En route truck–drone parcel delivery for optimal vehicle routing strategies

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Mario Marinelli*, Leonardo Caggiani, Michele Ottomanelli, Mauro Dell'Orco

D.I.C.A.T.E.Ch., Polytechnic University of Bari, Via Orabona 4, 70125 Bari, Italy
*mario.marinelli@poliba.it

Abstract: Recently, several prominent logistic companies in Europe and U.S. are seriously considering the idea of using drones launched from trucks and working in parallel to deliver packages. In the relevant literature, a novel problem formulation called Traveling Salesman Problem with Drone (TSP-D) has been introduced, and some modeling and solution approaches have been presented. Existing approaches are based on the main assumption that the truck can dispatch and pick up a drone only at a node, i.e., the depot or a customer location. In this work, we present a novel approach aimed to maximize the drone usage in parcel delivering. We consider that a truck can deliver and pick a drone up not only at a node but also along a route arc (*en-route*). In this way, the operations of a drone are not strictly related to the customers' position, but it can serve a wider area along the route. We tested the proposed heuristic on benchmark instances and analyzed the benefits introduced with the en-route approach.

1. Introduction

Several companies which are interested in logistics have put considerable effort into developing delivery systems using drones, also called unmanned aerial vehicles (UAVs), for transporting parcels, e.g. Amazon's Prime Air project. The new distribution method has been deployed to support parcel delivery traditionally handled only by trucks. It brings different benefits to logistic transportation such as avoiding the congestion of traditional road networks by flying over them, higher speeds than trucks, and lower transportation costs per kilometer. However, some disadvantages should be considered since the drones are small battery-powered vehicles. Indeed, their flight distance and loading capabilities are limited, resulting in restricted travel distance and parcel size. Instead, a truck has the advantage of long-range travel capability and can carry large and heavy cargo, but it is also heavy, slow and cost inefficient. For these reasons, the joint use of truck and drones working in parallel can overcome some disadvantages and increase benefits. In fact, a truck travels with the drone until reaching a close customer location, allowing the drone to serve a customer while remaining within its flight range (launch operation). In the meanwhile, the truck can serve other customers. The drone then returns to the truck at a different location (rendezvous operation). In this way, we can effectively increase the usability and make the schedule more flexible for both drones and trucks.

Several remarkable events occurred since 2013. First, Jeff Bezos announced Amazon's plans for drone delivery [1]. The project called Amazon Prime Air ambitiously plans to deliver packages using drones within 30 minutes [2]. Google was awarded a patent that outlines its drone delivery method [3]. Google project, called Wing, is expected to launch in 2017 [4]. In 2016, Australia Post successfully tested drones for delivering small packages [5]. Drone deliveries have also been tested for medical applications, such as Matternet, a startup in California [6]. Additionally, a Silicon Valley startup named Zipline International is now serving 21 hospitals across Rwanda [7].

However, there are some practical problems which are still limiting drone usage in parcel delivery. First, drones cannot work for heavy parcels and have a limited autonomy. Moreover, there are some safety reasons such as the presence of thieves, hacking activities and restricted areas or paths where drones cannot fly over.

In the literature, the truck drone distribution concept gives rise to a novel optimization problem called Traveling Salesman Problem with Drone (TSP-D) [8]. The problem generalizes the vehicle routing problem, which is already NP-hard, resulting in a harder problem. Its complexity motivates the development of heuristics to solve the problem approximately. In the literature, different heuristics have been proposed to solve the TSP-D. At the best of our knowledge, all these approaches assume that a truck can dispatch and pick up a drone only at a node, i.e., the depot or a customer location. This assumption can bring some disadvantages related to drone coverage limits and reduce its usage. In this paper, we propose a novel heuristic which considers the minimization of waiting times and battery consumption at truck-drone operations. It includes the possibility to launch and rendezvous the drone along a route arc. In this way, we can increase drone coverage and usage. Moreover, we can extend drone endurance since they travel for shorter distances.

The paper is organized as follows. Section 2 presents the literature review on existing methods. Section 3 describes the problem and its formulation. In Section 4, we present the proposed method based on *en-route* operations. Section 5 presents the proposed heuristic. We present the application to benchmark instances and the obtained results in Section 6. Finally, Section 7 presents our concluding remarks.

2. Existing approaches

The problem we are dealing with is related to the field of vehicle routing problems. The common idea of all these problems is that there is a given fleet of trucks which has to deliver a given set of packages to certain positions. We can find several approaches in the literature considering deliveries in urban areas and using electric vehicles [9-11].

An increasing number of works in the literature is investigating the routing problem related to the truck-drone joint delivery. First, Murray and Chu [12] introduce the problem, called the Flying Sidekick Traveling Salesman Problem (FSTSP). They introduced a mixed integer programming (MIP) formulation and a heuristic approach. Their heuristic starts from an initial TSP tour and iteratively tries to consider whether a node is suitable for use as a drone node. The relocation procedure for TSP-D results in an improvement approach since it evaluates all the possible moves and executes the best one.

Agatz et al. [8] proposed a slightly different problem, called Traveling Salesman Problem with Drone (TSP-D), in which the drone has to follow the same road network as the truck. This problem is also treated as a different MIP formulation and solved by a heuristic in which drone route construction is based on either local search or dynamic programming. Ponza [13] extended the work of Murray and Chu [9] to solve the FSTSP proposing an enhancement to the MIP model and solving the problem by a heuristic method based on Simulated Annealing.

