Joint Deployment and Trajectory Planning of Multiple UAVs for Emergency Communications

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Abstract—**In this paper, we study the unmanned aerial vehicle (UAV)-assisted emergency communication network, where multiple UAVs are dispatched from emergency centers and cruise the target region to provide service. To ensure timely communications, a strict requirement is that the time spent on the tour of each UAV is no greater than a delay threshold. Our optimization task is to minimize the total cost while satisfying the delay constraints, in which the total cost is a weighted sum of deployment cost and cruise cost. We propose a joint deployment and path planning scheme to address the NP-hard task from a load-balancing perspective. Specifically, we first adopt a continuous approximation method to estimate the number of needed emergency centers and locate them by clustering. Then, we assign the ground users to the emergency centers via load-balancing region partitioning, based on which the path planning of multiple UAVs can be reduced to independent traveling salesman problems. Numerical results demonstrate that our proposal can complete the delay-bounded mission at the lowest cost as compared with other methods, providing an efficient and cost-effective way for practical emergency communications.**

Index Terms—**Emergency communications, green communications, multi-depot vehicle routing, trajectory planning.**

I. Introduction

The frequent natural disasters and man-made calamities (e.g., hurricanes, floods, fires, and electrical outages) always inflict heavy losses of lives and properties. In the case of these emergency situations, the existing ground communication infrastructures generally cannot work properly. Therefore, emergency communication networks are crucially important for swiftly establishing a first contact with the affected victims so as to adopt rescue and assistance measures.

With the fast-paced progress in design and production, unmanned aerial vehicles (UAVs), which can act as base stations (BSs) [1], relay nodes [2], and mobile anchors [3], have been widely applied in various domains. Due to their mobility and agility, UAVs mounting small BSs are a promising option for post-disaster recovery [4]. In [5], the flight path of a single UAV is optimized to maximize the system throughput, where the optimization task is formulated as a multi-armed bandit problem and solved by online learning-based algorithms. A joint user association, power allocation and trajectory planning problem for multiple UAVs is presented in [6] to provide ubiquitous coverage, solving by a deep reinforcement learning scheme. In [7], an integrated post-disaster wireless network with both aerial and surviving ground BSs is developed to guarantee the quality of service experienced by a typical ground user (GU).

The trapped individuals, however, need prompt communication to report their situation, prioritizing in-time contact over access to long-term high data rate services. Consequently, how to efficiently scan and scout the entire region to provide service for all GUs is more crucial in emergency communications. A search-and-reconnaissance scenario with multiple UAVs is considered in [8], where the dispatching time and the flight path are jointly optimized to minimize the total time spent for collecting data from all the points of interests. Multiple UAVs which are dispatched from their corresponding depot simultaneously are investigated in [9], where an approximation algorithm is introduced to minimize the maximum mission time among a fleet of UAVs so as to reduce the latency of the whole system. Observing the fact that the urgency of communication is related to the damage severity of the area, the authors in [10] formulate the trajectory planning problem of the UAV as a variant of the classical traveling salesman problem (TSP) with soft time windows, where a deep reinforcement learning-based scheme is proposed to deal with this NP-hard optimization task. In [11], collecting data from GUs with the minimum number of UAVs while satisfying the delay constraints is considered and a graph theory-based approximation algorithm is developed. According to the investigations of the existing work, the imperative requirement of UAV-enabled emergency communications is the collaborative scheduling of multiple UAVs in a cost-effective manner, ensuring serving all GUs within stringent delay constraints.

