Collaborative Hybrid Delivery System: Drone Routing Problem Assisted by Truck

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Abstract. Unmanned Aerial vehicles (UAV) or drones have significant market potential due to their high mobility and cost savings. Simultaneously, the hybrid delivery system in which collaborative use of trucks and drones is also receiving much attention and intensively studied as traveling salesmen problem with drone (TSP-D). This delivery system has significant advantages since it can selectively exploit the strength of each vehicle. However, in many cases, drones are only used as an assistant method of supporting truck delivery. In this paper, as a reverse idea, we present a new model, named drone routing problem with truck (DRP-T), in the form of a truck assisting drones' delivery. We present a mathematical model formulated as mixed-integer linear programming (MILP) and conduct a comparative analysis with one of the existing TSP-D models with an actual map-based case study. Our experiments show that it is possible to have substantial savings with the proposed model compared to the truck-only and TSP-D model.

Keywords: Routing, Drone, Mixed integer programming.

1 Introduction

Logistic companies are always looking for the most costless methods to distribute goods across their networks. Unmanned aerial vehicles (UAV), drone, is the emerging technology-driven opportunity that recently received much attention for parcel delivery [1]. Compared to a regular delivery vehicle, a drone has essential advantages such as no costly human pilot are required, high mobility avoiding the congestion of road networks, spending much lower transportation cost per kilometer. Even though drones are fast and relatively inexpensive per mile, there are inherent limitations in their practical use. Since most drones are battery-powered, their flying range and loading capacity are much more limited than fuel-based trucks.

One way to overcome this limitation is by adopting a collaborative use of trucks and drones. The problem of this collaborative system is defined as a variant of the traveling salesman problem (TSP), the TSP with drones (TSP-D) [2]. The first model of the collaboration was suggested by Murray and Chu (2015), called "Flying Sidekick Traveling Salesman Problem (FSTSP)" [3]. In the model, the delivery truck moves between different customer locations to make deliveries, and the drone simultaneously serves another customer, launching from and returning to the truck each delivery. After the FSTSP, many following studies were poured out. TSP-D with

minimizing operational cost including transportation cost and the cost [4], FSTSP with considering drone's energy consumption and no-fly zone as FSTSP-ECNZ [5], extended TSP-D with multiple vehicles as mTSP-D [6] and similarly extending FSTSP to multi-drone case as m-FSTSP [7].

The above TSP-D based models are using both truck and drones the same or the drone as a secondary delivery method, despite the fact that the drone is faster and cheaper than the truck. In this paper, we present the drone routing problem with truck (DRP-T) that uses only drones as the final delivery method and trucks as supportive means to help deliver drones. In DRP-T, trucks are not delivering packages to customers but carrying drones to parking locations, and drones are serving customers directly and returning to trucks. Compared to the TSP-D, the DRP-T limits the truck's use and maximizes drones' use, thoroughly enjoying the wealth of drones' mobility and costlessness. This paper proposes a new delivery model DRP-T with a new mixed-integer linear programming (MILP) formulation. The performance of the new delivery model was verified with comparative analysis with existing models, TSP, and mFSTSP.

2 Problem description

The DRP-T can be considered an extension of the traveling salesman problem (TSP), which uses a single vehicle to serve all the customers. The FSTSP, or TSP-D, is an extension of TSP that first appeared that adds a subsidiary delivery vehicle, a drone, to help serve a part of customers in the existing route of TSP. As an extension of the FSTSP, Murray et al. recently proposed m-FSTSP, expanding the single drone availability to multi-drones that achieved further improvement in delivery time while increasing the problem's complexity [7].

The DRP-T is not an extension of the existing mFSTSP but is a model with a different approach to two delivery vehicles. In contrast to m-FSTSP, which uses drones as an auxiliary delivery method for the truck, DRP-T uses drones as the primary delivery method, and the truck does not directly serve the customers but only carrying drones to a parking location. This routing strategy constitutes an entirely different delivery network with m-FSTSP. The DRP-T can be defined as an extended model of the Two-Echelon Vehicle Routing Problem (2E-VRP) when replacing the parking location with a satellite that has flexible routing for delivery vehicles (drones) not restricted to the assigned satellite (parking location) and having flight endurance limit due to drone battery capacity. Fig 1 illustrates the routes of 4 different problems TSP, FSTSP, mFSTSP, and DRP-T.

