Flight Path Constrained Last-mile Parcel Delivery Using Drone

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Abstract. Delivering parcels from the distribution hub using Unmanned Aerial Vehicles(UAV)/Drones for last-mile delivery is gaining popularity for a smart city. The total path length of the drone while delivering at multiple locations in a single despatch depends on the order of traversal of those points. Determining the optimal tour in this context is the classical TSP (Traveling Salesman Problem) problem and is NP-complete. Since the drone has a limited capacity c, we need multiple tours, each traversing at most c delivery points. Also, the length of each tour cannot exceed the maximum flight length of the drone. In this paper, we have formulated an ILP that provides optimized multi-tour paths for the drone under these constraints. However, using the ILP solver to get the solution for large instances in real time is infeasible. Hence, our approach to solving this problem is to use an ensemble of two polynomial time heuristics - Maximum Distance Minimum Deviation (MDMD) and Highest Distance Reduced Next (HDRN). Experimental results show that our algorithm gives solutions quite close to the optimal solution from the ILP.

Keywords: Unmanned Aerial Vehicle(UAV) · Drone-based Delivery · Parcel Delivery · Last-mile Delivery · Multi-tour TSP · Heuristic Algorithm · Greedy Algorithm.

1 Introduction

The use of Unmanned Aerial Vehicles (UAVs) to deliver parcels from a distribution hub to recipients is gaining popularity. This type of delivery is fast and secure, as drones can take the shortest path without being affected by traffic, and the delivery process does not require human intervention. Additionally, since drones are battery-powered, they do not contribute to pollution in the delivery area [1]. Consequently, many logistics companies are swiftly embracing this new delivery system.

In traditional parcel delivery systems, parcels are gathered at a local distribution hub and then delivered to recipients by delivery personnel using vehicles.

However, companies like Amazon are in some places employing drones to replace these "last-mile" delivery systems[2]. In such cases, drones would start from the distribution hub, visit each recipient once, and then return to the hub. Optimizing the total distance traveled by the drone in these scenarios is similar to the classic Traveling Salesman Problem (TSP), a known NP-complete problem.

However, drones have limited battery power, which may prevent them from visiting all recipients in a single flight due to insufficient battery charge. The battery power determines a drone's maximum flight distance. This maximum distance is known as the drone's range in this context. Drones also have capacity limitations for the number of parcels they can carry in a single flight. Due to these limitations, drones may need to make multiple flights to deliver all parcels. The problem of minimizing the total tour distances for such multiple tours is akin to the multi-tour Traveling Salesman Problem (MTSP) that is NP-complete. We provided an Integer Linear Programming (ILP) formulation for the problem, but solving the ILP requires significant computational resources and is unsuitable for real-time solutions for large problems. Therefore, two polynomial time heuristics—Maximum Distance, Minimum Deviation (MDMD) algorithm, and Highest Distance Reduced Next (HDRN) are proposed to produce near-optimal solutions in real-time. Additionally, an ensemble algorithm that combines MDMD and HDRN to choose the better solution is proposed.

The review of drone-based delivery in the last mile is discussed in [4]. [5] explores cooperative vehicle drone parcel delivery, while [6] proposes heuristic-based solutions for delivery-by-drone problems. Additionally, [7] considers battery lifetime in determining feasible paths, and [8] discusses a multi-tour set TSP for drone-based power traffic line (PTL) inspection, inspiring a similar approach for drone-based parcel delivery. The literature indicates that no previous work has addressed the problem of multi-tour drone-based delivery with capacity and flight distance constraints. As a result, the ILP formulation of this problem and the development of polynomial time heuristics to solve it are of academic and practical significance.

The rest of the paper goes as follows. The formal definition of the problem is discussed in the next section, followed by the ILP formulation for the problem in section 3. Section 4 describes the proposed heuristic-based solutions. Simulation results appear in section 6, and the paper concludes with remarks in section 7.

2 Problem Description

Let us consider a distribution hub and a set of n delivery points where the drone will drop the parcels in a Region of Interest(RoI). We model the hub and all delivery points by a complete graph $G(V, E)$ where $V = \{v_1, v_2, \dots v_{n+1}\}$. Here, v_1 represents the hub and $v_2, v_3, \dots v_{n+1}$ are the distribution points. The weight of an edge $E = (v_i, v_j)$ is the Euclidean distance $d[v_i, v_j]$ between v_i and v_j.