In this paper, we investigate the joint deployment and trajectory planning of multiple UAVs for delay-bounded emergency communications. Aiming at providing service timely in a cost-effective way, we take both deployment cost and cruise cost into account. The former is related to the number of deployed emergency centers which reflects the economic cost, and the latter is related to the longest tour time among the UAVs which reflects the timeliness and the energy-efficiency. The optimization task is to minimize the weighted sum of deployment cost and cruise cost under delay constraints, which is a variant of the min-max multi-depot vehicle routing problem (MDVRP) [12]. Due to its NP-hardness, we first

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analyze the objective under the continuous approximation paradigm, and then propose an equitable region partitioning-based path planning approach to optimize the deployment of emergency centers and the trajectories of UAVs cooperatively. Numerical results verify that our proposal is effective and efficient, shedding light on constructing a green emergency communication network.

The rest of this paper is organized as follows. Section II introduces the system model and the formulation of the optimization task. Section III presents our proposed joint deployment and path planning algorithm in detail. Section IV evaluates the performance of our proposal through extensive numerical experiments, followed by conclusions in Section V.

II. System Model And Problem Formulation

A. Network Description

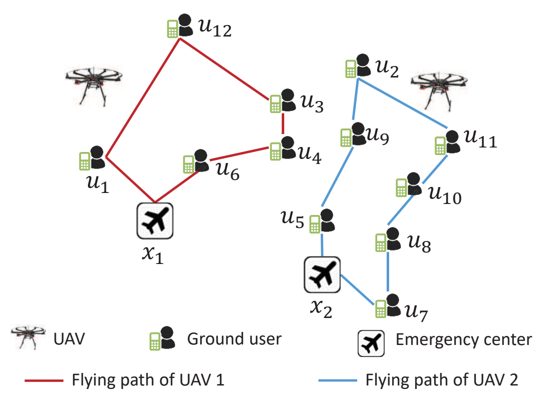


Fig. 1. An illustration of dispatching two UAVs to provide emergency communications.

We consider a square region of interest $\mathcal{R}$, where the existing network infrastructures are overloaded or broken. Timeliness of communication is critical in this case, thus multiple UAVs are dispatched as mobile aerial BSs to provide temporary communication connection for the GUs while satisfying a given delay threshold B (e.g., 30 minutes). As depicted in Fig. 1, the emergency communication network consists of M GUs, and K emergency centers, each with one UAV. Assume that the GUs follows a distribution $f(u)$ and the set of GUs' locations is denoted by $U = \{u_1, u_2, ..., u_M\}$, the traffic demand of GU u_m is denoted by D_m. The set of deployed K UAVs is denoted by $\mathcal{K} = \{1, 2, ..., K\}$, the locations of their corresponding emergency centers are collected in set $X = \{x_1, x_2, ..., x_K\}$. The k-th UAV takes off from the emergency center located at x_k to cruise the area, during which it hovers directly above each GU to establish a communication link. The index set of GUs assigned to the UAV k is denoted by U_k, and the sequence of visiting GUs in U_k is denoted by σ_k. Taking Fig. 1 as an instance, we have $U_1 = \{u_1, u_3, u_4, u_6, u_{12}\}$, $|U_1| = 5$, and $\sigma_1 = \{1, 12, 3, 4, 6\}$.

B. Channel Model

Let P denote the transmission power by the UAV and let N_0 denote the power spectral density of noise at the GU receiver. The communication bandwidth is denoted by W, the average signal to noise ratio of the channel between the UAV and the GU is expressed as [13]:

$$\Upsilon = \frac{P\omega^{-\alpha}}{WN_0}\left(\frac{p_{LoS}}{\eta_{LoS}} + \frac{1-p_{LoS}}{\eta_{NLoS}}\right), \tag{1}$$

where α is the path-loss exponent, ω is the distance between the GU and the UAV. η_{LoS} and η_{NLoS} are the mean excessive path-loss values of line-of-sight (LoS) and non-light-of-sight (NLoS), respectively. And p_{LoS} is the probability of LoS, which is closely approximated to a modified sigmoid function of the following form:

$$p_{LoS}(\phi) = \frac{1}{1 + a\exp\left[-b\left(\phi - a\right)\right]}, \tag{2}$$

where ϕ is the elevation angle between the devices and the UAV, a, b are environment constants, for instance, $a = 4.88$ and $b = 0.43$ for suburban environment.