Wang et al. introduced the vehicle routing problem with drones (VRPD) [14]. They considered a fleet of trucks equipped with drones delivering packages to customers. Drones can be dispatched from and picked up by the trucks at the depot or any of the customer locations. They extended the work in [15].

All the works mentioned above aim to minimize the total traveling time to complete the route and return to the depot. Ha et al. [16] considered a min-cost objective function to solve TSP-D taking into account the total transportation cost. More recently, Dorling et al. [17] proposed a cost function that considers an energy consumption model and drone re-use. They applied it in a simulated annealing (SA) heuristic to solve the VRPD.

At the best of our knowledge, all the mentioned studies consider as a basic assumption that launch and rendezvous operations must be performed at customer nodes. This paper presents a novel variant of TSP-D relaxing the constraint mentioned above. Starting from a greedy heuristic based on the waiting time that can occur at each truck-drone operation, we improve the TSP-D solution inserting arc-based truck-drone operations. In this way, we implicitly consider in the optimization approach the maximization of drone coverage and usage.

3. Problem description and formulation

In the TSP-D, we consider a list of customers to whom a truck and a drone will deliver parcels. In a truck-drone operation, the drone is launched from the truck and later re-joins the truck at another location. Each customer is visited only once and is served by either the truck or the drone. Both vehicles must start from and return to the depot. When a customer is served by the truck, this is called a truck delivery, while when a customer served by the drone, this is called a drone delivery. We can represent a truck-drone operation by a 3-tuple (v_i, v_j, v_k) as shown in Fig.1. Node v_i is a *launch node* at which the truck launches the drone. The launching operation must be carried out at a customer location. Node v_j is a node served by the drone, called *drone node*. Node v_k is a customer location where the drone re-joins the truck, called *rendezvous node*. The truck can make other truck deliveries $(v_.)$, while the drone is performing a delivery too.

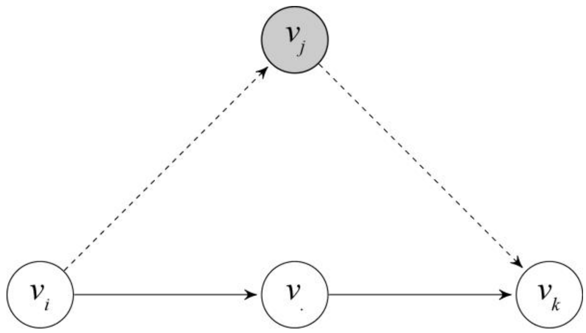


Fig. 1. *A truck-drone operation composed by a launch node (v_i), a drone node (v_j), a rendezvous node (v_k), any possible truck node ($v_.$) between node v_i and v_k.*

A truck-drone operation is called *feasible* if it contains one drone node, two combined nodes (launch and rendezvous) and a non-negative number of nodes served only by the truck. Moreover, it must take into account whether the drone has sufficient endurance to launch from v_i, deliver to v_j and re-join the truck at v_k. The drone can be launched from the depot but must subsequently re-join the truck at a customer location. When not actively involved in a delivery, the drone is carried by the truck. Furthermore, the truck and the drone each have their own transportation costs per unit of distance. In practice, the drone's cost is much lower than the truck's cost because it is not run by gasoline but by batteries.

The TSP-D can be modeled in a graph $G = (V, E)$ where the node v_o represents the depot and nodes $(v_1, \dots, v_N)$ are the locations of N costumers. Let O be the set of feasible operations, and let c_o denote the cost of operation $o \in O$. We can consider the following IP formulation as proposed by Agatz et al. [8]:

$$\min \sum_{o \in O} c_o x_o \tag{1}$$

subject to

$$\sum_{o \in O(v)} x_o \geq 1 \qquad \forall v \in V \tag{2}$$

$$\sum_{o \in O^+(v)} x_o \leq n \cdot y_v \qquad \forall v \in V \tag{3}$$

$$\sum_{o \in O^+(v)} x_o = \sum_{o \in O^-(v)} x_o \qquad \forall v \in V \tag{4}$$

$$\sum_{o \in O^+(v)} x_o \geq y_v \qquad \forall S \subset V\{v_0\}, v \in S \tag{5}$$

$$\sum_{o \in O(v_0)} x_o \geq 1 \tag{6}$$

$$y_{v_0} = 1 \tag{7}$$

$$x_o, y_v \in \{0, 1\} \tag{8}$$

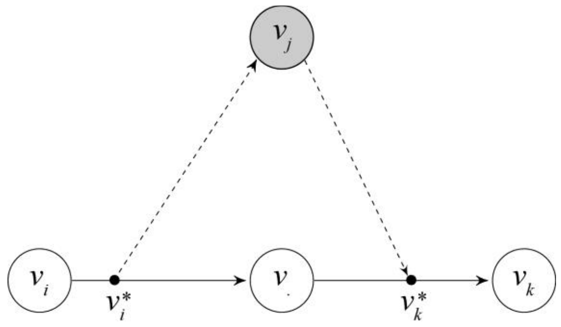


Fig. 2. *An arc-based truck-drone operation composed by a new launch node (v_i^*), a drone node (v_j), a new rendezvous node (v_k^*), any possible truck node ($v_.$) between node v_i^* and v_k^**

where x_o indicates whether an operation o is chosen ($x_o = 1$) or not ($x_o = 0$). Sets $O^-(v) \subset O$ and $O^+(v) \subset O$ represent the set of operations with node v as end node and start node respectively, while $O(v) \subset O$ is the set of all operations containing node v. Similarly, for each set of nodes $S \subset V$, $O^-(S) \subset O$ is the set of all operations with start node in S and end node in $V \backslash S$, $O^+(S) \subset O$ represents the set of all operations with end node in S and start node in $V \backslash S$. y_v is an auxiliary variable indicating whether node v is chosen as start node in at least one operation.

