Trajectory Planning for Multi-UAV Assisted Wireless Networks in Post-Disaster Scenario

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***Abstract*—Recently, unmaned aerial vehicle (UAV) assisted wireless network has been recognized as a promising technology for post-disaster communications, in which multiple UAVs are dynamically deployed in the air as cellular base stations to provide public wireless connectivities when the ground infrastructure collapses. However, due to the non-uniformity of post-disaster traffic distribution and the large scale of post-disaster area, trajectory planning is considered as a major challenge for UAV-assisted post-disaster communications in many aspects including coverage, energy efficiency and computational complexity. In this paper, we consider a general trajectory planning problem for multi-UAV assisted wireless networks in a post-disaster scenario. We show that the problem can be formulated as a multi-depot vehicle routing problem. Then, we propose two heuristic algorithms that can efficiently utilize the battery of UAVs to improve the coverage performance. Simulation results show that, compared to the intuitive greedy algorithm, the coverage ratio can be improved by 8% and 28%, respectively, by using the proposed algorithms.**

***Index Terms*—Unmaned aerial vehicle, multi-depot vehicle routing, emergency communications.**

I. Introduction

Unmaned aerial vehicle (UAV) has been recently used in a variety of industrial verticals for its unique advantages of low risk, low cost and high flexibility. Fixed-wing UAVs have good aerodynamic performance with long fight distance and large payload capacity, which makes them well suited for long-distance missions, such as mapping and military surveillance. Compared with fixed-wing UAVs, rotary-wing UAVs have limited flight distance and payload capacity. However, their good maneuverability in take-off, landing and hovering makes them well suited for flexible and point-specific missions, such as aerial photography and infrastructure monitoring.

Recently, rotary-wing UAV has been introduced in wireless communications, where UAVs are utilized as air base stations [1]–[5] or relay nodes [6] to provide extra coverage and capacity, or as mobile anchors to help locate sensors in wireless sensor networks [7]. In [1], a multi-UAV deployment algorithm which minimizes the number of needed UAVs to cover a certain area is proposed. In [2], the throughput gains that can be obtained by exploiting the mobility feature of the UAVs is analyzed, and a genetic algorithm is proposed to optimize the hovering locations of UAVs that maximize downlink aggregate rate. In [3], a connectivity-based UAV mobility model is established for monitoring and sensing a target area. In [4], [5], the authors deal with the burning issue on how to determine the position and the service region of each UAV and solve it from a load balancing perspective. The authors of [6] study the optimal positioning of UAV relays to improve the system throughput and link reliability. In [7], the authors propose a new localization framework for wireless sensor networks, in which UAVs are utilized as virtual anchors to achieve high positioning accuracy with negligible cost.

Recently, UAV-assisted wireless networks are considered for emergency communications in post-disaster scenarios, in which the ground infrastructure is damaged or ruined by natural disasters. Rotary-wing UAVs can be easily deployed in such a post-disaster scenario to provide location-specific wireless coverage. In [8], two energy-efficient UAV path planning algorithms based on the multi-armed bandit algorithm are proposed to maximize the throughput in a post-earthquake scenario. In [9], the authors propose a UAV-assisted heterogeneous network for post-disaster communications. In [10], the authors maximize the minimum throughput of all mobile terminals by jointly optimizing the UAV's trajectory, bandwidth allocation, and user partitioning. The existing literature mainly focuses on position optimization to improve system throughput. However, since the energy of user equipments is limited, people in the disaster area generally need just a timely contact with their family or the rescuers instead of long-time communication service. Moreover, quantity and power supply of the UAVs are limited, which means it is not energy-efficient to provide long-time communication service for a place. Based on the aforementioned reasons, we believe that it is more crucial for UAVs to traverse all users in the post-disaster area instead of serving certain high-traffic points. Therefore, trajectory planning, instead of position optimization, is studied for UAV-assisted emergency communications in this paper.

UAV trajectory planning has been widely studied in the literature. The authors of [11] propose efficient schemes for the trajectory planning based on the concept of virtual base station placement in a UAV-enabled multicasting system. In [12], the A* search algorithm is adopted for UAV path planning, so as to ensure that the UAV is within the transmission range of a base station. However, such general trajectory planning

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Fig. 1. Multi-UAV assisted wireless network in a post-disaster area.

algorithms did not consider the characteristics of emergency communications, and they may not be extended to multi-UAV scenarios. Therefore, we need to reconsider the multi-UAV trajectory planning problem for emergency communications.

