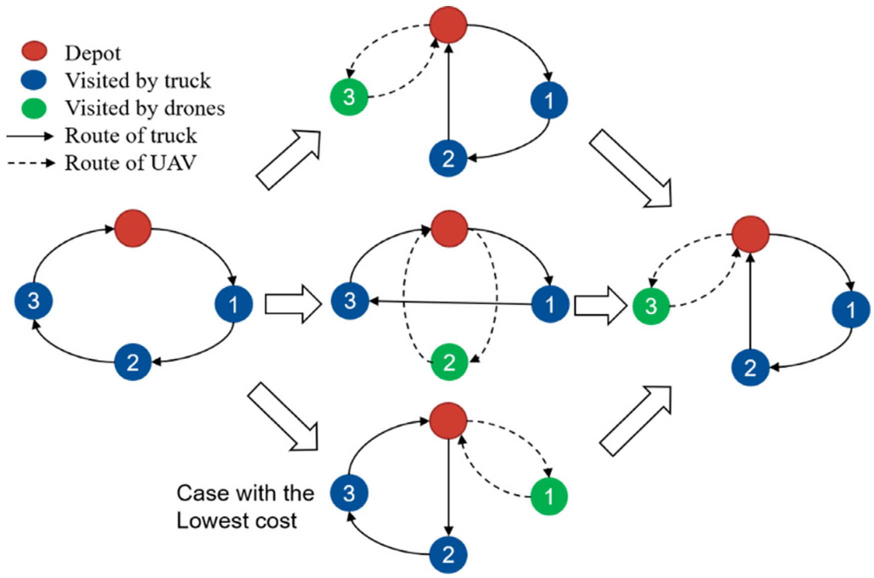

Fig. 5. The procedure to update the customer assignment of drones and truck in the two-step iterative heuristic method.

when not pertinent to the optimal TSP-D solution. Addressing this, Bouman et al. (2018a) propose an A*-based searching algorithm. This approach aims to skip irrelevant subproblems and conduct informed searches. The optimal drone and truck tours are obtained via the A* algorithm, seeking the shortest path from source to destination on a state-graph. For the heuristic function estimating distance to the sink state, authors employ the length function of a minimum spanning tree (MST) connecting remaining unvisited nodes and the depot. They theoretically prove that this MST-based heuristic never overestimates the distance to the goal state, ensuring an optimal solution approach.

4.3. Solution techniques for PDSTSP

Similar to the FSTSP and the TSP-D, the MILP formulation of the PDSTSP can be directly solved by commercial optimization solvers but the runtime is unaffordable in practical application. Accordingly, existing literature mainly focus on developing heuristic algorithms to obtain a near-optimal feasible solution in reasonable time. In this section, two heuristic methods adopted in this benchmark are introduced, including the two-step iterative heuristic method and the random restart local search.

4.3.1. Two-step iterative heuristic method

Murray and Chu (2015) propose a two-step iterative heuristic (TSIH) for the PDSTSP. This algorithm divides the problem into two independent optimization problems: Parallel Machine Scheduling (PMS) for drone-serviced customers and TSP for truck-serviced customers. Initially, all eligible customers are assumed to be served by drones, with the truck serving the remainder. A PMS determines drone assignments and makespan, while a TSP determines the truck's tour. The algorithm iteratively improves the makespan by reassigning customers between drone and truck partitions to balance their workload. Fig. 5 illustrates the customer assignment update procedure.

4.3.2. Random restart local search (RRLS)

Dell'Amico et al. (2020) propose a random restart local search for PDSTSP. This approach is finely tuned for PDSTSP's unique attributes, combining model-based and random search advantages to tackle complex optimization effectively. Initially, the algorithm optimizes the truck tour with TSP heuristics, then utilizes an MILP model to adjust the tour by inserting drone nodes. The truck tour undergoes iterative re-optimization following MILP adjustment. Upon reaching a local minimum, a segment of the truck's tour is disrupted, prompting a restart to escape the local minimum.

5. Computational results

In this section, we report the computational results of the three CDTD models. Section 5.1 provides a general description of the experimental dataset. Section 5.2 compares the system performance of the three CDTD models under different scenarios. Section 5.3 evaluates the optimality, efficiency and scalablity of different algorithms for CDTD models. Section 5.4 then analyzes the impact of different parameters on system performance. Finally, Section 5.5 conducts a case study to demonstrate the superior performance of CDTD model as compared to classical TSP model.

5.1. Dataset description

For the purpose of obtaining a benchmark comparsion, we conduct experiments based on the TSP-D instances generated by Bouman et al. (2018b). The node locations are created on a two-dimensional plane and it is assumed that the time taken by the truck to travel between any two locations is proportional to their Euclidean distance. This dataset contains three categories of instances. Among them, the *Basic* dataset consists of a total of 462 instances, with the number of nodes (i.e., customer locations and the depot) ranging from 5 to 375. The *Maxradius* dataset, which restricts the drone from flying beyond a certain distance in a single operation, comprises a total of 440 instances, with the number of nodes ranging from 5 to 200. The *Novisit* dataset, which imposes restrictions on the drone from visiting certain prohibited nodes, includes a total of 2400 instances, with the number of nodes ranging from 10 to 80.