The objective function (1) minimizes the total cost of the tour, which is the sum of the costs of the operations. Constraints (2) ensure that all nodes are covered. Due to constraints (3), y_v is 1 if at least one chosen operation uses v as a start node. The left-hand side of (3) is at most n because each operation must contain at least one previously unvisited node in any optimal solution.

Considering operations as arcs from their start node to their end node, constraints (4-6) ensure that the chosen operations represent a feasible truck-drone tour. Constraint (7) ensures that this tour starts (and ends) at the depot. Constraint (8) forces the variables x_o and y_v to be binary.

4. En-route truck-drone operations

In this work, we include in the problem formulation the possibility to construct arc-based truck-drone operations, i.e. launch and rendezvous operations can be performed along a route arc (*en-route*). In practice, the truck should stop at a point of an arc (e.g. parking space), execute the launch operation and start again. Similarly, the truck should stop at a rendezvous point, complete the operation and start again. These *en-route* operations need an additional time which will be taken into account. Fig.2 shows how the truck-drone operation has been modified. We obtain a new launch point v_i^* and rendezvous point v_k^*. Note that these points can be placed wherever along the partial truck tour, also between two different arcs as reported in the example shown in Fig.3. The optimal positioning of v_i^* and v_k^* is obtained finding the intersections between the best drone coverage circle with radius R^* around node v_j and arcs along the partial truck tour. The best radius R^* corresponds to minimum waiting time $t^w_{i^*,j,k^*}$ defined as:

$$R^* = argmin_{R_{min} < R < R_{max}} \; t^w_{i^*,j,k^*}(R) \tag{9}$$

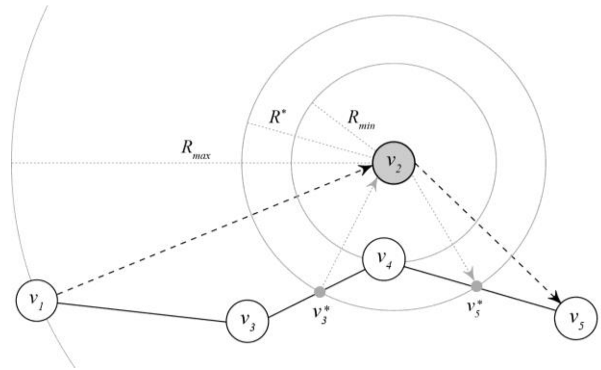


Fig. 3. *An example of an en-route truck-drone operation obtained by Eq. 9*

$$t^w_{i^*,j,k^*}(R) = \left| t_{i^*,k^*}(R) - \left(\tau_{i^*,j}(R) + \tau_{j,k^*}(R)\right)\right| \tag{10}$$

where R_{min} and R_{max} are respectively the minimum and maximum coverage radius related to the closest and farthest node along the partial truck tour; $t_{i^*,k^*}(R)$ is the truck travel time between the points v_i^* and v_k^* obtained by intersecting the circle of radius R with the arcs in the route; $\tau_{i^*,j}(R)$ and $\tau_{j,k^*}(R)$ are the drone travel time between the drone node v_j and points v_i^* and v_k^* respectively. The new truck-drone operation is considered feasible if the following condition is satisfied:

$$t^w_{i^*,j,k^*}(R) + c^* < \; t^w_{i,j,k} \tag{11}$$

where c^* is an additive cost representing the time spent by the truck to stop and start for drone launch and rendezvous along the arcs. In other words, eq. (11) means that an *en-route* operation is useful if and only if the waiting time of the new assignment (v_i^* , v_j , v_k^*) is lower than the node-based assignment (v_i, v_j, v_k).

Therefore, we can easily understand all the possible benefits that can occur using *en-route* drone operations, such as:

- a reduction of drone traveling time along a given 3-tuple;
- an increase in drone remaining endurance with a consequent increase in battery life;
- an increase in drone coverage and usage with a consequent reduction of total traveling costs.

5. The proposed heuristic

In this section, we present the proposed optimization approach based on a novel greedy heuristic. The proposed heuristic is a modification of the Greedy Randomized Adaptive Search Procedure (GRASP) proposed by Ha et al. [16]. Like GRASP, the procedure begins by considering the basic assumption that a truck-drone operation must be performed at customer nodes. Moreover, the heuristic constructs the TSP-D solution starting from a solution of the related TSP that assigns to the truck all the customers in the network. In this work, since we want to consider also medium/large sized problems (more than 20 customers), we skipped the integer programming (IP) solution of the TSP due to the well-known high computational times in finding the global optimum. Hence, in our approach, we considered the Lin-Kernighan heuristic [18] to obtain low computational times in solving the overall TSP-D. We chose this heuristic for its good performances in finding near-optimal TSP solutions.