We consider the distribution hub to possess a single drone to deliver all the parcels. The drone is constrained by the capacity, c, i.e., the maximum number of parcels that it can carry in a single flight, and the radius of flight, r, i.e., the maximum stretch from the distribution hub that the drone can travel and return to the hub before draining all its battery power in a single flight. These limitations may cause the drone to take multiple tours, each starting from the distribution hub and serving at most c delivery points before returning to the distribution hub. The total length of each flight cannot exceed $2 * r$.

Therefore, the drone will make a set of tours $\mathcal{T} = \{\tau_1, \tau_2, ..., \tau_k\}$ to deliver the packages. Any tour $\tau \in \mathcal{T}$ is represented by a sequence $< u_1, u_2, \ldots u_p >$, where u_1 is the first vertex, and u_k is the last vertex visited in the tour. Also, $|\tau| = p$ should be less than or equal to the capacity c. Let $L(\tau)$ denote the length of the tour where $L(\tau) = d[v_1, u_1] + \sum_{i=1}^{p-1} d[u_i, u_{i+1}] + d[u_p, v_1]$.

Hence, our parcel delivery problem can be stated as follows:

Definition 1. *Given c, r, a distribution hub v_1 and a set of delivery points $\{v_2, v_3, \ldots v_{n+1}\}$, determine a set of tours $\tau_1, \tau_2, \ldots$, that minimizes $\sum_i L(\tau_i)$ satisfying the constraints :*
i) $|\tau_i| \leq c$ for each i
ii) $L(\tau_i) \leq 2 * r$ for each i

3 ILP Formulation

We can formulate the multi-tour TSP problem as the following Integer Linear Program (ILP). The ILP has to solve a two-dimensional decision variable $X \in \{0, 1\}^{(n+1)\times(n+1)}$ where,

$$X_{i,j} = \begin{cases} 1, & \text{if the link } (v_i, v_j) \text{ is in some tour.} \\ 0, & \text{otherwise } j. \end{cases} \tag{1}$$

Represnting $d[v_i, v_j]$ by $d_{i,j}$, the ILP is formulated as below:

$$\text{Minimize } \mathcal{L} = \sum_{i=1}^{n+1} \sum_{j=1}^{n+1} d_{i,j}.X_{i,j} \tag{2}$$

Subject to,

$$X_{i,i} = 0 \qquad 1 \leq i \leq n+1 \tag{3}$$

$$\sum_{i=1}^{n+1} X_{i,j} = 1 \qquad 2 \leq j \leq n+1 \tag{4}$$

$$\sum_{j=1}^{n+1} X_{i,j} = 1 \qquad 2 \leq i \leq n+1 \tag{5}$$

$$u_i - u_j + X_{i,j} \leq (1 - X_{i,j})(c-1) \qquad 2 \leq i \neq j \leq n+1 \tag{6}$$

$$D_i \geq d_{1,i} \qquad 2 \leq i \leq n+1 \tag{7}$$

$$D_i - D_j + d_{i,j}.X_{i,j} \leq (1 - X_{i,j})2 * r \qquad 2 \leq i \neq j \leq n+1 \tag{8}$$

$$D_i + d_{i,1} \leq 2 * r \qquad 2 \leq i \leq n+1 \tag{9}$$

The objective function described by 2 is to minimize the overall distance traversed by the drone. The constraints 3 - 4 ensure that each delivery point is visited once except the distribution hub (it might be visited by the drone multiple times). As in [9], the constraint 6 ensures that the tours satisfy the capacity constraints of the drone. The variable D_i denotes the distance of node i from the source along the tour. Constraints 7 to 9 together ensure that each tour is of length at most $2 * r$.

The tours $\mathcal{T}$ of the drone can be determined from the decision variable X.

4 Proposed Solution

The ILP solution, though optimal, demands very high computational resources to determine the solution and may not be feasible in the real-world scenario, and a quick sub-optimal solution may be preferable.

4.1 MDMD Algorithm

The heuristic-based algorithm we thought of is named Maximum Distance Minimum Deviation (MDMD). Since the drone must deliver all the packages, we try to find out if it can deliver other packages in the same tour while serving a location v_{max} farthest from the hub. If there is another delivery point near v_{max}, the drone should try to include it in the same tour. It means the drone should try to deliver another parcel whose delivery point is as far as possible from the hub but as near as possible to the path of the maximum distant delivery point.