Regarding the spatial distribution of nodes, three types of instances are distinguished in each dataset, briefly described as belows:

- *uniform instances*: The x and y coordinates for every node are drawn independently from $\{0, 1, ..., 100\}$
- *single-center instances*: For each location of the node, the angle a is uniformly drawn from $[0, 2\pi]$ and the distance r is drawn from a normal distribution with mean 0 and standard deviation 50. The x and y coordinates for each node is $r \cos a$ and $r \sin a$, respectively. In general, this type of instance mimics a circular city.
- *double-center instances*: They are generated in the same way as the single-center instances, but every node is translated in the x direc-

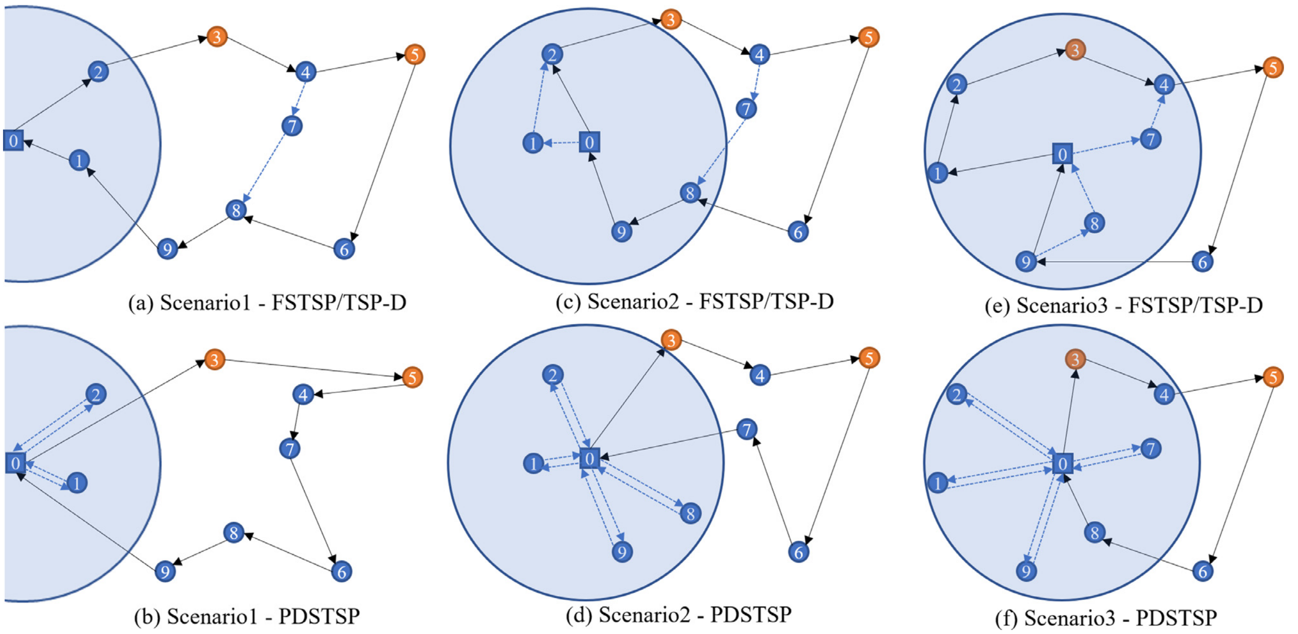

Fig. 6. The optimal routing solution of FSTSP/TSP-D and PDSTSP under three distinct scenarios for a uniform instance of ten nodes.

tion by 200 units with a probability of 50%. In general, this type of instance mimics a city with two centers.

In all cases, the first node generated is the depot node. By default, the drone is assumed to be twice as fast as the truck on all edges, i.e., $\alpha = \tau_{i,j}/\tau'_{i,j} = 2$, but experiments are also conducted with the case where the truck and drone have equal speed ($\alpha = 1$) and the case where the drone is three times as fast as the truck ($\alpha = 3$). All the experiments in this paper were performed by a laptop with 16GB RAM and an Intel Core i7-12700 CPU. The code used in this study was implemented in Python 3.7, and the source code is available online.[1]

5.2. Comparison of operational models

In the following, we compare the system performance of the three CDTD models under different scenarios. The FSTSP and the TSP-D are both motivated by the scenario where the majority of customers are out of the flight range of drone departing from the depot, and thus the drone is beneficial to operate in tandem with the truck. In contrast, the PDSTSP is motivated by the scenario where a large percentage of customers are located within the flight range of the drone(s) departing from the depot, and thus it is beneficial for the drone(s) to work independently with the truck. In the following, we conduct a set of experiments to quantify the benefits of two operational models (i.e., operating in a synchronized manner or operating in an independent manner) under three distinct scenarios. For the sake of comparison, we assume a single drone for both the PDSTSP and FSTSP (although the model for PDSTSP can set up multiple drones).

Fig. 6 visualizes the optimal solution of FSTSP/TSP-D and PDSTSP under three distinct scenarios for an instance in the uniform dataset. The spatial distribution of customers are identical for the three scenarios, however, the location of the depot varies and thus the number of customers covered by the flight range of drone departing from the depot changes. We assume 20%, 40% and 80% of customers are covered in scenario 1, 2 and 3, respectively. The rectangular node 0 represents the depot and the remaining circular nodes represent customers, in which the orange nodes are drone-ineligible. The solid black arcs represent the flow of the truck, while the dashed blue arcs represent the flight of the drone. Table 4 tabulates the comparison results of FSTSP/TSP-D and PDSTSP under three distinct scenarios for the instance in Fig. 6. For each operational model, we report the truck travelling time (Truck), drone travelling time (Drone), drone utilization rate (D-Util, i.e., the quotient of drone travelling time and the makespan), objective value (Obj., i.e., the makespan) and the saving with respect to the truck-only TSP (Sav.). The saving statistics is defined by the relative difference between the objective value of the model and the optimal objective value of standard TSP.