The average communication data rate between the GUs and the UAV can be written as:

$$r_{tran} = W\log_2\left(1 + \Upsilon\right). \tag{3}$$

C. Problem Formulation

Denote by V the flying speed of the UAV, and the flying time between two locations is represented by $t_f(\cdot,\cdot) = \frac{d(\cdot,\cdot)}{V}$, where $d(\cdot,\cdot)$ is the Euclidean distance between two locations. The spent time of each cruise consists of the traveling time between GUs and the hovering time for communicating with GUs. Let $T(x_k, U_k)$ denote the mission time of UAV k, which can be written as:

$$\begin{aligned} T(x_k, U_k) = {} & t_f(x_k, u_{\sigma_k(1)}) + t_f(u_{\sigma_k(|U_k|),x_k}) + \\ & \sum_{i=1}^{|U_k|-1} t_f(u_{\sigma_k(i)}, u_{\sigma_k(i+1)}) + \sum_{i\in U_k} \rho(u_i), \end{aligned} \tag{4}$$

where $\rho(u_i) = \frac{D_i}{r_{tran}}$ is the time that the UAV takes to communicate with the GU.

For the purpose of cruising the entire region timely as well as saving the deployment cost, we define the mission's total cost as a weighted sum of deployment cost and cruise cost, which can be written as follows:

$$C_{total} = \gamma K + \max_{k\in\{1,...,K\}} T(x_k, U_k), \tag{5}$$

where the first term is related to the number of emergency centers, and the second term is the longest mission time among the fleet of UAVs. γ is a coefficient reflecting the importance of the deployment cost and the cruise cost.

The key point of our optimization task is to jointly plan the deployment of the emergency centers and the trajectories of UAVs to minimize the total cost, where the number and locations of emergency centers, the user assignment, and the path of UAVs need to be optimized. We collect the assignment sets of GUs and the paths of the UAVs into sets $\mathcal{U} = \{U_1, ..., U_K\}$ and $\mathcal{S} = \{\sigma_1, ..., \sigma_K\}$, respectively. The task can be mathematically formulated as follows:

$$\begin{aligned} \underset{K,X,\mathcal{U},\mathcal{S}}{\text{minimize}} \quad & C_{total} \\ \text{s.t. } & C_1 : T(x_k, U_k) \leq B, \forall k \in \mathcal{K}, \\ & C_2 : \cup_{k=1}^{K} U_k = U, \\ & C_3 : U_k \cap U_l = \emptyset, \forall k \neq l, \end{aligned} \tag{6}$$

where constraint C_1 guarantees that the mission time of each UAV is no greater than the delay threshold, constraint C_2 and C_3 ensures that the GU is served by and only by one UAV.

Note that problem (6) can be reduced to a min-max MDVRP when setting $\gamma = 0$ and setting C_1 aside [12]. Thus, (6) is difficult to solve since the MDVRP is NP-hard, which is featured by discrete search space and intractable computation to seek the optimal solution.

III. Our Proposed Algorithm

The complex quantities of cruise cost make the optimization task (6) intractable, we first adopt the continuous approximation paradigm to analyze the cruise cost, based on which the total cost is transformed into a function of K. Then, the cruise cost under the given number and locations of deployed emergency centers is minimized from a load-balancing perspective, based on which a joint deployment and trajectory planning algorithm is proposed.

A. Analysis of Cruise Cost

Eq. (6) is equivalent to minimizing the longest tour time among a fleet of UAVs when given K, which can be addressed from the following two aspects. On the one hand, the shortest path, i.e., the TSP tour, which traverses and serves each assigned GU once and returns to the starting emergency center should be found for each UAV. On the other hand, the mission time of UAVs should be approximately balanced. Otherwise, the cruise cost would be large if the tour time of a UAV is much longer than that of others.