In this paper, we consider a general trajectory planning problem for UAV-assisted networks with multiple UAVs in a post-disaster scenario, in which the traffic distribution differs from traditional communication scenarios and the communication delay is emphasized rather than the throughput. We show that the problem can be formulated as a multi-depot vehicle routing problem (MDVRP), which is NP-hard in general. Then, we propose two heuristic trajectory planning algorithms, i.e., nearest assignment (NA) and trajectory balancing (TB), which efficiently design which service points should be visited and which path should be used for each UAV. Simulation results show that, compared with the intuitive greedy algorithm, the coverage ratio can be improved by 8% and 28%, respectively, by using the proposed NA and TB algorithms.

The rest of the paper is organized as follows: In Section II, we describe the system model and formulate an optimization problem. In Section III, we reconsider the problem as an MDVRP and propose our trajectory planning algorithms. Simulation results are presented and analyzed in Section IV, and conclusions are given in Section V.

II. System Model and Problem Formulation

As shown in Fig. 1, we consider a UAV-assisted wireless network composed of K rotary-wing UAVs deployed at K temporary air stations, respectively. The air station can provide a proper place for take-off and landing, as well as the electricity to recharge UAV battery. We assume that there are N service points in the area, where people tend to gather after a natural disaster. The UAVs take off at air stations, traverse the service points along their trajectories and return to air stations to recharge before the battery is used up. We assume that the UAVs are equipped with both cellular base station module and LEO satellite communication module, such that they can provide cellular communication services above a service point by using satellite links as the backhaul.

We denote by $s_i = \{n_0, n_1, \dots, n_{t_i}, n_{t_i+1}\}$ as the trajectory of UAV i, where each element n_t represents the t-th service point. The trajectory contains t_i service point, and $n_0 = n_{t_i+1}$ represents the air station of UAV i. Also, we denote by S_i as the set of all possible trajectories of UAV i, i.e., $s_i \in S_i, \forall i = 1, 2, ..., K$. For each service point, we assume that the corresponding UAV needs to hover T_h time to provide emergency communications, during which the hovering power and the communication power are given by e_h and e_c, respectively. For the journey between adjacent points, the flying speed is given by V_f and the flying power is given by e_f. The total battery capacity of UAV is uniformly given by E.

The objective of trajectory planning is to maximize the number of service points served by UAVs, while at the same time, we need to guarantee that all UAVs can return to their air stations before the battery is used up. Thus, the considered problem can be formulated as follows:

$$\begin{aligned} &\max_{s_1,\dots,s_K} \left|\bigcup_{i=1}^{K} s_i\right| \\ s.t.\quad &t_i e_h T_h + t_i e_c T_h + \sum_{t=0}^{t_i} e_f \frac{d_{n_t,n_{t+1}}}{V_f} \\ &\leq E, i = 1, 2, ..., K, \end{aligned} \tag{1}$$

where $d_{n_t,n_{t+1}}$ represents the distance between the service point n_t and n_{t+1}. Note that problem (1) is an integer programming problem, which is NP-hard in general.

III. Trajectory Planning as MDVRP

We reconsider the trajectory planning problem from an MDVRP point of view and propose two heuristic algorithms to address it efficiently.

A. MDVRP

For an MDVRP, there are multiple vehicles and multiple depots. These vehicles depart from the depots, visit all customers in the map, and return to the depots. The objective is to find the trajectories that minimize the total distance travelled by all vehicles (min-sum) [13], or the trajectories that minimize the maximal travel length of all vehicles (min-max) [14].

Compared with the MDVRP, our considered trajectory planning problem has a strict and uniform battery constraint, and the objective is to maximize the number of visited service points. We adopt the min-max MDVRP model to efficiently utilize the battery of all UAVs, and the considered trajectory planning problem is reformulated as follows:

$$\min_{s_1,\dots,s_K} \max_i \sum_{t=0}^{t_i} d_{n_t,n_{t+1}} \tag{2}$$

TABLE I
NEAREST ASSIGNMENT ALGORITHM

Algorithm
Assign service points according to (3);
Solve the TSP given in (4);

B. Nearest Assignment Algorithm

We denote by d_{ij} as the distance between air station i and service point j, and by x_{ij} the assignment indicator where $x_{ij} = 1$ represents service point j is assigned to air station i, and $x_{ij} = 0$ represents service point j is not assigned to air station i.