In Scenario1, the depot is far from the customers and only two customers are within the flight range of the drone. Although the optimal FSTSP solution only assigns one customer to the drone while the drone in the optimal PDSTSP solution visits two customers, the saving (7.2%) of FSTSP is higher than that of the PDSTSP (2.5%). Meanwhile, the utilization rate of drone in FSTSP (49.4%) is higher than that in PDSTSP (23.2%). In Scenario2, the flight range of drone departing from the depot covers four customers, which are all served by the drone in the optimal PDSTSP solution. We observe that the saving of the PDSTSP is higher than that of the FSTSP. In Scenario3, seven of the nine customers are within the drone's flight range. We observe that the utilization rate of the drone in PDSTSP (84.2%) is especially high compared to that of the FSTSP, which leads to a saving of 45.3% higher than that of the FSTSP, 22.5%.

In Table 5, we further conduct experiments to compare the two operational models under the three scenarios, and the results are averaged by 10 single-center instances. As is similar to the results in Table 4, the saving statistics and the drone utilization rate of FSTSP is higher that those of the PDSTSP when the depot is remote from the customers (i.e., Scenario1). In contrast, the saving statistics and the drone utilization rate of FSTSP is lower than those of the PDSTSP when the depot is close to the customers (i.e., Scenario2 and Scenario3). This observation suggests that the combination/synchronization of truck and drone can overcome the short travel range and improve delivery efficiency, but an independent operational mode is preferable when the travel range of the drone is enough to cover the majority of customers.

5.3. Comparison of solution algorithms

To evaluate the performance of different algorithms for the FSTSP, we conduct benchmark comparison on the *Basic* dataset. The instances

[1] https://github.com/LouisLINWEI/DTCO.

Table 4
Comparison of FSTSP/TSP-D and PDSTSP under three distinct scenarios for the instance in Fig. 6.

Scenario	FSTSP/TSP-D					PDSTSP				
	Truck	Drone	D-Util.	Obj.	Sav.	Truck	Drone	D-Util.	Obj.	Sav.
Scenario1	310.2	153.2	49.4%	310.2	7.2%	325.8	75.5	23.2%	325.8	2.5%
Scenario2	301.5	165.2	54.8%	301.5	6.1%	278.9	152.9	54.8%	278.9	13.1%
Scenario3	303.6	130.3	42.9%	303.6	22.5%	214.0	180.1	84.2%	214.0	45.3%

Table 5
Comparison of FSTSP/TSP-D and PDSTSP under three distinct scenarios, averaged by 10 single-center instances.

Scenario	FSTSP/TSP-D					PDSTSP				
	Truck	Drone	D-Util.	Obj.	Sav.	Truck	Drone	D-Util.	Obj.	Sav.
Scenario1	280.5	168.9	60.2%	280.5	12.5%	303.9	80.2	26.4%	303.9	5.2%
Scenario2	262.4	134.6	51.3%	262.4	17.3%	237.0	148.1	62.5%	237.0	25.3%
Scenario3	258.6	105.5	40.8%	258.6	21.2%	175.9	149.7	85.1%	175.9	46.4%

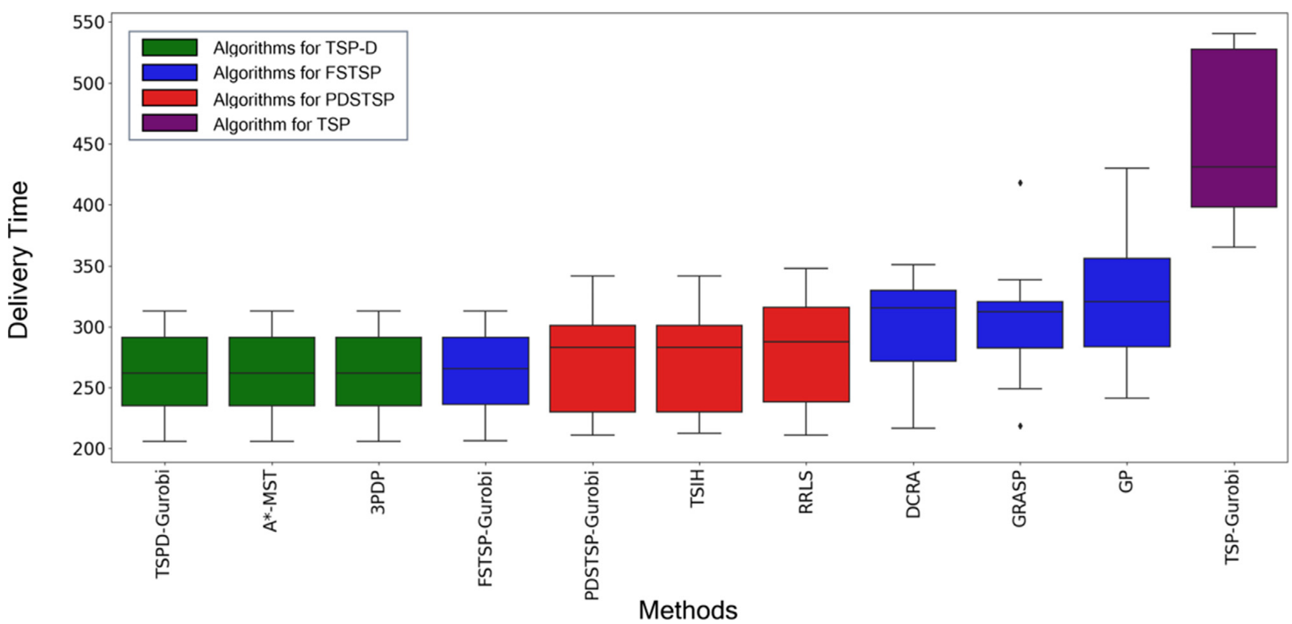

Fig. 7. Comparison of the objective function values of various algorithms in solving the CDTD models.

used in this base comparison are small-scale single-centered instances with $\alpha = 2$. More specifically, we select single-centered instances of less than ten nodes since the Gurobi solver cannot solve larger scale instance in reasonable amount of runtime, and the speed ratio of the drone and truck is equal to two. Regarding the computational time of solving these instances, all heuristic methods can generate the results within 0.1 seconds, while the Gurobi solver takes runtime between 398 to 3601 seconds, which demonstrates the efficiency of heuristic methods in solving the three typical CDTD models.