Let $T_{tsp}(x, U)$ denote the cruise cost of serving the entire region by a single UAV following the TSP tour. Under ideal assignment where the tour times of K UAVs are exactly equal, we have:

$$T(x_k, U_k) = \frac{1}{K} T_{tsp}(x, U), \forall k \in \mathcal{K}. \tag{7}$$

Eq. (7) is still intractable since finding the TSP tour is also NP-hard. However, as we focus on the time of the tour, we can adopt the continuous approximation paradigm to estimate the tour time, where the combinatorial quantities that are difficult to compute are replaced with simpler mathematical formulas, thus (under certain conditions) can provide accurate estimations of the desired quantity.

The following classical theorem, known as BHH theorem [14], relates the length of a TSP tour of a sequence of points with the distribution from which they were sampled:

Theorem 1: Suppose that $X = \{X_1, X_2, ..., X_N\}$ is a sequence of random points independent and identically distributed according to an absolutely continuous probability density function f defined on a compact planar region $\mathcal{D}$. Then with probability one, the length $TSP(X)$ of the optimal traveling salesman tour through X satisfies

$$\lim_{N \to \infty} \frac{TSP(X)}{\sqrt{N}} = \beta \iint_{\mathcal{D}} \sqrt{f(x)} dA, \tag{8}$$

where $0.6250 \leq \beta \leq 0.9204$ *is a constant* [15].

Then, the expected cruise cost $T_{tsp}(x, U)$ consisting of the hovering time and the flying time can be expressed as follows:

$$T_{tsp}(x, U) = M\bar{\rho} + \beta\sqrt{M}/V \iint_{\mathcal{R}} \sqrt{f(u)} dA, \tag{9}$$

where $\bar{\rho}$ represents the mean value of the time spent for communicating with one GU.

It is noteworthy that the expected cruise cost mainly depends on the number, the traffic demand, and the distribution of GUs, which can be regarded as a constant under a given instance. Let $\psi := M\bar{\rho} + \beta\sqrt{M}/V \iint_{\mathcal{R}} \sqrt{f(u)} dA$, problem (6) can be transformed into the following problem, where the ideal cruise cost is expressed as an inversely proportional function of K:

$$\begin{aligned} \underset{K}{\text{minimize}} \ & \gamma K + \psi/K \\ \text{s.t.} \quad & \psi/K \leq B, \forall k \in \mathcal{K}. \end{aligned} \tag{10}$$

Solving (10), we can obtain the expected number of needed emergency centers as follows:

$$K = \left\lceil \max\left\{\psi/B, \sqrt{\psi/\gamma}\right\} \right\rceil, \tag{11}$$

which is also a lower bound of K since the objective function decreases first and then ascends as K increases.

B. Load-Balancing User Assignment

Set the delay constraint aside, problem (6) is equivalent to minimize the cruise cost when given the number and locations of deployed emergency centers, which can be written as the following min-max MDVRP:

$$\begin{aligned} \underset{\mathcal{U},\mathcal{S}}{\text{minimize}} \ & \max_{k \in \{1,...,K\}} T(x_k, U_k) \\ \text{s.t.} \quad & C_2, \ C_3 \text{ in (6)}. \end{aligned} \tag{12}$$

Denote R_k the service zone of the k-th UAV, (12) can be transformed to the following region partitioning problem:

$$\begin{aligned} \underset{R_1,...,R_K \subset \mathcal{R},\mathcal{S}}{\text{minimize}} \ & \max_{k \in \{1,...,K\}} T(x_k, U_k) \\ \text{s.t.} \quad & C_1 : R_k \cap R_l = \emptyset, \forall k \neq l, \\ & C_2 : \cup_{k=1}^{K} R_k = \mathcal{R}. \end{aligned} \tag{13}$$