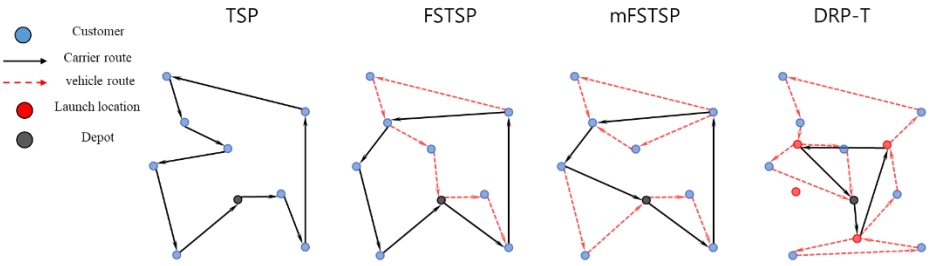


Fig. 1. Example of solutions for TSP, FSTSP, mFSTSP, and DRP-T.

2.1 Mathematical model

The DRP-T aims to minimize the truck's arrival time at the depot after serving all the customers. The truck selectively visits parking location j $(j \in J)$, close enough for drones to make delivery. After the truck arrives at a particular location, more than one drone is launched to serve the customer i $(i \in I)$. While drones are delivering items to customers, the vehicle moves to another location and collects returning drones. The following represent notations and the mathematical model of DRP-T.

Notations

Variables		
I	:	Set of customer locations.
J	:	Set of parking locations and depot locations.
$0, \lvert J \rvert$	:	Starting and ending depot location (0, $\lvert J \rvert \in J$).
N	:	Set of all locations. (I, $J \subset N$).
K	:	Set of vehicles flights
$\tau_{ij'}$	:	Traveling time (sec) between location j and j' by truck
$\tau_{nn'}{}^{d}$	:	Traveling time (sec) between location n and n' by drone
E	:	Maximum flight time (sec) of drones
M	:	Positive and large number
Decision variables		
x_{jj}	:	Binary decision variable, 1 if carrier travels from location j to j'
$y_{nn'}{}^{k}$	:	Binary decision variable, 1 if vehicles travel from location n to n' in k-th flight.
$z_{jj'}$	:	Integer decision variable, equal to available vehicles when carrier travel from location j *to* j'.
$b_n{}^{k}$	:	Real number decision variable, equal to available endurance of vehicle k when vehicle visit location n.
T^{t}_{j}	:	Real number decision variable, time when the truck arrives at location j.
$Td_n{}^{k}$	:	Real number decision variable, time when the vehicle k arrives at location n.

Mixed integer linear programming		
Minimize	$T_{\lvert J \rvert}$	(1)
Subject to	$\sum_{\substack{j \in J \\ j \neq 0}} x_{0j} = 1$	(2)

$$\sum_{\substack{j\in J\\ j\neq |J|}} x_{j|J|} = 1 \tag{3}$$

$$\sum_{j\in J} x_{jj'} = \sum_{j\in J} x_{j'j} \qquad \forall j \in J^{+} \tag{4}$$

$$\sum_{n\in N} y_{jn}^{k} \le M \cdot \sum_{j'\in J} x_{j'j} \qquad \forall k \in K,\ j \in J \tag{5}$$

$$\sum_{\substack{n\in N\\ n\neq j}} y_{nj}^{k} \le M \cdot \sum_{\substack{j'\in J\\ j\neq j'}} x_{j'j} \qquad \forall k \in K,\ j \in J \tag{6}$$

$$\sum_{\substack{n\in N\\ n\neq i}} \sum_{k\in K} y_{ni}^{k} = 1 \qquad \forall i \in I \tag{7}$$