Starting from a TSP solution to construct the TSP-D tour, differently from the other approaches, we considered as cost function c_o of a single truck-drone operation the sum of the total travel time $c_{i,j,k}$, the waiting time $t_{i,j,k}^{w}$ and the inverse of the remaining endurance $e_{i,j,k}$. They are defined by the following equations:

$$c_{i,j,k} = t_{0,i} + t_{k,0} + \max\{t_{i,k}, \tau_{i,j} + \tau_{j,k}\} \tag{12}$$

$$t_{i,j,k}^{w} = |t_{i,k} - (\tau_{i,j} + \tau_{j,k})| \tag{13}$$

$$e_{i,j,k} = (\tau_{i,j} + \tau_{j,k} - E_D)/E_D \tag{14}$$

$$c_o = c_{i,j,k} + t_{i,j,w}^{w} + (e_{i,j,k})^{-1} \tag{15}$$

where $t_{0,i}$ and $t_{k,0}$ are the truck travel times between the depot and a launch node v_i, and between a rendezvous node v_k and the depot, respectively. $t_{i,k}$ is the truck travel time between a launch node v_i and a rendezvous node v_k (see Fig.1). $\tau_{i,j}$ and $\tau_{j,k}$ are the drone travel time between node pairs (v_i, v_j) and (v_j, v_k), respectively. E_D is the drone endurance time. The travel times are defined as:

$$t_{i,k} = d_{i,k}^{MAN}/s_T \tag{16}$$

$$\tau_{i,j} = d_{i,j}^{EUCL}/s_D \tag{17}$$

where $d_{i,k}^{MAN}$ is the sum of the Manhattan distances of all node pairs between node v_i and v_k in the truck route; $d_{i,j}^{EUCL}$ is the Euclidean distance between node v_i and v_k in the drone route;

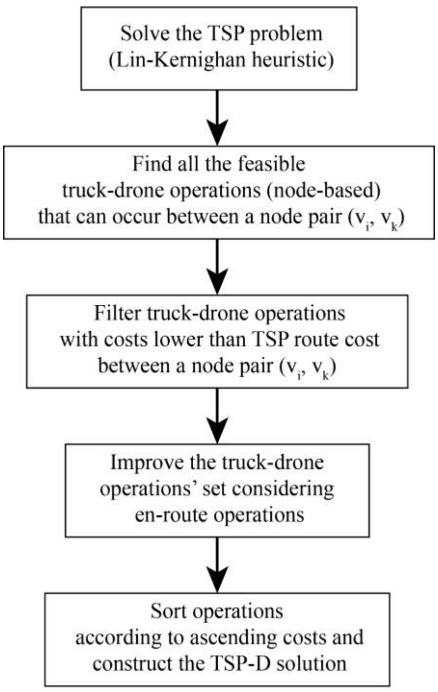


Fig. 4. *Block diagram of the proposed heuristic approach.*

s_T and s_D are the truck and drone speed respectively. We considered two different distance metrics to take into account road network for the truck and straight line paths for the drone.

The proposed greedy heuristic, starting from the TSP tour, finds all the feasible truck-drone operations that can occur between a node pair (v_i, v_k) so that the time to reach v_i (T_i) is lower than the time to reach v_k (T_k). In particular, the procedure considers all the possible insertions of a drone node v_j, where $T_i < T_j < T_k$, subject to the drone endurance constraint. Moreover, for each node pair (v_j, v_k), we evaluate if the truck-drone operation cost $c_{i,j,k}$ is lower than the TSP route cost between the nodes v_i and v_k. In other words, we should obtain a saving over TSP solution by using truck-drone operations as represented by the following expression:

$$(v_i, v_j, v_k) \epsilon\, O \Leftrightarrow c_{i,k}^{TSP} - c_{i,j,k} > 0 \tag{18}$$

In this way, the procedure constructs the set O of all the best feasible operations. In the next step, the procedure sorts operations in the set O according to ascending costs. Then, according to the previous order, each truck-drone operation is inserted in the TSP tour by removing node v_j from the truck tour and adding the 3-tuple (v_i, v_j, v_k) in the drone tour list. At the end of the procedure, we obtain two subtours, one related to the truck and the other one related to the drone.

The improvement to the proposed heuristic consists in optimizing the construction procedure of the truck-drone operations' set O through *en-route* drone operations. Thus, each operation can be modified if a feasible *en-route* operation exists along the related 3-tuple according to (11). At the end of the procedure, we obtain a new set O^* containing both node-based and *en-route* operations. The block diagram of the proposed approach is reported in Fig. 4.

6. Numerical Example

In this section, we present a numerical example for a better understanding of the proposed approach. Let us consider a small test network with one depot (node 0) and 7 customers distributed in a region of 5.5 by 7 km as reported in Fig. 5. Let us assume that the speed of both truck and drone is 40 km/h. The endurance of the drone has been chosen to be 30 min and the *en-route* operation cost $c*$ is one minute.

First, we found the initial TSP tour by applying the Lin-Kernighan heuristic (Fig. 5a). The total traveling time of the TSP tour is 0.49 h, considering Manhattan distances between all node pairs.

In the second step, we constructed the initial set of all feasible truck-drone operations for each node pair (v_i, v_k). In this case, we obtained a set of 56 drone operations as 3-tuples. For example, between the node pair (0, 2) we have four feasible 3-tuples: (0, 7, 2), (0, 5, 2), (0, 6, 2) and (0, 4, 2).