According to (7) and (9), the tour time of the k-th UAV can be measured by $\iint_{R_k} \sqrt{f(u)} dA$. Thus, (13) can further be written as follows:

$$\begin{aligned} \underset{R_1,...,R_K \subset \mathcal{R}}{\text{minimize}} \ & \max_{k \in \{1,...,K\}} \iint_{R_k} \sqrt{f(u)} dA \\ \text{s.t.} \quad & C_1, \ C_2 \text{ in (13)}, \end{aligned} \tag{14}$$

We introduce $\Psi_k(u) = \|u - x_k\|$ to guarantee the connectivity. (14) can be reformulated as:

$$\begin{aligned} \underset{t, I_1(\cdot), I_2(\cdot), \ldots, I_K(\cdot)}{\text{minimize}} \quad & t \\ \text{s.t.} \quad & C_1 : t \geq \iint_{R_k} \sqrt{f(u)} \Psi_k(u) I_k(u) dA, \ \forall k \in \mathcal{K}, \\ & C_2 : \sum_{k=1}^{K} I_k(u) = 1, \ \forall u, \\ & C_3 : I_k(u) = \{0, 1\}, \ \forall k, u. \end{aligned} \tag{15}$$

The integer variables $I_k(u)$'s make (15) difficult to solve. We relax the integer variables into continuous ones, the linear programming relaxation of (15) is given by:

$$\begin{aligned} \underset{t, I_1(\cdot), I_2(\cdot), \ldots, I_K(\cdot)}{\text{minimize}} \quad & t \\ \text{s.t.} \quad & C_1, C_2 \text{ in (15)}, \\ & I_k(u) \geq 0, \ \forall k, u. \end{aligned} \tag{16}$$

Then, we discretize (16) to get an approximate formulation. The region is discretized into J grid cells Δ_j with the area ϵ. f_j represents the average values of $\sqrt{f(u)}$ on Δ_j. Let z_{kj} be the fraction of Δ_j served by UAV k. Ψ_{kj} denotes the average value of $\Psi_k(u)$. The discretization of (16) is given by:

$$\begin{aligned} \underset{t, z_{(\cdot)}}{\text{minimize}} \quad & t \\ \text{s.t.} \quad & C_1 : t \geq \sum_{j=1}^{M} \epsilon f_j z_{kj} \Psi_{kj}, \ \forall k, \\ & C_2 : \sum_{k=1}^{K} z_{kj} = 1, \ \forall j, \\ & C_3 : z_{kj} \geq 0, \ \forall k, j. \end{aligned} \tag{17}$$

The dual problem to (17) is:

$$\begin{aligned} \underset{\xi_{(\cdot)}, \mu_{(\cdot)}}{\text{maximize}} \quad & \sum_{j=1}^{M} \mu_j \\ \text{s.t.} \quad & C_1 : -\epsilon f_j \Psi_{kj} \xi_k + \mu_j \leq 0, \ \forall k, j, \\ & C_2 : \sum_{k=1}^{K} \xi_k = 1, \\ & C_3 : \xi_k \geq 0, \ \forall k. \end{aligned} \tag{18}$$

Let $\lambda_j := \frac{\mu_j}{\epsilon f_j}$, (18) can be simplified to:

$$\begin{aligned} \underset{\xi_{(\cdot)}, \lambda_{(\cdot)}}{\text{maximize}} \quad & \sum_{j=1}^{M} \epsilon f_j \lambda_j \\ \text{s.t.} \quad & C_1 : \lambda_j \leq \Psi_{kj} \xi_k, \ \forall k, j, \\ & C_2, C_3 \text{ in (18)}, \end{aligned} \tag{19}$$

which is a discretization of the following problem

$$\begin{aligned} \underset{\xi_{(\cdot)}, \lambda(\cdot)}{\text{maximize}} \quad & \iint_{\mathcal{R}} \sqrt{f(u)} \lambda(u) dA \\ \text{s.t.} \quad & C_1 : \lambda(u) \leq \xi_k \Psi_k(u), \ \forall k, u, \\ & C_2, C_3 \text{ in (18)}. \end{aligned} \tag{20}$$