$$\sum_{\substack{n\in N\\ n\neq i}} y_{nik} = \sum_{\substack{n'\in N\\ n'\neq i}} y_{in'k} \qquad \forall k \in K, i \in I \tag{8}$$

$$T_{j'} \ge T_{j'} + \tau_{jj'} - M \cdot (1 - x_{jj'}) \qquad \forall j \in J,\ j' \in J \tag{9}$$

$$Td_{j'}^{k} \ge T_{j'} - M \cdot (2 - \sum_{j\in J} x_{jj'}^{t} - \sum_{i\in I} y_{j'i}^{k}) \qquad \forall k \in K,\ j \in J \tag{10}$$

$$Td_{n'}^{k} \ge Td_{n}^{k} + \tau_{nn'}^{d} - M \cdot (1 - y_{nn'}^{k}) \qquad \forall k \in K, n \in N, n' \in N \tag{11}$$

$$T_{j'}^{k} \ge Td_{j'} - M \cdot (2 - \sum_{j\in J} x_{jj'} - \sum_{i\in I} y_{ij'}^{k}) \qquad \forall k \in K,\ j \in J \tag{12}$$

$$z_{0j}^{t} = |K| \qquad \forall t \in T,\ j \in J,\ j \neq 0 \tag{13}$$

$$\sum_{\substack{j''\in J\\ j''\neq j'}} z_{j'j''} = \sum_{\substack{j\in J\\ j\neq j}} z_{jj'} - \sum_{k\in K}\sum_{i\in I} y_{j'i}^{k} + \sum_{k\in K}\sum_{i\in I} y_{ij'}^{k} \qquad \forall j' \in \{J : j' \neq 0\} \tag{14}$$

$$\sum_{k\in K}\sum_{\substack{i\in I\\ i\neq j'}} y_{j'i}^{k} \le z_{jj'} \qquad \forall j, j' \in \{J : j \neq j\} \tag{15}$$

$$b_{i}^{k} \ge \tau_{ij}^{d} - M \cdot (1 - y_{ji}^{k}) \qquad \forall k \in K, i \in I, j \in \{J : j \neq 0\} \tag{16}$$

$$b_{n}^{k} \ge b_{i}^{k} + \tau_{in}^{d} - M \cdot (1 - y_{in}^{k}) \qquad \forall k \in K, i \in I, n \in N, n \neq 0 \tag{17}$$

$$0 \le z_{jj'} \le |K| \qquad \forall j, j' \in \{J : j \neq j\} \tag{18}$$

$$0 \le b_{n}^{k} \le E \qquad \forall k \in K, n \in N \tag{19}$$

The objective function (1) seeks to minimize the truck's returning time to the depot after completing the delivery job. Constraint (2) and (3) describe that the truck has a fixed start and end location to the depot. Constraint (4) preserves the truck routing by forcing it to depart from node j' when visiting node j''. Constraints (5) and (6) allow all drones to depart/return only to the parking location that has been visited by the truck. In constraint (7), each customer should be served precisely once by drones. Constraint (8) works the same way as a constraint (4), providing flow balance for the drones. Constraint (9) cumulatively calculates the arrival time at each parking location j that has been visited by the truck. Constraint (10) calculates the arrival time of drones at customer i that has been visited just after launched from the carrier. The constraint (11) works under the same logic as a constraint (9), which calculates the arrival time at each node n that drones have visited. Constraint (12) allows both truck and drone to wait for each other at rendezvous points.

The constraints (13) to (15) ensure that the available number of drones exceeds when the truck launch drones. First, constraint (13) states that the initial number of drones when the truck departs from the depot should be equal to the drone's index. The constraint (14) updates the number of available drones whenever the drones are launched or returned to the truck. In constraint (15), the number of drones launched from trucks should not exceed the number of drones available on the truck at that moment. The Fig 2 illustrates the way of how the decision variable z_{jj} works as an example.