The initial operations' set is then filtered according to (18). In this case, the obtained set O contains 12 feasible truck-drone operations. Table 1 reports the list of the obtained 3-tuples and corresponding travel time, waiting time, remaining endurance and cost according to equations (12)-(15). Moreover, the reported list is already sorted by ascending costs as required for constructing the final TSP-D solution. The greedy construction procedure considers one 3-tuple at a time, according to the ordered list. The procedure inserts a 3-tuple when no overlaps occur with previously entered operations. In this case, the final drone tour list

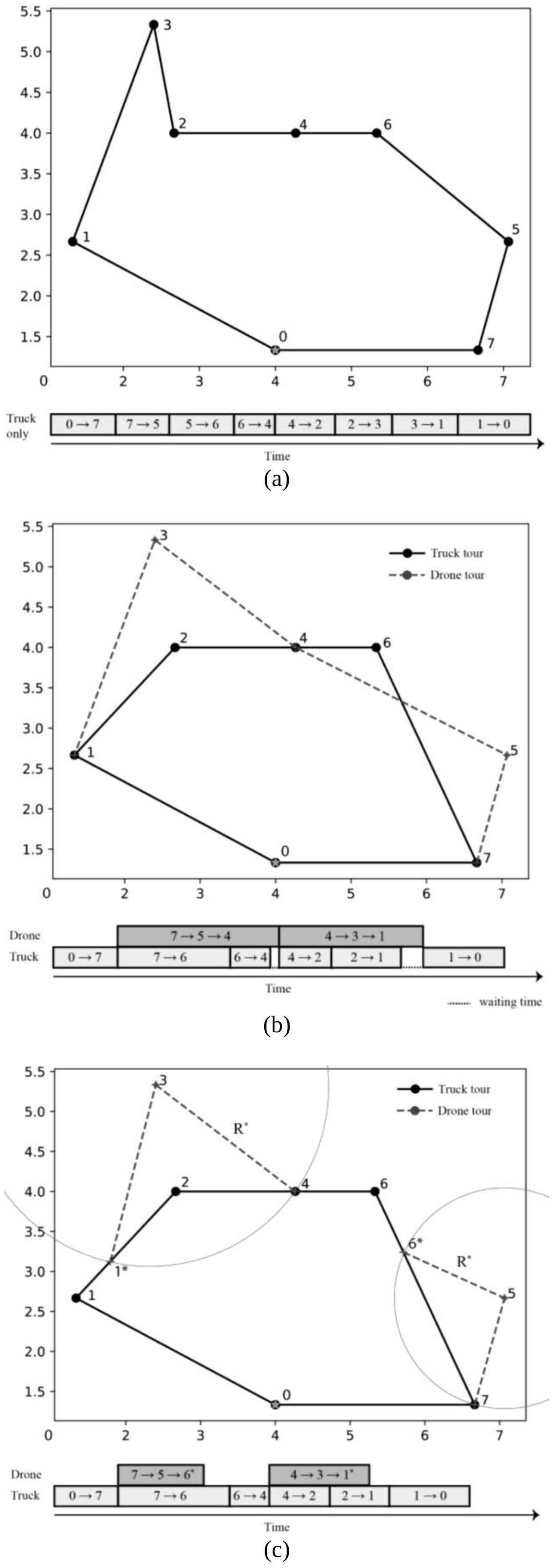


Fig. 5. *The test network: (a) initial TSP solution; (b) greedy heuristic solution; (c) improved heuristic solution using en-route operations.*

contained the operations (7, 5, 4) and (4, 3, 1). All the other operations were skipped, e.g. operation (0, 5, 6) overlapped with the operation (7, 5, 4). Fig. 5b shows the obtained tours without considering *en-route* operations. We can observe the waiting time that occurs at each truck-drone operation. In particular, the truck should wait for 0.02 h at node 4 and 0.05 h at node 1. The resulting total travel time is 0.46 h, obtaining a saving of 0.04 h over the TSP tour.

Finally, we applied the proposed *en-route* approach to the set O reported in Table 1. We obtained for each operation the best radius value according to (9). Table 2 reports the final set O^* of the feasible *en-route* operations according to (11).

Table 1 The obtained set O of feasible truck-drone operations

Operation	$c_{i,j,k}$ [h]	$t^w_{i,j,k}$ [h]	$e_{i,j,k}$	c_o [h]
(7, 5, 4)	0.48	0.02	0.77	1.80
(0, 5, 6)	0.47	0.004	0.72	1.86
(4, 3, 1)	0.48	0.05	0.74	1.88
(7, 5, 2)	0.48	0.02	0.70	1.93
(0, 5, 4)	0.46	0.002	0.67	1.95
(6, 3, 1)	0.47	0.05	0.69	1.96
(7, 5, 3)	0.47	0.004	0.66	1.98
(0, 3, 1)	0.42	0.10	0.64	2.08
(0, 5, 2)	0.47	0.002	0.60	2.12
(5, 3, 1)	0.45	0.03	0.58	2.18
(7, 3, 1)	0.42	0.002	0.56	2.19
(0, 5, 3)	0.47	0.02	0.56	2.26

Table 2 The obtained set O^* of feasible *en-route* operations

Operation	R^*	$c_{i,j,k}$ [h]	$t^w_{i,j,k}$ [h]	$e_{i,j,k}$	c_o [h]
(7, 5, 6^*)	1.39	0.46	0.001	0.86	1.62
(4, 3, 1^*)	2.29	0.43	0.03	0.77	1.76

We can see that operation (7, 5, 6^*) replaced the operation (7, 5, 4) resulting in a very low waiting time (0.001 h) and a higher remaining endurance (0.86). Similarly, operation (4, 3, 1) changed in (4, 3, 1^*) reducing the cost from 1.88 to 1.76 h. The construction procedure is then applied as previously described. Fig. 5c shows the tours obtained using *en-route* operations. The resulting total travel time is 0.40 h, with a saving (0.09 h) greater than the basic heuristic (0.04 h) over the TSP tour. Moreover, the average remaining endurance (0.82) is greater than the basic heuristic (0.76).