To compare the solution algorithms for three types of CDTD models, we unify the settings of the three models in the following manner. The FSTSP and the TSP-D both consider a single drone operating in tandem with a single truck. Despite slightly different assumptions regarding the modelling side, the performance of algorithms for the FSTSP can be directly compared with that of the TSP-D. However, the PDSTSP is distinct from the other two models since it considers the drones operating independently with the truck. To unify the problem setting, we set the number of drones in PDSTSP to one, thus all models consider the operation of a single drone and a single truck. Then, the comparison of results for the FSTSP and the PDSTSP can present the difference between two operating mode, i.e., operating in a synchronized manner and operating in an independent manner.

Fig. 7 visualizes the objective function values of various algorithms in solving the CDTD models. Different colors of boxes are presented to distinguish the algorithms for different type of CDTD model: green boxes for the TSP-D results, blue boxes for the FSTSP results, red boxes for the PDSTSP results and purple box for the standard TSP result. We first compare the Gurobi optimal solutions for all four models, which represents how different operating mode affects the system performance (i.e., the total delivery time). The optimal solution of the TSP-D model is 261.9 on average, being the lowest amount of delivery time among all four models. The optimal solution of the FSTSP model is 264.9 on average, being slightly higher than that of the TSP-D. In contrast, the PDSTSP yields an optimal solution of 282.9 on average, which is of 8.0% higher than that of the FSTSP. This difference of result demonstrates the superiority of operating the truck and drone in a synchronized manner over an independent manner, since the synchronization can effectively reduce the waiting time for either type of vehicle. The optimal solution of the TSP model is 431.0 on average, which is of 64.6% higher than that of the FSTSP. This significant difference demonstrates the superiority of deploying truck-drone coordinated system over the truck-only delivery system.

Regarding the results of algorithms in solving the TSP-D model, both A*-MST and 3PDP algorithms achieve the same optimal solution as the

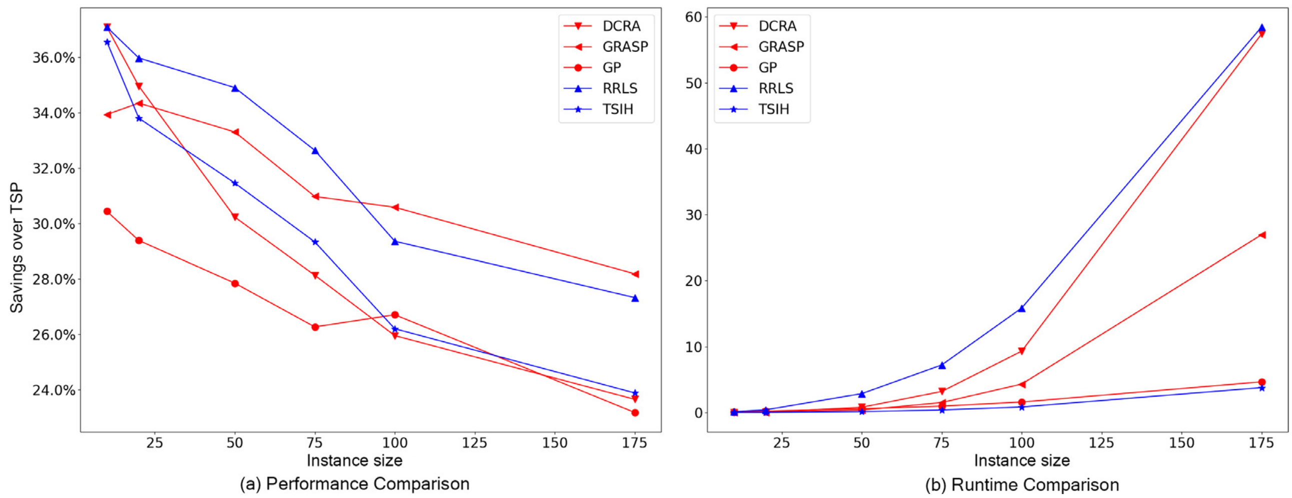

Fig. 8. Comparison of the five heuristics on medium/large-scale instances regarding solution quality and solving efficiency.

Gurobi optimal solution, since both algorithms search for the optimal sequence of operations in an exact manner (i.e., the algorithms will not terminate until the optimal solution is found). Regarding the results of algorithms in solving the FSTSP model, none of the three heuristic methods (i.e., DCRA, GRASP and GP) can achieve the optimal solution as Gurobi solver. The DCRA generally performs better than the other two heuristics, primarily due to its incorporation of cost saving mechanism and customer redistribution scheme. Regarding the results of algorithms in solving the PDSTSP model, both of the heuristics TSIH and RRLS achieve close objective value to the Gurobi optimal solution, which demonstrates the reliability of both heuristics in solving the PDSTSP.