The NA algorithm assigns each service point to the nearest air station, i.e.,

$$x_{ij} = \begin{cases} 1 & d_{ij} < d_{i'j}, \forall i' \neq i, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

For each air station i with a given set of service point r_i, we formulate a travelling salesman problem (TSP), where the UAV needs to traverse all service points as well as the air station. The TSP for UAV i is then given by

$$\begin{aligned} &\min_{s_i \in S_i} \sum_{t=0}^{t_i} d_{n_t, n_{t+1}} \\ s.t. \quad & n_t \in s_i, \forall n_t \in r_i. \end{aligned} \tag{4}$$

TSP is a combinatorial optimization problem which is NP-hard in general. Here, we use the genetic algorithm to solve the TSP, in which a population of candidate solutions is evolved towards better solutions by performing bio-inspired operators such as mutation, crossover and selection [15]. The NA algorithm is shown in Table I.

C. Trajectory Balancing Algorithm

As similar with the NA algorithm, the proposed TB algorithm first assigns the service points to different UAV air stations, and then solves the TSP for each UAV. The difference is that the service points assignment solution is based on linear programming (LP).

The service point assignment procedure is an iterative LP process with R rounds, in which the number of service points N_i assigned to UAV i is updated iteratively according to the TSP results of the previous assignment. We denote by $X(r)$ as the assignment indicator matrix at iteration r. The LP at iteration r is then given by

$$\begin{aligned} &\min_{X(r)} \sum_{1 \leq i \leq K, 1 \leq j \leq N} d_{ij} x_{ij}(r) \\ s.t. \quad & C_1 : \sum_{1 \leq j \leq N} x_{ij}(r) = N_i(r), \forall i, \\ & C_2 : \sum_{1 \leq i \leq K} x_{ij}(r) = 1, \forall j, \\ & C_3 : x_{ij}(r) \in \{0, 1\}, \forall i, j. \end{aligned} \tag{5}$$

TABLE II
TRAJECTORY BALANCING ALGORITHM

Algorithm
Initialization: $N_i(1) = N/K, \forall i = 1, ..., K$;
for $r = 1 : R$
Solve the LP given in (5);
Solve the TSP given in (4);
if $(L_{max} - L_{min})/L_{min} > p$
Update $N_i(r)$ according to (6), $\forall i = 1, ..., K$;
else
Break;
endif
endfor

As we can see in (5), the LP intends to minimize the total distance between service points to their corresponding air stations. Constraint C_1 implies that each UAV i is assigned $N_i(r)$ service points, and C_2 implies that a service point can be assigned to only one air station.

Given point assignment $X(r)$, the TSP results of UAV i is denoted by s_i, and the length of s_i is denoted by L_i. The average length of all the trajectories is given by $\overline{L} = \sum_{i=1}^{K} L_i / K$. Also, we denote by L_{max} and L_{min} as the maximal and minimal length, respectively, among all the UAVs. For a given threshold parameter p, if $(L_{max} - L_{min})/L_{min} < p$, $X(r)$ is the optimal point assignment solution and the algorithm ends. Otherwise, N_i is updated by

$$N_i(r+1) = N_i(r) + [c * (L_i - \overline{L})/\overline{L}]. \tag{6}$$

The number of points to be adjusted is in proportion to the relative drift between the trajectory length and the average length, and c is an empirical parameter to control the degree of adjustment. Repeat the above procedure until the relative drift between the maximal and minimal length is below the threshold p, or r reaches R. The initial value of $N_i(1)$ is set as N/k for all UAV $i = 1, 2, .., K$. The TB algorithm is shown in Table II.