7. Application and results

We carried out some numerical experiments were conducted to assess the effectiveness of the proposed heuristic. We compared the proposed greedy heuristic and the same heuristic including *en-route* drone operations. All computational work was conducted on a desktop PC equipped with a quad-core Xeon processor and 4 GB RAM. The heuristic has been coded in Python version 3.5 to obtain good computational performances. Numerical experiments are based on the benchmark instances by Bouman et al. [19]. We adapted the coordinates range to obtain almost real travel times since the basic coordinates refer to a 100 by 100 square region. We considered 90 instances with 10, 20 and 50

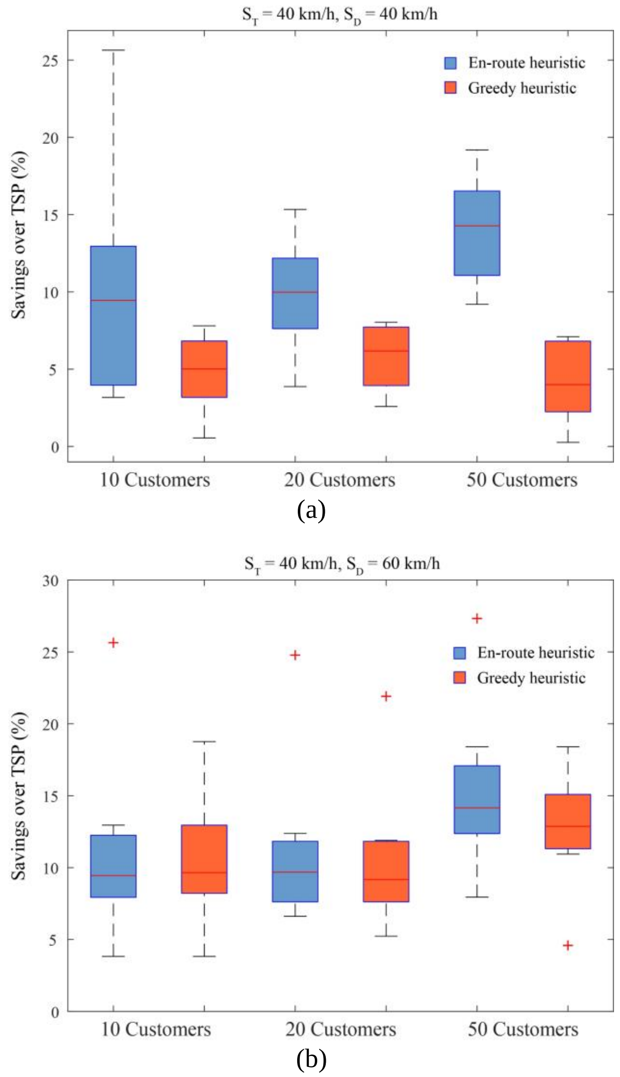


Fig. 6. *Comparison of savings over TSP route between the proposed heuristic with and without en-route operations for (a) experiments with the same speed and (b) experiments with drone faster than truck.*

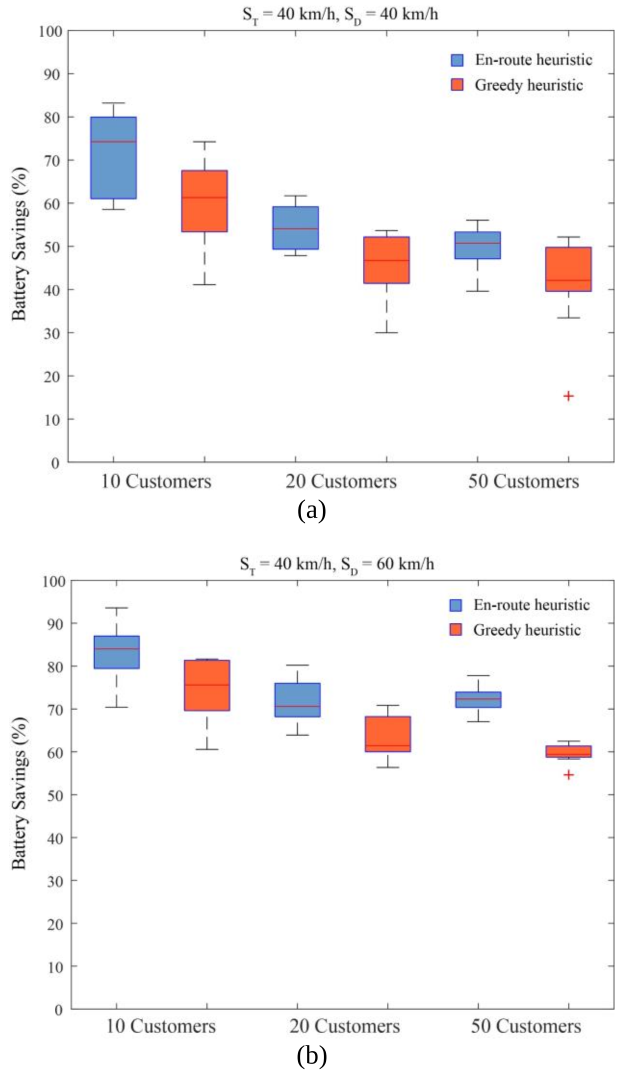


Fig. 7. *Comparison of battery savings between the proposed heuristic with and without en-route operations for (a) experiments with the same speed and (b) experiments with drone faster than truck.*

customers arranging the square region to 15 by 15 km, 30 by 30 km and 50 by 50 km respectively. Each group is composed of 30 instances where customers are generated using a uniform, single center and double center random distributions. The endurance of the drone has been chosen to be 30 min. Drone speeds have been selected as 40 or 60 km/h. We have not considered the case in which the drone is slower than the truck since it has resulted not useful neither realistic. The truck speed was assumed to be 40 km/h. The *en-route* operation cost c^* has been assumed to be one minute.