Fig. 1 describes how the heuristic is determined. Let D be the maximum distant delivery point from the source S and i be any other delivery point whose distance from the source is d_i, and the deviation from the original path SD is h_i. Therefore, as per our reasoning, the heuristic value for the delivery point i, denoted as μ_i, is

$$\mu_i \propto d_i \tag{10}$$

and,

$$\mu_i \propto \frac{1}{h_i} \tag{11}$$

Combining 10 and 11, together we calculate the MDMD heuristic value for a node i as,

$$\mu_i = \frac{d_i}{h_i} \tag{12}$$

Algorithm 1: MDMD Algorithm

Input : Set of nodes V. Distance matrix d. Flight range(radius) of drone r. drone capacity c.

Output : All sub-tours of drone in $\mathcal{T}$.

```
T ← {}
while | V | ≠ 1 do
    v_f ← node in V farthest from v_1;
    Before ← [ ] /* node in tour before v_f in increasing order of their
      distance from v_1 */;
    After ← [ ] /* node in tour after v_f in decreasing order of their
      distance from v_1 */;
    V ← V − {v_f};
    for i ← 2 to | V | do
        h_i ←
          signed height of v_i from the straight line connecting v_1 and v_f
        μ_i ← | d_{1,i} / h_i |
    Sort V in descending order of μ value
    foreach v_i ∈ V − {v_1} do
        if h_i < 0 then
            Put v_i in Before maintaining order;
            τ' ←< Before, v_f, After >;
            if L(τ') > 2 * r then
                remove v_i from Before
            else
                remove v_i from V;
        else
            Put v_i in After maintaining order;
            τ' ←< Before, v_f, After >;
            if L(τ') > 2 * r then
                remove v_i from After
            else
                remove v_i from V
        τ ←< Before, v_f, After >;
        if |τ| = c then
            break;
    T ← T ∪ τ
```

The algorithm determines the farthest unattended delivery point and includes it in the tour. Then, it calculates the heuristic value μ for all other unserved delivery points. Next, each delivery point is considered individually in decreasing order of the heuristic value. The algorithm goes on adding these points to the tour as long as the flight length constraint and the capacity constraint is not

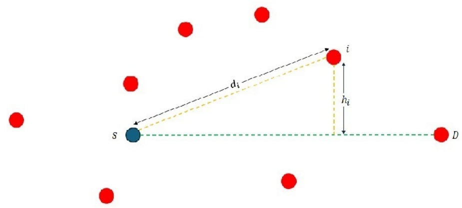

Fig. 1: MDMD Algorithm

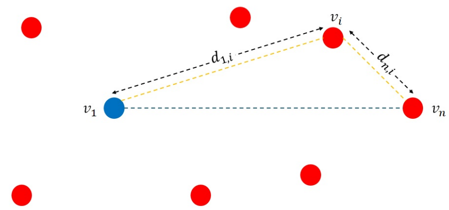

Fig. 2: HDRN Algorithm

violated. If it cannot add more delivery points, it starts a new tour to serve the rest of the unattended delivery points following the same process. Eventually, the algorithm will produce a set of tours that provides a sub-optimal solution of minimizing total flight distance to deliver all the parcels in considerably less time than solving the ILP.

4.2 HDRN Algorithm

Highest Distance Reduced Next(HDRN) is straightforward and based on a greedy approach. Like MDMD, Algorithm HDRN first determines the farthest unattended delivery point, say v_f, and includes it in the tour. When the drone visits a delivery point, the next delivery point it selects is the one that most reduces the flight distance when traversing from the current delivery point rather than from the distribution hub. As shown in Fig. 2, v_1 is the hub, and v_f is the current node the drone is visiting. Let v_i be the node that the drone can visit next. The distances of the node v_i from v_1 and v_n is given by $d_{1,i}$ and $d_{f,i}$ respectively. Then, the flight distance reduced to deliver the parcel at v_i is:

$$\delta_{i,n} = d_{1,i} - d_{n,i} \tag{13}$$

The algorithm calculates δ_i for all $2 \leq i \neq n \leq \mid V \mid$ and includes the node v_j such that $\max\limits_{\substack{2 \leq j \leq |V| \\ j \neq n}} \delta_j$, in the tour if the drone can return to the hub after visiting v_j without disobeying the flight distance constraint. If the flight distance constraint is not satisfied, then the node with the next highest δ value is checked for inclusion in the tour. In this way, if the tour includes a node v_j, the value of δ is recalculated for all the unattended nodes with reference to the node v_j. The algorithm will follow the same greedy approach to add an unserved node to the tour if the capacity and the flight distance constraint permit. Otherwise, a new tour will start to serve the remaining delivery points. Once the delivery points of a tour is determined, a 3/2 approximation solution of TSP as given in [10] is applied on those points. If the approximation algorithm of [10] provides a shorter tour of the selected points, the tour will be included in the solution. Otherwise, the solution include the tour generated by the greedy apporach. In

Algorithm 2: HDRN Algorithm

Input : Set of nodes V. Distance matrix d. Flight range(radius) r. drone capacity c.
Output : All sub-tours of drone $\mathcal{T}$.

$\mathcal{T} \leftarrow \{\}$
while $\mid V \mid \neq 1$ **do**
  $v_f \leftarrow v_i$, such that $v_i \in V \wedge \max\limits_{\{2 \leq k \leq |V|\}} d_{1,k} = d_{1,i}$
  $\tau \leftarrow < v_f >$
  $\ell_\tau \leftarrow d_{1,f}$;
  $continue \leftarrow True$;
  while $\mid \tau \mid < c$ *and* $continue = True$ **do**
    $V \leftarrow V - v_f$
    for $i \leftarrow 2$ **to** $\mid V \mid$ **do**
      $\delta_{i,f} \leftarrow d_{1,i} - d_{f,i}$
    Sort V in descending order of δ value
    $continue \leftarrow False$;
    foreach $v_i \in V - v_1$ **do**
      if $L(\tau) \leq 2 * r$ **then**
        Append v_i with τ.
        $v_f \leftarrow v_i$
        $continue \leftarrow True$
        break
  $\tau_c \leftarrow Christofides - TSP(\tau, d)$
  if $L(\tau_c) < L(\tau)$ **then**
    $\mathcal{T} \leftarrow \mathcal{T} \cup \tau_c$
  else
    $\mathcal{T} \leftarrow \mathcal{T} \cup \tau$

this way, the algorithm will produce a set of tours that provides a sub-optimal solution of minimizing total flight distance.

4.3 The Ensemble Algorithm

As shown in the result section, it is found that both the MDMD and HDRN algorithms performs much faster than ILP solver. More over, while MDMD provides better solution than HDRN in some cases, for rest of the cases, HDRN performs better than MDMD. As a result, we propose an ensemble algorithm that compares the results obtained from both of these algorithms and suggests the tours of the drone that takes shorter total distance.

5 Simulation Result

The flight distance of a drone largely depends on the model of the drone along with its configuration, as given in Table 1. To simulate the algorithms, we con-

Algorithm 3: Ensemble Algorithm

Input : Set of nodes V. Distance matrix d. Flight range(radius) of drone r. Maximum number of parcels the drone can carry in a single flight c.

Output : All sub-tours of drone $\mathcal{T}$.

$\mathcal{T}_M \leftarrow MDMD(V, d, r, c)$

$\mathcal{T}_H \leftarrow HDRN(V, d, r, c)$

$\mathcal{L}_M = \sum_{\tau \in \mathcal{T}_M} L(\tau)$

$\mathcal{L}_H = \sum_{\tau \in \mathcal{T}_H} L(\tau)$

if $\mathcal{L}_H < \mathcal{L}_M$ **then**

  $\mathcal{T} \leftarrow \mathcal{T}_H$

else

  $\mathcal{T} \leftarrow \mathcal{T}_M$

sider a random distribution of parcel requests with a drone range(radius) of 10 Kilometers. To simulate the algorithms, we generated random distributions of delivery points having a count of 5 to 20 with a gap of 5. For each of those distributions, we performed a simulation for drone capacity of 2 to 5. The simulation is performed on a computer having 7^{th} generation Intel Core i7 processor with 2.7 GHz clock speed and 8 GB of RAM. The ILP is solved using the PuLP CBC solver, and the proposed algorithm is implemented in Python 3.10 on the same computer. Matplotlib is used for visualization purposes.