In practical application, the number of customers to serve is much larger than 10, leading to combinatorial challenge for commercial optimization software and exact solution approach. In our experiment, the Gurobi solver and the exact algorithms for TSP-D cannot obtain the optimal solution for instances with 20 nodes within three hours. Accordingly, heuristic algorithms are necessary to obtain solutions of high quality in an efficient manner. In the following, we conduct scalability analysis regarding five heuristics applied to solve the FSTSP and the PDSTSP. Fig. 8 visualizes the comparison of the five heuristics on medium/large-scale instances regarding solution quality and solving efficiency. The number of nodes for the instances ranges from 10 to 175. In Fig. 8(a), the ordinate *saving over TSP* is defined by the relative difference between the objective value of the heuristic and the optimal objective value of standard TSP. As the size of instances increases, the saving statistics decreases. A possible explanation is that the solution space increases exponentially with the number of nodes, while the search space of the heuristics only increases linearly. The objective value of the heuristics for the FSTSP is generally similar to that of the PDSTSP. The GRASP and RRLS perform better than the other heuristics regarding the FSTSP and the PDSTSP, respectively. In Fig. 8(b), the runtime of heuristics grows with respect to the size of instances. The GP and TSIH have significantly lower runtime than the other heuristics on large-scale instances.

5.4. Impact of different parameters on system performance

In this section, we analyze how various parameters affect the performance of the drone-truck combined delivery system. The results of this study can provide valuable insights for companies experimenting with this innovative mode of transportation. To evaluate the performance, we compare the total delivery/completion time of the FSTSP model with that of the truck-only TSP model.

5.4.1. Distribution of customer locations

Fig. 9 visualizes box plots of savings of the solutions of the FSTSP over the truck-only TSP. Two types of instances are used in this study, i.e., the single-center instances and the uniform instances, with number of nodes ranging from 10 to 250. It can be observed that the combination of a drone and a truck leads to substantial time savings in single-center instances, on average, between 20% to 30%. The time savings in uniform instances range from 13% to 23%. The results suggest that the FSTSP is especially beneficial if the demand locations are clustered around a center, which is intuitive since the time needed to serve customers far from the center is long.

5.4.2. Drone speed

The speed of the drone may be a major factor affecting the performance of the system. Drones are thought to travel much faster than trucks, since they can conduct point-to-point travel rather than adhering to the road network. Table 6 presents the characteristics of FSTSP solutions for different drone speeds. We set up three different scenarios in this experiment, in which the speed ratio of the drone and truck α is equal to one, two and three, respectively. The uniform instances are used in this experiment, and we average the objective values over 10 instances for each group of instances with c number of nodes. In addition to the savings over TSP statistics, we also record the ratio of truck nodes, drone nodes and combined nodes (i.e., nodes that are visited by both vehicles), as well as the utilization rate of both vehicles. The utilization rate is measured by the actual travelling time of the vehicle divided by the total makespan.

The savings over TSP increase as the speed of the drone increases, since the drone is able to complete the delivery task in less time for the same distance. In line with this observation, the number of drone nodes also increases, as faster drones could visit more customer nodes while the truck is delivering goods. Besides, we observe that the utilization rate of the drone generally reduces as it becomes faster, since it has to wait for the truck to rendezvous more.

5.4.3. Drone range

In this section, we investigate the effect of drone range on the system performance. We conduct a set of experiments for different instance sizes, i.e., $c = 20, 50, 75, 100$, and under different drone ranges. Fig. 10 visualizes the savings of the FSTSP system over the truck-only TSP, and the number of customers served by the drone for different ranges. The x-coordinates represent increasing the range of drone by various percentage based on the default value of range.

As expected, we observe that the savings of the system increase as the flight range of the drone increases. Fig. 10(a) also shows that the savings of the medium/large-scale instances ($c = 50, 75, 100$) are more sensitive to the increase of drone range than small-scale instances (i.e., $c = 20$). A possible explanation for this result is that the average distance

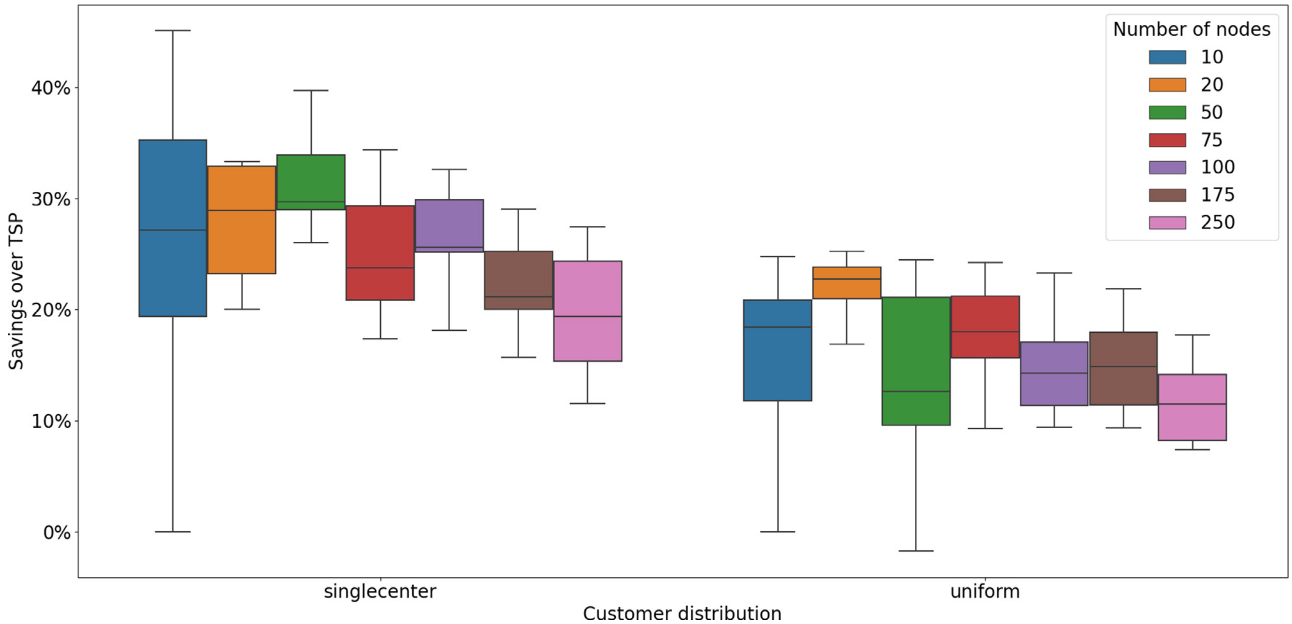

Fig. 9. Comparison of savings of solutions for instances with different customer distribution.