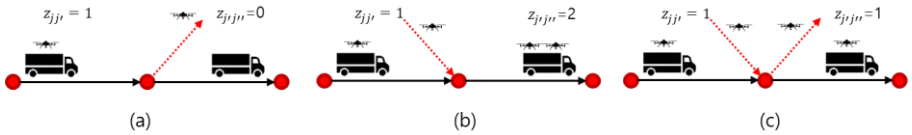


Fig. 2. Tracking the number of available drones at each location.

The available flight time is calculated through constraints (16) and (17). Constraint (16) accounts for the drone's flight time in node i where is the first visit after drone launch. From the second visit, the flight time is updated in the constraint (17). Since the drones' available flight time is limited to its endurance in constraint (19), the flight time from launch to return will not exceed the drone's endurance. The flight time limit mechanism is illustrated in detail through an example in Fig 3.

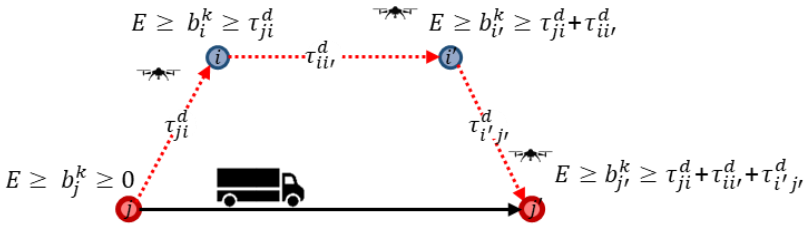


Fig. 3. Flight time monitoring formulation.

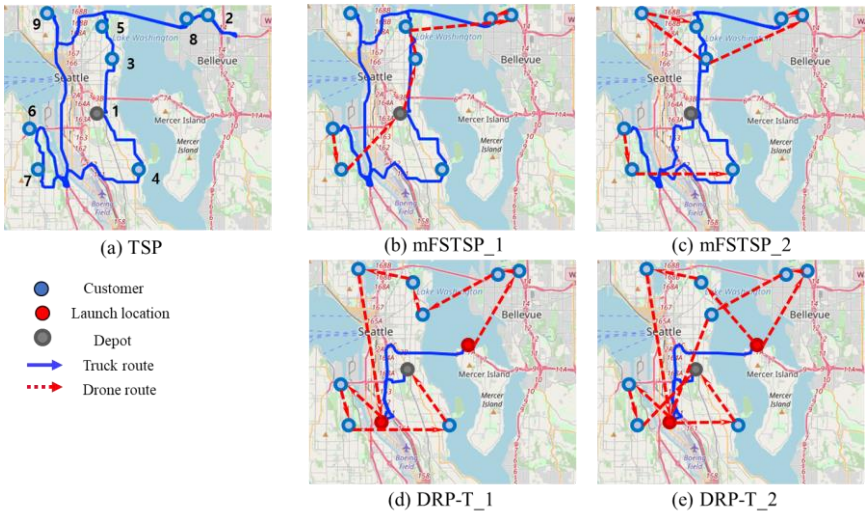
3 Computational result

This section presents the comparative analysis result of the comparison between mFSTSP and DRP-T with a case study. The case study uses problem instances generated by GPS data of two cities Seattle and Buffalo, which is online-available at https://github.com/optimatorlab/mFSTSP [8]. The instance set 1 (Seattle) has a broader operation area with a longer average distance than set 2 (Buffalo). The detailed specification of each instance is provided in Table 1. Each instance set has 20 problems, 10 problems with 8 customers, and 10 problems with 10 customers. Each instance has $|I|/2.5$ parking locations including the depot. The parking locations are centroid of customers found by k-mean clustering. The truck speed is set to 13 m/s. The drone of 23 m/s with a 55minute flight time is assumed according to DJI's MATRICE 300 RTK [9].

Table 1. Case study map specification.