We can find that (20) is equivalent to the following problem:

$$\begin{aligned} \underset{\xi_{(\cdot)}}{\text{maximize}} \quad & \iint_{\mathcal{R}} \min_k \{ \sqrt{f(u)} \xi_k \Psi_k(u) \} dA \\ \text{s.t.} \quad & C_1 : \sum_{k=1}^{K} \xi_k = 1, \\ & C_2 : \xi_k \geq 0, \ \forall k. \end{aligned} \tag{21}$$

Eq. (21) is a convex problem and can be efficiently solved by standard convex optimization techniques. Then, we obtain the optimal dual variables ξ^*. For any GU, it will be assigned to emergency center x_k which minimizes $\sqrt{f(u)} \xi_k \Phi_k(u), k \in \mathcal{K}$. Therefore, the boundaries between service zones are:

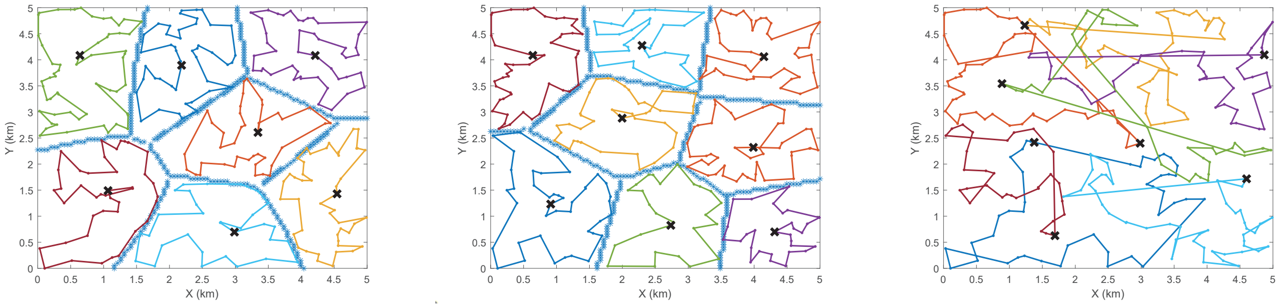
$$\partial(R_i^*) \cap \partial(R_j^*) \subseteq \{u | u \in \mathcal{R}, \xi_i^* \Phi_i(u) = \xi_j^* \Phi_j(u)\}. \tag{22}$$

Then, we explain that the solution to (14) can be recovered from the optimal solution to (21).

Algorithm 1 Load-balancing deployment and path planning

1: **Input:** region of interest $\mathcal{R}$, the set of GUs U, the traffic demand $D_{(\cdot)}$ of each GU, the delay threshold B, the coefficient γ, and the flying speed V of the UAV.
2: Initialize $K = 1$, randomly deploy the emergency center at x_1;
3: Use LKH algorithm to construct the TSP tour σ_1 of U with a start point x_1;
4: Calculate $T(x_1, U)$ by (4);
5: **if** $T(x_1, U) > B$ **then**
6: Calculate K by (11);
7: Use K-means algorithm to find clusters, the locations of emergency centers $X = \{x_1, ..., x_K\}$ are set as the centroids of the clusters;
8: Calculate ξ that satisfies the problem (21);
9: Recover the service zones $\{R_1, R_2, ..., R_K\}$ from ξ by (22), find GUs U_k in the corresponding service zone R_k, update $\mathcal{U}$;
10: **for** $k \in \mathcal{K}$ **do**
11: Use LKH algorithm to solve the TSP tour σ_k of U_k with a start point x_k;
12: Calculate $T(x_k, U_k)$ by (4);
13: **end for**
14: **if** $\max_{k \in \{1,...,K\}} T(x_k, U_k) > B$ **then**
15: $K \leftarrow K + 1$;
16: Return to step 7;
17: **else**
18: Calculate C_{total} by (5), set $\mathcal{S} = \{\sigma_1, ..., \sigma_k\}$;
19: **end if**
20: **else**
21: Calculate C_{total} by (5);
22: Set $X = \{x_1\}$, $\mathcal{U} = \{U\}$, $\mathcal{S} = \{\sigma_1\}$;
23: **end if**
24: Return K, X, $\mathcal{U}$, $\mathcal{S}$, and C_{total}.