Table 6
Characteristics of the FSTSP solutions for different drone speeds (α).

		Savings (%)	Number of nodes (%)			Utilization (%)	
			Truck	Drone	Combined	Truck	Drone
$\alpha = 1$	$c = 10$	19.4	24.0	6.6	69.4	100.0	33.8
	$c = 50$	19.6	53.3	7.4	39.3	97.2	69.0
	$c = 100$	18.3	63.5	6.4	30.1	96.7	73.0
$\alpha = 2$	$c = 10$	31.0	16.0	16.2	67.8	93.3	37.1
	$c = 50$	29.4	42.8	15.2	42.0	88.0	60.1
	$c = 100$	22.1	50.1	14.2	35.7	82.5	62.2
$\alpha = 3$	$c = 10$	36.6	4.0	23.0	73.0	93.7	31.3
	$c = 50$	37.2	29.0	19.4	51.6	75.5	45.4
	$c = 100$	29.3	40.9	18.7	40.4	73.5	52.3

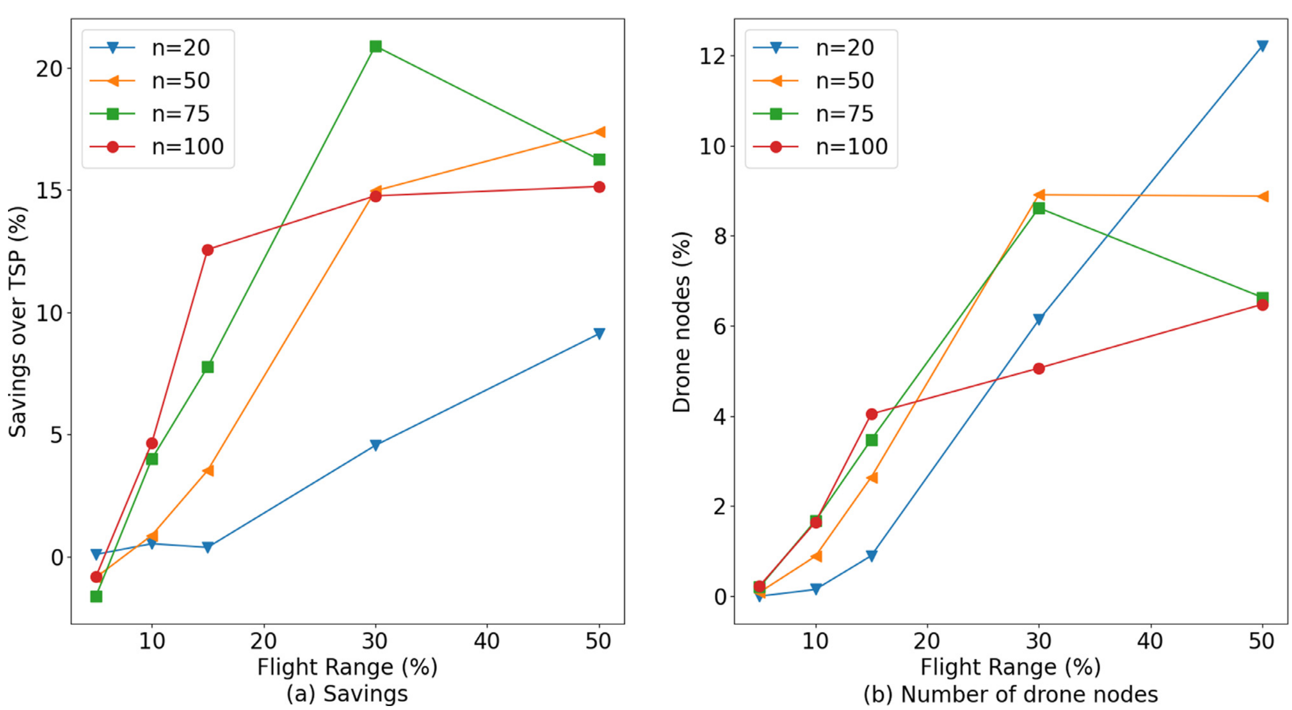

Fig. 10. Characteristics of the FSTSP solutions for different flight ranges.

Fig. 11. A case study to demonstrate the TSP-D operations among nine universities in Beijing.

between customer locations are smaller in large-scale instances, so the drone can cover more customers under a specific range. Accordingly, the increase in drone range can cover much more customers in large-scale instances.

Fig. 10 (b) shows the change in the number of drone nodes with respect to the change of drone range. As the drone travels larger amount of distance, it is assigned to more delivery tasks. For the instances of $c = 20, 50, 100$, the number of drone nodes increases monotonically with respect to the increase of flight range, which is intuitive since the drone with larger range can serve more customers. However, for the instances of $c = 75$, we observe a decline of the percentage of drone nodes. This observation may be associated with the fact that the longer-range drone may be scheduled to fewer but longer drone flights.