Set 1 (Seattle)			**Set 2 (Buffalo)**		
Avg. Distance [m]	Width [m]	Length [m]	Avg. Distance [m]	Width [m]	Length [m]
11,758.10	27,277.01	22,713.15	2,636.99	17,024.88	15,068.17

As shown in Fig. 4, the TSP, mFSTSP, and DRP-T have a distinct difference in their route. The TSP displays only truck routes because TSP is truck-only delivery. In mFSTSP, parts of the TSP route are removed and replaced by drones, and more routes are replaced as drones are added. In the case of DRP-T, compared to the other two cases, the use of trucks decreased significantly, and drones were actively used.



(a) TSP (b) mFSTSP_1 (c) mFSTSP_2

(d) DRP-T_1 (e) DRP-T_2

Fig. 4. Solution examples of (a) TSP, (b) mFSTSP with 1 drone, (c) mFSTSP with 2 drones, (d) DRP-T with 1 drone, (e) DRP-T with 2 drones.

Table 2 shows the computational results of mFSTSP [7] and DRP-T obtained by MILP. The "% saving" captures the percentage difference of completion time compared with the TSP, truck-only delivery. The central processing unit time (CPU time) is limited to 600 seconds, and the best feasible solution is recorded when reached the limit. The result shows that the completion time decreases consistently with a rise in the number of drones. Specifically, when there was only one drone, the DRP-T showed a slightly shorter makespan, but the difference expanded as more drones are used. The mFSTSP and DRP-T have a maximum of 44.5% and 55.8% saving, respectively, compared to truck-only delivery.

Table 2. Computational result of mFSTSP and DRP-T.

			mFSTSP			DRP-T		
Customer		Num. Drones	Obj value	% Savings	CPU time	Obj value	% Savings	CPU time
8	**Set 1 (Seattle)**	1	2288.23	26.2317	15.8650	2211.25	29.2235	71.4610
		2	1914.69	38.0834	37.3093	1646.75	47.1858	111.8248
		3	1714.68	44.5361	49.5717	1531.63	50.8134	102.5860
	Set 2 (Buffalo)	1	587.67	26.6612	14.6771	550.49	31.3512	61.6904
		2	519.15	35.2892	33.8145	400.26	50.0400	69.0164
		3	479.58	40.2486	21.0144	353.25	55.8329	50.0477
10	**Set 1 (Seattle)**	1	2460.69	1.0584	495.4631	2156.96	13.4086	600.0061
		2	2168.00	12.8826	568.6874	1597.41	36.0450	600.0182
		3	2019.12	18.7561	481.1503	1446.93	41.9793	600.0315
	Set 2 (Buffalo)	1	631.81	2.7722	520.2	547.57	15.5319	600.0162
		2	537.75	17.2982	310.9816	405.13	37.8392	600.0148
		3	515.84	20.8747	385.516	359.78	44.7325	600.0337

In problem instance set 1 with a broader operation area, the completion time tends to be longer than 2 sets. Besides, the time reduction effect by the additional use of drones seemed stronger in a large area. Interestingly, however, savings showed alike in the two regions. It can be seen that the use of drone trucks in a large area can save more delivery time, but the saving ratio is constant regardless of the size of the area. However, for 10 customers cases, it was difficult to find such a trend since we often failed to find an optimal solution due to the limitation of computation time. Two more customers extended the calculation time exponentially which can be seen that the complexity of the problems is very sensitive to the number of customers. In most cases, mFSTSP takes less computation time than DRP-T, and both models consume more computation time in set1. The calculation time seems to increase as the number of drones increases, but some discrepancy has been observed. Fig. 5 illustrates the computational result of two models in a bar graph.