Table 1: Drone Models along with Delivery Range [11] - [13]

Model	Delivery Range	Payload
Amazon Prime Air model	12 KM	25Kgs
JOUAV PH-20	15 KM	10 Kgs
DJI FlyCart 30	8 KM	30 Kgs

Table 2 shows the simulation result. The first column of the table refers to the number of delivery points, and the second column refers to the drone capacity for which the simulation is performed. The 'Time' column under the ILP, HDRN, and MDMD heading refers to the execution time of the ILP, HDRN algorithm, and MDMD algorithm in the above system. The Execution time is measured in Seconds. $\mathcal{L}_I, \mathcal{L}_H, \mathcal{L}_M$ columns refer to the total flight distance, measured in kilometers, that the drone needs to fly to deliver all the parcels in the given scenario for the tours provided by the solutions of ILP solver, HDRN algorithm and MDMD algorithm respectively. The '% Error' column under the HRDN and MDMD heading shows how worse HDRN and MDMD algorithms performed, respectively, when compared to the optimal solution, as provided by the ILP solver.

Table 2: Simulation Result

Points (n)	Capacity (c)	ILP		HDRN			MDMD		
		$\mathcal{L}_I$	Time	$\mathcal{L}_H$	% Error	Time	$\mathcal{L}_M$	% Error	Time
5	2	47.97	7.31	47.97	0%	0.128	47.97	0%	0.660
	3	47.97.89	0.15	47.97	0%	0.008	47.97	0%	0.001
	4	47.97	0.25	47.97	0%	0.006	47.97	0%	0.001
	5	47.97	0.60	47.97	0%	0.011	47.97	0%	0.001
10	2	93.51	1.72	93.51	0%	0.010	93.51	0%	0.003
	3	86.61	1.21	86.61	0%	0.011	86.61	0%	0.003
	4	86.04	1.22	86.04	0%	0.008	86.04	0%	0.004
	5	86.04	1.06	86.04	0%	0.010	86.04	0%	0.005
15	2	133.70	5.54	136.59	2.17%	0.016	139.43	4.29%	0.008
	3	127.00	3.12	130.45	2.72%	0.016	138.23	8.85%	0.009
	4	127.00	6.71	128.75	1.38%	0.014	128.75	1.38%	0.006
	5	126.92	4.52	128.75	1.44%	0.017	128.75	1.44%	0.007
20	2	129.37	3060	129.83	0.35%	0.016	146.85	13.51%	0.088
	3	119.23	2831	124.04	4.03%	0.015	125.91	5.60%	0.007
	4	118.61	8729	123.70	4.30%	0.015	121.23	2.21%	0.031
	5	117.39	2720	122.64	4.47%	0.012	119.21	1.55%	0.011

As the result suggests, even if the ILP provides an optimal solution, the time for execution of ILP is much slower than the other two algorithms. As the size of the simulation instance increased, the time taken by the ILP solver increased exponentially, showing its nature of being an NP-Hard problem. Beyond 20 delivery points, the ILP solver could not produce the tours in a reasonable time. It justifies the need for algorithms like MDMD or HDRN that provide a sub-optimal solution in real-time. It is observed that while in a few scenarios, MDMD produces better results than HDRN, in other cases, HDRN produces better ones. As both of these algorithms take very little time to execute, the ensemble algorithm can be implemented to generate better results among these two in real-time.

Due to lack of space, visuals of only one simulation instance are provided from Fig. 3 to Fig. 6. Fig. 3 depicts an instance of 15 delivery points with drone capacity 3. The blue circle in Fig. 3 refers to the distribution hub, and the red ones are the delivery points. For this problem instance, Fig. 4 shows the optimal set of tours the ILP solution provides. For the same problem instance, sets of tours produced by HDRN and MDMD algorithms are given in Fig. 5 and Fig. 6, respectively.

The experiment is further extended to determine the characteristics of the HDRN and MDMD algorithms by simulating them for delivery points ranging from 5 to 40 with a gap of 5, with the drone capacity varying from 2 to 5. For