D. Low-Battery Warning

Due to the limited battery capacity of UAV, we adopt the low-battery warning procedure at the end of the proposed algorithms, so that the UAVs can return to the air station to recharge before the battery energy is used up. When the trajectory planning is completed, calculate the energy required for each UAV. If the battery capacity is sufficient to support the journey, the algorithm ends. Otherwise, for the trajectory that contains M points, try to remove one of the service points and recalculate the trajectory with $M-1$ service points. Select the trajectory with the minimal length from the M removing schemes and repeat the above procedure until the battery constraint is satisfied.

IV. SIMULATION RESULTS

In this section, we present the simulation results of the proposed NA and TB algorithms, and compare them with

TABLE III
SIMULATION PARAMETERS

$e_h = 200$ W	Average engine power for hovering
$e_f = 240$ W	Average engine power for flying
$e_c = 60$ W	Average power of communication modules
$V_f = 20$ km/h	Flying speed
$T_h = 120$ s	Hovering interval

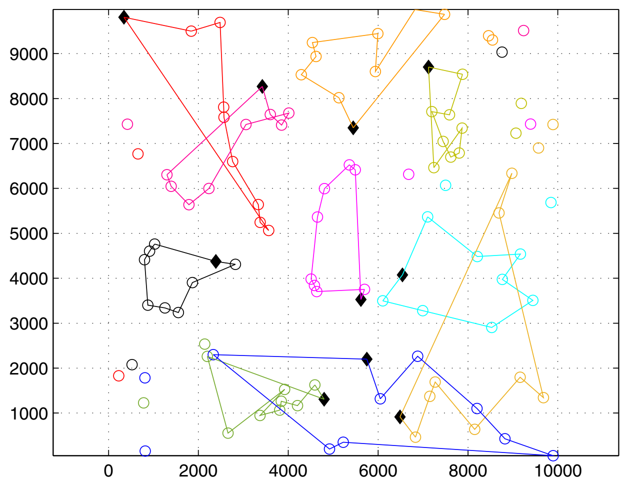

Fig. 2. Trajectory planning result of the greedy algorithm with $N = 100, K = 10$ and $E = 400$ Wh.

the intuitive greedy algorithm in which each UAV chooses the nearest point as its next service point. The low-battery warning procedure is applied in all three algorithms to ensure that all the UAVs can return to their air stations. Specifically, we consider a 10 km×10 km area with randomly distributed service points and air stations. We set the parameters of UAVs based on [16], which are given Table III. In the TB algorithm, we set R as 20, p as 25% and c as 8.

In Figs. 2, 3 and 4, we illustrate the trajectory planning results of the greedy and the proposed NA and TB algorithms, respectively, in which the number of service points is $N = 100$, the number of UAVs is $K = 10$ and the battery capacity is $E = 400$ Wh. The diamonds and the circles represent the air stations and the service points respectively. The different colors of the circles show the result of point assignment. As we can see, the coverage ratio of the greedy algorithm is 80%, while the proposed two algorithms achieve 100% coverage ratio. Also, the TB algorithm can balance the UAV trajectories by considering the actual tour length of each UAV, while the NA algorithm only considers the direct distances between the air station and the service points.

In Table IV, we show the maximal and minimal trajectory length, as well as their corresponding standard deviation (SD), in four different scenarios for all three algorithms. In scenario 1, we set $K = 5$ and $N = 50$ to represent the scenario with low traffic density and small number of UAVs. In scenario 2, we set $K = 5$ and $N = 300$ to represent the scenario with high

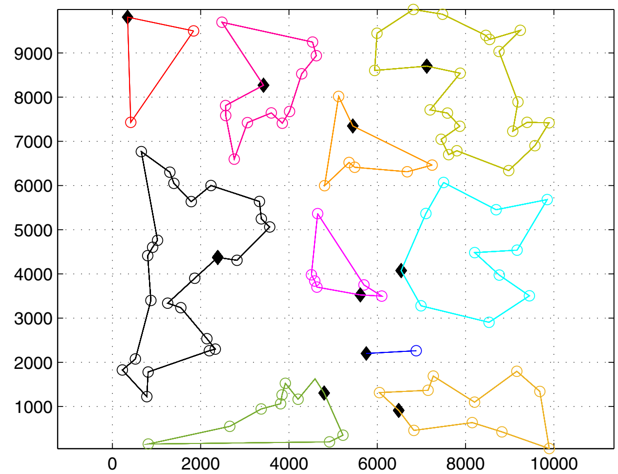

Fig. 3. Trajectory planning result of the NA algorithm with $N = 100, K = 10$ and $E = 400$ Wh.