In Figs. 6-8, we reported the obtained results considering the following indicators:

- the percentage of savings over TSP solution cost (Sav. %);
- the percentage of battery savings related to the remaining endurance for each operation (Bat. %);
- the waiting time in minutes as defined in (10) and (13) (Wait.).

Tables 3-5 report the statistical comparison between the greedy and the *en-route* heuristic in terms of average, minimum and maximum values of the considered indicators. We can observe that the proposed heuristic with *en-route* operations outperformed the greedy heuristic for all the considered indicators. It is interesting to see that, regarding savings over TSP solution, the *en-route* operations seem to be less useful when the drone is faster than the truck. In this case, better results are obtained when truck and drone have the same speed. This result is understandable since the faster the drone, the higher the number of truck-drone operations that can be selected by both approaches. However, significant improvements can be seen regarding battery savings and waiting time. We obtained an average increase of 10% in battery savings using *en-route* operations. Moreover, the best results are observable regarding waiting times. We obtained an average waiting time of less than 1 minute when the drone is faster than the truck compared to 3 minutes on average without *en-route* operations. Thus, the waiting time is highly related to the relative speed between the truck and the drone. We should expect that the drone flies faster than the truck to significantly reduce waiting times.

Fig. 9 shows a solution for an instance with 20 customers and s_T = 40 km/h, s_D = 60 km/h. The initial TSP

Table 3 Statistical comparison of the obtained results for instances with 10 customers

S_T/S_D [km/h]	Index	Avg G	Avg E	Min G	Min E	Max G	Max E
40/40	Sav. %	4.83	**10.4**	0.01	**3.18**	7.80	**25.6**
	Bat. %	60.0	**71.8**	41.1	**58.5**	74.2	**83.2**
	Wait.	2.03	**1.01**	0.45	**0.00**	4.87	**3.88**
40/60	Sav. %	10.5	**10.6**	3.83	**3.83**	18.7	**25.6**
	Bat. %	74.2	**83.1**	60.6	**70.4**	81.7	**93.5**
	Wait.	2.26	**0.27**	1.29	**0.00**	3.95	**1.64**

* G: Greedy Heuristic; E: En-route Heuristic.

Table 4 Statistical comparison of the obtained results for instances with 20 customers

S_T/S_D [km/h]	Index	Avg G	Avg E	Min G	Min E	Max G	Max E
40/40	Sav.%	5.73	**9.83**	2.58	**3.88**	8.04	**15.3**
	Bat.%	45.2	**54.5**	30.0	**47.8**	53.7	**61.7**
	Wait.	3.57	**2.02**	1.59	**0.36**	8.86	**5.28**
40/60	Sav.%	10.4	**10.9**	5.23	**6.62**	21.9	**24.8**
	Bat.%	63.7	**71.6**	56.3	**63.9**	70.8	**80.2**
	Wait.	3.63	**0.22**	2.12	**0.00**	4.96	**1.02**

* G: Greedy Heuristic; E: En-route Heuristic.

Table 5 Statistical comparison of the obtained results for instances with 50 customers

S_T/S_D [km/h]	Index	Avg G	Avg E	Min G	Min E	Max G	Max E
40/40	Sav.%	4.12	**14.2**	0.27	**9.19**	7.10	**19.2**
	Bat.%	40.9	**49.9**	15.3	**39.6**	52.2	**56.1**
	Wait.	4.02	**2.37**	**0.44**	1.34	9.34	**4.08**
40/60	Sav.%	13.2	**15.2**	4.59	**7.95**	18.4	**27.3**
	Bat.%	59.6	**72.2**	54.6	**67.0**	62.5	**77.7**
	Wait.	4.42	**0.51**	2.98	**0.02**	7.46	**1.09**

* G: Greedy Heuristic; E: En-route Heuristic.