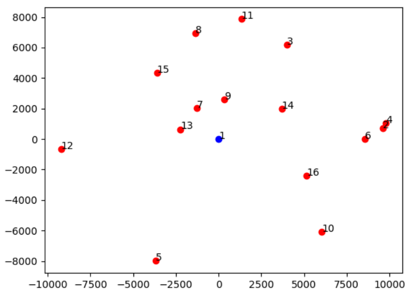

Fig. 3: Simulation Scenario

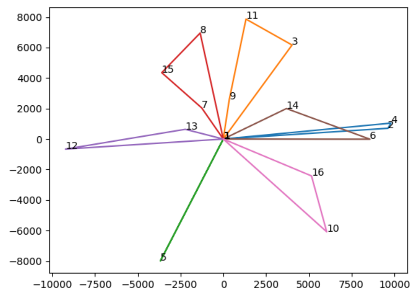

Fig. 4: ILP Solution

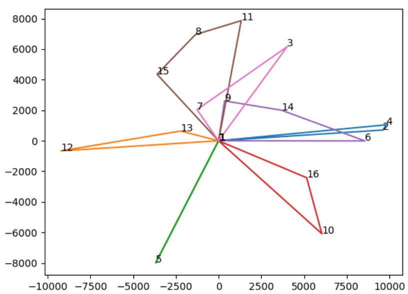

Fig. 5: HDRN Solution

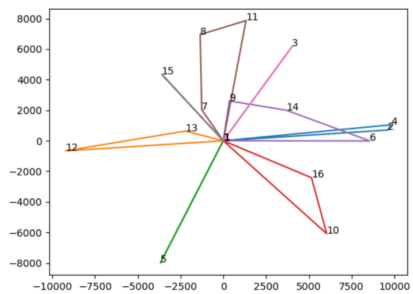

Fig. 6: MDMD Solution

Table 3: Mean total distance for MDMD Algorithm

	Delivery Points							
Capacity	5	10	15	20	25	30	35	40
2	41.22	76.69	106.51	147.75	187.94	223.46	258.03	291.18
3	38.75	68.72	90.99	119.08	147.06	176.39	201.51	225.85
4	38.64	65.90	84.62	109.69	133.98	157.34	174.51	193.21
5	38.64	65.49	84.78	104.76	125.92	143.92	158.44	179.35

Table 4: Mean total distance for HDRN Algorithm

	Delivery Points							
Capacity	5	10	15	20	25	30	35	40
2	39.19	70.92	97.47	130.62	161.69	191.98	218.22	245.92
3	38.49	66.55	85.87	112.67	136.19	158.46	175.69	199.01
4	38.41	65.89	83.94	108.42	128.95	149.73	162.67	185.44
5	38.41	65.98	83.60	108.06	127.26	146.42	159.17	180.94

each of these scenarios, the simulation is performed over ten different random distributions of delivery points, and the mean of the results is considered to reduce the effect of the distribution of the delivery points on the simulation result. The results are given in the Table 3 and Table 4. The total distance traversed(in kilometers) by the drone reduces as the capacity of the drone increases, as expected. The output of the Ensemble algorithm for the same is plotted on the chart given in Fig. 7. Fig. 8 shows the results of the MDMD and the HDRN algorithms for drones of capacities 2 and 5 plotted on a chart. It is observed that for the low-capacity drone, the HDRN algorithm performs better than the MDMD algorithm. However, the MDMD algorithm starts performing better as the capacity of the drone increases.

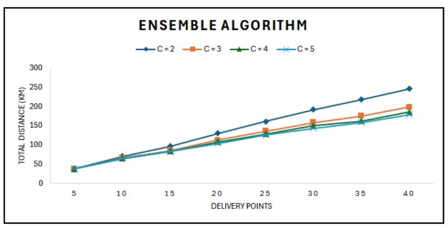

Fig. 7: Output of Ensemble Algorithm

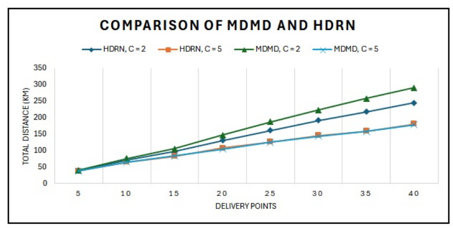

Fig. 8: MDMD vs HDRN

6 Conclusion

In this paper, a variant of the multi-tour Travelling Salesman Problem considering the capacity and flight range of the drone addresses the problem of last-mile drone-based parcel delivery. The solution of the formulated ILP provides the optimal solution to the problem. An ensemble algorithm that uses a heuristic-based MDMD algorithm and a greedy-based HDRN algorithm is proposed along with. The ILP and proposed algorithms are experimentally verified using computer simulation. Though the MDMD and the HDRN algorithms provide suboptimal solutions, they produce solutions almost instantaneously.

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