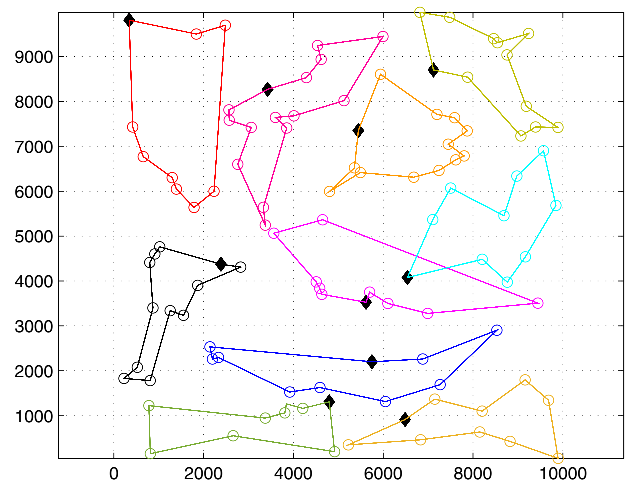

Fig. 4. Trajectory planning result of the TB algorithm with $N = 100, K = 10$ and $E = 400$ Wh.

traffic density and small number of UAVs. In scenario 3, we set $K = 10$ and $N = 50$ to represent the scenario with low traffic density and large number of UAVs. In scenario 4, we set $K = 10$ and $N = 300$ to represent the scenario with high traffic density and large number of UAVs. As we can see, the TB algorithm achieves smaller deviation than the NA algorithm, which implies that the TB algorithm can achieve a balance of trajectories. We can also see that the standard deviation of the two proposed algorithms is better in high traffic density scenarios than low traffic density scenarios.

In Fig. 5, we show the coverage ratio as a function of the battery capacity when the number of UAVs is $K = 5$ and the number of service points is $N = 100$. As we can see, for the considered three algorithms, the marginal increase of coverage

TABLE IV
TRAJECTORY LENGTH OF THE GREEDY, NA AND TB ALGORITHMS.

		Greedy			NA			TB		
Number of UAVs	Number of service points	Maximal	Minimal	SD	Maximal	Minimal	SD	Maximal	Minimal	SD
5	50	20656.0	9291.6	806.3	20846.0	6473.8	1044.2	19668.6	11508.4	549.1
5	300	16188.6	13753.5	67.1	19193.6	10641.3	301.26	8923.2	16031.0	70.6
10	50	16166.3	13800.7	66.7	14888.0	1828.1	769.5	17193.0	7214.7	448.6
10	300	18071.5	13346.7	146.4	17321.3	5868.7	412.9	17726.0	13216.6	102.0

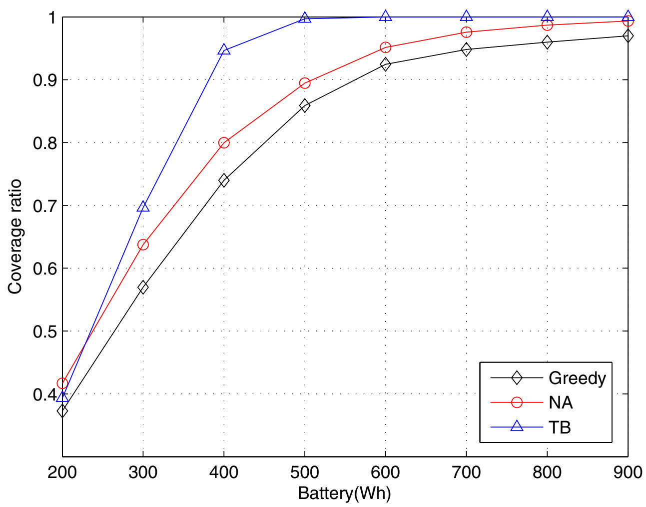

Fig. 5. Coverage ratio as a function of battery capacity with $N = 100$ and $K = 5$.