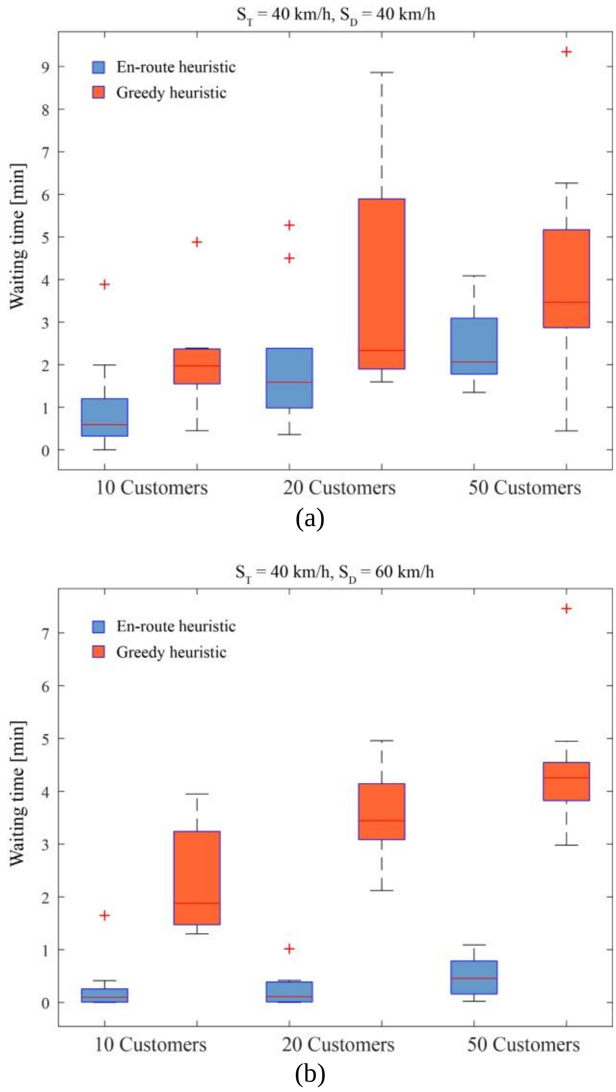
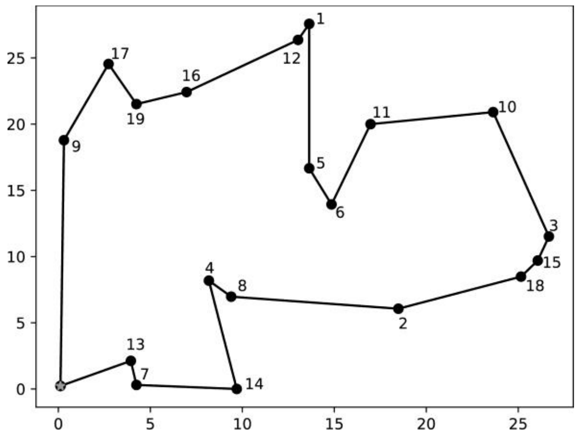


Fig. 8. *Comparison of waiting times between the proposed heuristic with and without en-route operations for (a) experiments with the same speed and (b) experiments with drone faster than truck.*

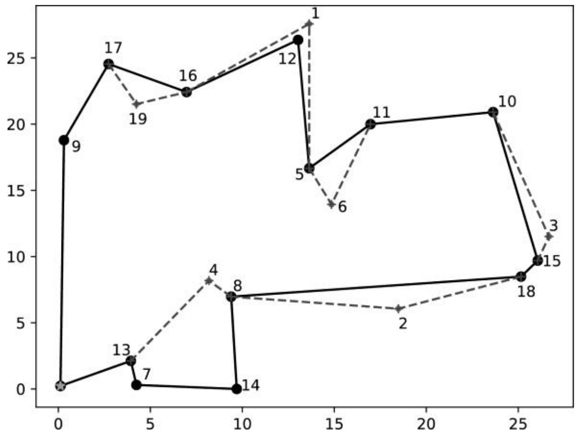
solution obtained by the Lin-Kernighan heuristic [18] is reported in Fig. 9a. Fig. 9b and 9c report the solution found by the greedy heuristic and the heuristic with *en-route* operations respectively. In this case, we obtained the same drone nodes and truck tour, but the solution has been improved regarding waiting time and battery savings.

8. Conclusion

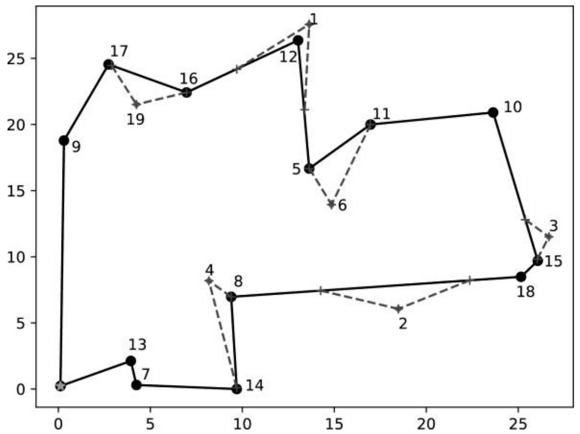
In this paper, we presented a novel approach to solving the Traveling Salesman Problem with Drone (TSP-D). The problem is of current interest, and many logistic companies are seriously considering this new concept in parcel delivery. In our approach, we relaxed the basic assumption of all methods in the literature which consider that truck-drone operations must be performed at customer nodes. We introduced the possibility of performing truck-drone operations also along arcs, called *en-route* operations. In this way, we can obtain some benefits regarding drone battery life and usage. To solve the problem with *en-route* operations, we developed a greedy heuristic, based on the GRASP [16], and modified to take into account the waiting time in the cost function. Thus, we included the *en-route* operations in the procedure related to operations' list generation. To evaluate the outcomes of the proposed approach, we applied the heuristic to 90 benchmark instances proposed by Bouman et al. [19], arranged to obtain realistic scenarios. Results have been carried out regarding savings over TSP solution, battery savings and waiting time. The obtained results have highlighted the effectiveness of the proposed approach and give new ideas for further works. First, a dynamic simulation model can be developed considering *en-route* operations in urban traffic networks. Moreover, we can consider performing these operations also when the truck travels along congested arcs. In this way, we can overcome congestion situations and significantly reduce total transportation costs.



(a)



(b)



(c)

Fig. 9. *Comparison of the obtained solutions for an instance with 20 customers (s_T = 40 km/h, s_D = 60 km/h): (a) initial TSP solution; (b) greedy heuristic solution; (c) improved heuristic solution using en-route operations.*

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