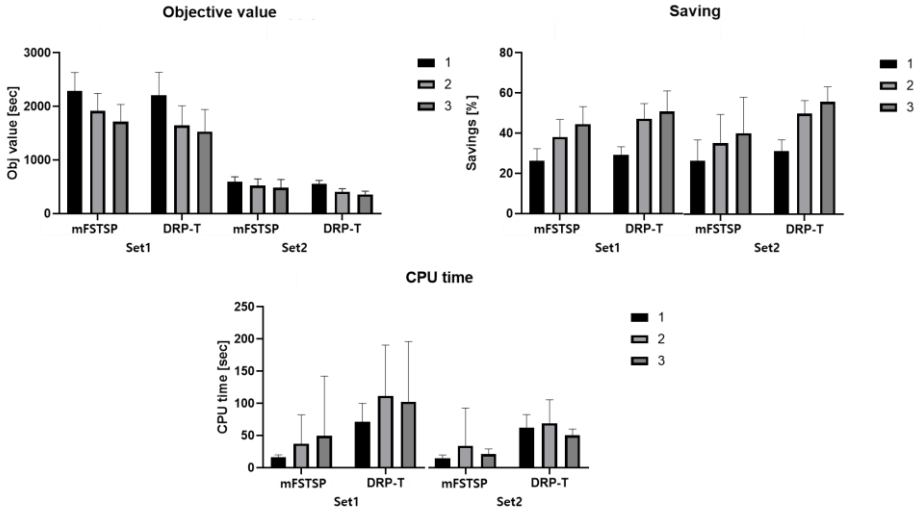


Fig. 5. Computational result of the case study.

4 Sensitivity analysis

Drone delivery is fundamentally limited by its battery capacity. In this section, sensitivity analysis was performed to explore how these limitations work in the delivery performance in mFSTSP and DRP-T. This analysis used instance set 1 with 8 customers presented in section 3. All parameters except flight time were applied the same and the flight time was set at intervals of 1000 from 2000 to 6000 seconds.

Table 3. Computational result with different flight time.

		mFSTSP			DRP-T		
Flight time	Num. Drones	Obj value	% Savings	CPU time	Obj value	% Savings	CPU time
2000	1	2169.896	1.65246	17.8794	2122.861	4.576837	64.02608
	2	1761.376	19.57147	51.35456	1483.226	32.74349	73.70463
	3	1540.837	29.41033	43.46896	1327.384	39.47884	96.59067
3000	1	2169.896	1.65246	16.96552	2091.502	5.898057	79.17365
	2	1761.376	19.57146	48.53522	1470.155	33.36129	110.835
	3	1540.837	29.41033	27.97567	1327.384	39.47884	96.57239
4000	1	2169.896	1.65246	15.08001	2058.466	7.440601	81.24646
	2	1761.376	19.57146	54.9315	1470.155	33.36129	104.1505
	3	1540.837	29.41033	59.97488	1327.384	39.47884	87.4991
5000	1	2169.896	1.65246	18.95264	2058.466	7.440601	81.0333
	2	1761.376	19.57146	45.27003	1470.155	33.36129	110.9936
	3	1540.837	29.41033	33.0208	1327.384	39.47884	94.08144
6000	1	2169.896	8.326094	126.4467	2058.466	7.440601	82.34652

2	1761.376	19.11009	177.7154	1470.155	33.36129	120.6758
3	1540.837	29.41033	81.27164	1327.384	39.47884	104.9229

Table 3 provides the results of mFSTSP [7] and DRP-T with different flight time of drones. Among the 10 instances, 3 has appeared to be infeasible for the DRP-T model with 1 drone. This is because the DRP-T uses only drones, so the low flight time or the low number of drones can lead to unserviceability, unlike mFSTSP, which can serve customers by a truck when the drone's battery is not enough. Except the infeasibility, the result shows that there is not noticeably difference between flight times. With longer flight time, the DRP-T shows slightly improved performance, but there was no significant change.

5 Concluding remarks

In this paper, we study a new type of collaborative delivery with drones and trucks. Empirical study shows that substantial saving is possible in the system compared to truck-only and previous truck-drone systems. Since this study proposed a new delivery system, there are many potential future research topics. One promising area is to develop a solution approach that provides a near-optimal solution with reasonable computational time. In addition, extension of the DRP-T problem with multiple trucks and consideration of drone recharging can be another interesting study. Since the model includes the battery monitoring formulation, a flexible recharging policy can be another extension.

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