5.5. Case study

In this section, we conduct a real-world case study, in which we schedule the parcel delivery operations among universities in Haidian District, Beijing. As is shown in Fig. 11, we consider a region of size approximately 8 km×8 km on Amap Web API (Amap, 2024; Chen et al., 2022). The delivery network behind the case study is composed of a set of locations and a set of arcs including both road arcs and flying arcs. The nodes include a JD Haidian depot (indexed by zero) and nine universities (Beihang University, Tsinghua University and etc) in Haidian District, Beijing. The longitude and latitude of each location are obtained by reverse geocoding module in Amap Web API, and the road paths between every two locations are obtained by path planning module in Amap Web API. As for the drone, the distance between every two locations is obtained based on the haversine distance, since the movement of the drone does not adhere to the road network. The distance matrix for truck and that for drone is accordingly different.

The model and related specifications of the drone and the truck is shown in Fig. 11. The "H4 quadcopter", operated by SF Express for delivering medical supplies, has a cruise speed of 43.2 km/h and a range of 15 km, with a takeoff weight of 25 kg and maximum payload of 10 kg. The "ISUZU N series" truck operated by SF Express has a cruise speed of 40 km/h and a maximum range of 800 km. The maximum payload of the truck is 20 t and we assume that it can carry a drone.

Given the road-network distance matrix for truck and the haversine distance matrix for drone, we then solve the underling TSP and TSP-D problem respectively. We utilize the dynamic programming approach to obtain the optimal solution of the truck-only TSP, and the three-pass dynamic programming approach in Section 4.2.1 to obtain the optimal solution of the TSP-D. The routing decisions of TSP and TSP-D are visualized in Fig. 12, with the corresponding objective value and optimal solution of paths.

As for the routing of the truck, detours are common which lead to relatively long travelling distance and accordingly, the travelling time. The truck-only TSP mode takes 2743 s (i.e., 46 min) to serve all the universities and return to the depot. When effectively combining the truck with the drone, the total travelling distance of the truck decreases from 30480 m to 21076 m, which is an over 30% decrease. Four nodes which are scheduled to be served by the truck in TSP is now assigned to the drone in TSP-D. The final objective value of TSP-D is 1905 s (i.e., 32 min). This leads to a large saving of delivery time with respect to the truck-only TSP mode,

$$Saving = (2743.20 - 1904.79)/2743.20 \times 100\% = 30.56\%$$

This amount of delivery time saving is beneficial for logistics companies to enhance the efficiency of delivery service. The result also demonstrates the effectiveness of the parallelization of two types of vehicles, which can make up for the weakness of each other, i.e., the range concern of the drone and the disadvantage of detour for the truck.

We conduct a sensitivity analysis regarding the variation of drone speed on the objective value of TSP-D, visualized in Fig. 13. The baseline scenario (left) considers a drone speed of 43.2 km/h, and the second scenario (middle) considers an increase of 20% while the third scenario (right) considers an increase of 50%. As is shown in Fig. 13, the routing structures of the three scenarios are significantly different. The truck experiences smaller driving distance while the drone travels more as the speed of the drone increases. The drone even visits the same location repeatedly to ensure a valid connection to the truck. The objective values of the three scenarios are 32, 31 and 29 minutes, respectively. This indicates that the increase of drone speed leads to only a small magnitude of decrease of objective value.

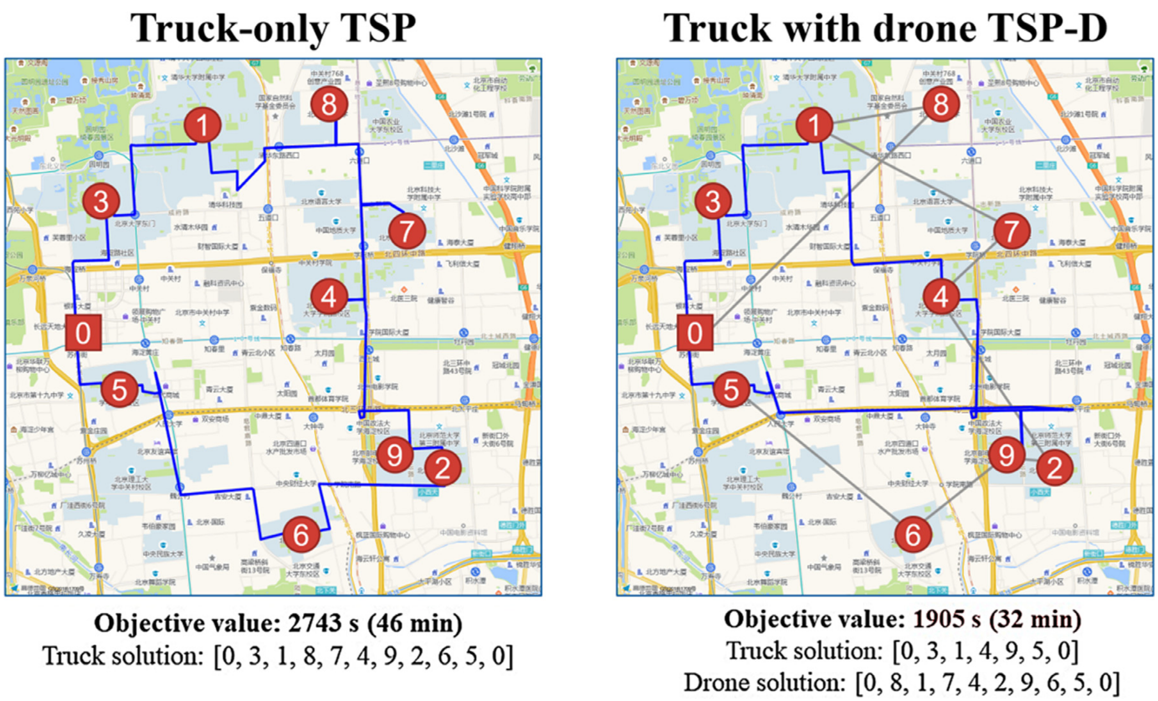

Fig. 12. Routing decisions of truck-only TSP (left) and TSP-D (right) in the case study.