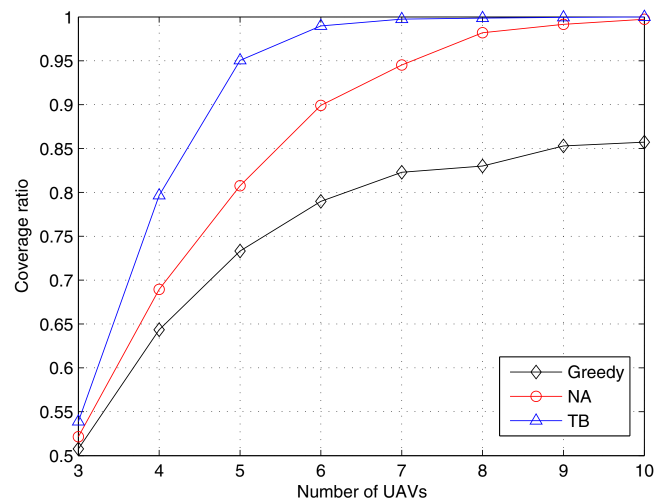

Fig. 6. Coverage ratio as a function of number of UAVs with $N = 100$ and $E = 400$ Wh.

ratio decreases with the battery capacity. The proposed NA and TB algorithms outperform the greedy algorithm by 8% and 28%, respectively, when the battery is 400 Wh. The TB algorithm requires 500 Wh to fully cover the post-disaster area, while the NA algorithm requires 900 Wh and the greedy algorithm requires about 1200 Wh. The TB algorithm performs better than the NA algorithm in terms of trajectory balance and coverage ratio, but the computational complexity is higher.

In Fig. 6, we show the coverage ratio as a function of the number of UAVs when the number of points is $N = 100$ and the battery capacity is $E = 400$ Wh. As we can see, for the considered three algorithms, the marginal increase of coverage ratio decreases with the number of points. The TB algorithm outperforms the other two algorithms with different number of UAVs. The TB algorithm can achieve full coverage by using 7 UAVs, while the NA algorithm needs 10 UAVs and the greedy needs more.

In Fig. 7, we show the coverage ratio as a function of the number of points when the number of UAVs is $K = 5$ and the battery capacity is $E = 400$ Wh. As we can see, the coverage ratio of the three algorithms decrease with the number of service points. The TB algorithm has highest coverage ratio when the number of service points is small, while the greedy algorithm has the highest coverage ratio when the number of service points is large.

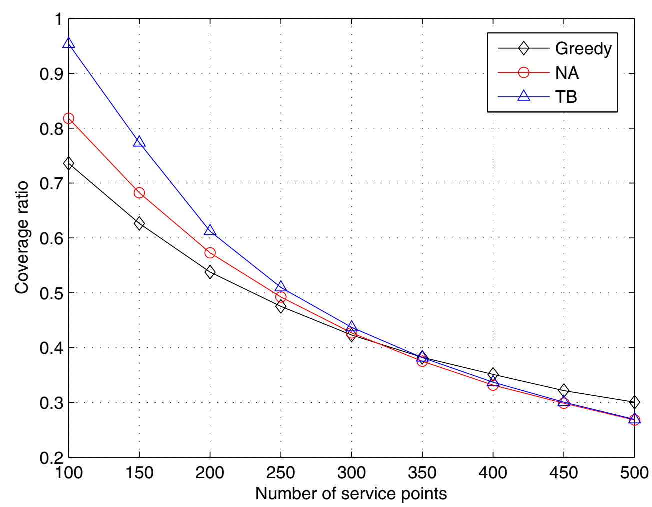

Fig. 7. Coverage ratio as a function of number of points with $K = 5$ and $E = 400$ Wh.

V. CONCLUSIONS

In this paper, we studied the trajectory planning problem for UAV-assisted networks with multiple UAVs in a post-disaster scenario, for which we proposed two heuristic algorithms, i.e., the NA and the TB algorithms to improve the coverage performance. Simulation results showed that, compared to the greedy algorithm, the coverage ratio can be improved by 8% and 28%, respectively, by using our proposed NA and TB algorithms. The proposed TB algorithm can achieve a better coverage performance as the trajectories are balanced by using LP techniques, while the proposed NA algorithm has advantages in computational complexity. The network should select the most suitable algorithm according to the practical parameters of different post-disaster scenarios.

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