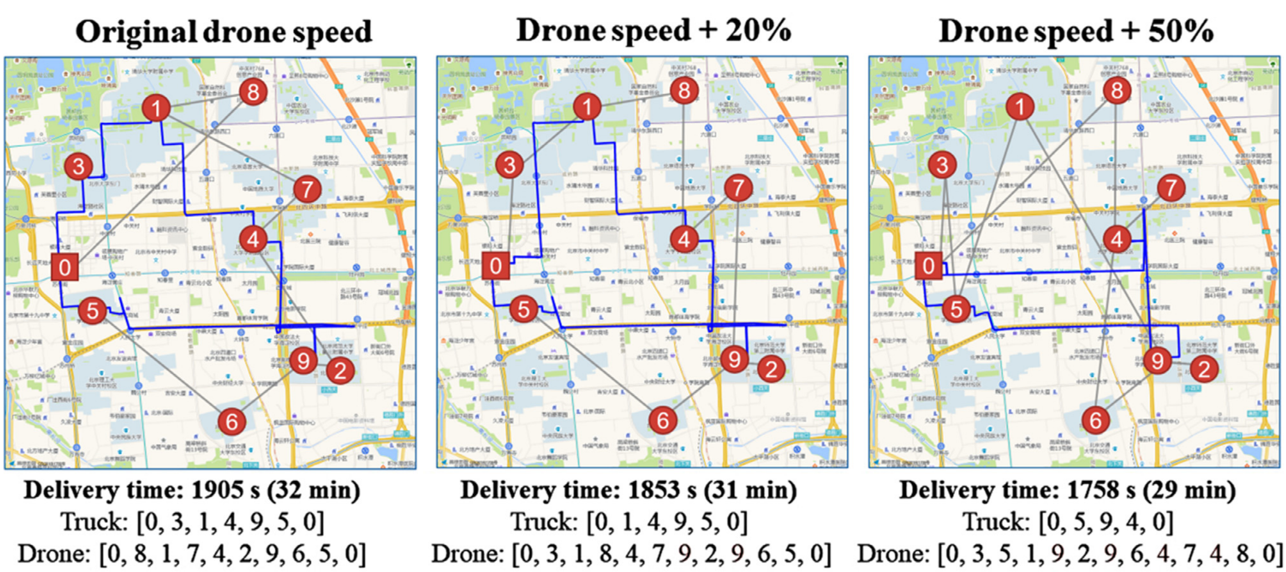

Fig. 13. A sensitivity analysis regarding the variation of drone speed on the objective value of TSP-D.

6. Conclusion

In this paper, we conduct a comparative study of three representative operational models and their corresponding solution techniques: the flying sidekick traveling salesman problem (FSTSP), the traveling salesman problem with drone (TSP-D), and the parallel drone scheduling traveling salesman problem (PDSTSP). We summarize our major insights as follows:

Comparison of operational models. The FSTSP and TSP-D are useful when most customers are beyond the drone's range, making truck-drone tandem operations beneficial. The PDSTSP is effective when many customers are within the drone's range, allowing the drone to operate independently. Besides, the FSTSP is advantageous if customer demand is clustered, reducing service time for distant customers. The reasons behind this superiority in these specfic scenarios are two-folded: synchronizing truck and drone operations reduces waiting times compared to independent operations; in addition, combining truck and drone overcomes the drone's short range and boosts delivery efficiency. Finally, TSP-D saves approximately 30% of delivery time compared to truck-only TSP regarding benchmark instances, highlighting the effectiveness of parallel vehicle operations to compensate for each other's limitations.

Comparison of solution techniques. In practical applications, the number of customers to serve is significantly larger than 10, leading to a combinatorial challenge for commercial optimization software and exact solution approaches. Thus, heuristic algorithms are essential to obtain high-quality solutions efficiently. For large-scale instances, the GRASP (Greedy Randomized Adaptive Search Procedure) and RRLS (Randomized Restart Local Search) heuristics outperform other heuristics for the FSTSP/TSP-D and the PDSTSP in terms of solution quality and efficiency, respectively. As the size of instances increases, the saving statistics regarding truck-only TSP decrease. This is possibly because the solution space expands exponentially with the number of nodes, while the search space for the heuristics only increases linearly.

Sensitivity analysis of system parameters. The savings over TSP increase as the speed of the drone increases, since the drone is able to complete the delivery task in less time for the same distance. Besides, the utilization rate of the drone generally reduces as it becomes faster, since it has to wait for the truck to rendezvous more. In addition, the savings of the system increase as the flight range of the drone increases, since the increase in drone range can cover much more customers in large-scale instances.

Case study. We conduct a case study to demonstrate the superior performance of CDTD model as compared to classical TSP model based on the city road network data of Beijing. The result demonstrates an average saving of 30% over truck-only TSP mode. This amount of delivery time saving is beneficial for logistics companies to enhance the efficiency of delivery service. The result also demonstrates the effectiveness of the parallelization of two types of vehicles, which can make up for the weakness of each other, i.e., the range concern of the drone and the disadvantage of detour for the truck. In addition, sensitivity analysis shows that a higher drone speed can improve the delivery efficiency of the CDTD system and also reduce the distance travelled by the truck, thus reducing the carbon released.

Future studies may incorporate more realistic objective functions and constraints into the models as well as the algorithms, for instance, including the fixed setup cost and operating cost into the objective function and introducing drone's energy consumption model into the constraints. Furthermore, large-scale real-world transportation data can be used for the purpose of verification.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Kai Wang reports financial support was provided by National Natural Science Foundation of China. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Yida Ding: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Data curation, Conceptualization. **Jiaqi Wan:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Wei Lin:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kai Wang:** Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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