Let $\{I_1^*(\cdot), ..., I_K^*(\cdot)\}$ denote the optimal solution to (16). Consider any point $u \in \mathcal{R}$ and suppose $\bar{k}$ is the index such that $\xi_k^* \Psi_k(u)$ is minimal, we can know from the complementary



(a) Load-balancing (b) Cluster-Voronoi (c) Tour-splitting

Fig. 2. The deployment and trajectory planning results. The locations of emergency centers are denoted by the black crosses, and the trajectories of the UAVs are represented by solid lines with different colors.

slackness conditions of (20) that it should be the case that $I_k^*(u) = 0$ for all indices k other than $\bar{k}$, and consequently $I_{\bar{k}}^*(u) = 1$.

C. Joint Deployment and Trajectory Planning of Multi-UAV

We then propose an efficient algorithm to jointly optimize the number of emergency centers and their locations, as well as the service zone and the trajectory of each UAV. The details are given in Algorithm 1, which can be summarized as follows:

- First, we initialize the network with a randomly deployed emergency center and one UAV. The initial trajectory of the UAV is set as the optimal TSP tour of serving all the GUs. The methods to solve TSP are diverse, here, we adopt an LKH solver constructed in [16] to find a promising TSP solution.
- We check whether the delay threshold is violated or not. If not, the algorithm stops, otherwise, the number of needed emergency centers is calculated by (11). Considering the locations of GUs, the emergency centers are deployed by a clustering method. Here we use the classical K-means algorithm [17] to find the clusters, the centroids of which are chosen as the locations of the emergency centers.
- Then, we refine the assignment of GUs by the load-balancing region partitioning, where the entire region is divided into several service zones to achieve approximately equal mission time among UAVs. The optimal assignment of the GUs can be found by solving (22).
- We construct the TSP tour for each UAV and check the feasibility of serving all the GUs. If the delay threshold is violated, we add another emergency center and go back to step 7 to restart the clustering process and update the corresponding variables. The algorithm will stop until the mission time of all the UAVs is within the delay threshold.

IV. Numerical Results

We consider a region of interest with a size of $5 \times 5\text{km}^2$, where 100 to 500 GUs are randomly distributed. The traffic demand D_m of the GU u_m is randomly chosen from an interval from 40MB to 60MB. The carrier frequency is $f_c = 2$ GHz. The environment parameters are for the urban one $(a, b) = (9.61, 0.16)$, $(\eta_{LoS}, \eta_{NLoS}) = (1, 20)$ [13]. The communication bandwidth is $W = 10$ MHz, the transmission power and the noise power are $P = 10$ dBm and $N_0 = -170$ dBm/Hz, respectively. The flying speed and height of the UAV is set as 10m/s and 100meters, respectively. The coefficient γ is set as 1 without loss of generality. Unless otherwise specified, the delay threshold B is set as 30 minutes.

We compare our proposed joint deployment and trajectory planning scheme (Load-balancing) with the following two baseline methods: cluster and Voronoi diagram-based method (Cluster-Voronoi) and tour-splitting-based approximation method (Tour-splitting) proposed in [11]. The former only differs from our proposal in the region partitioning, where the plane is divided according to the nearest neighbor rule and each GU is assigned to the emergency center closest to it [18]. The latter is a state-of-the-art 4-approximation algorithm proposed based on graph theory, where the tours are found by splitting the entire tour according to the delay threshold.

First of all, taking one randomly generated instance of 300 GUs as an example, we illustrate the deployment and trajectory planning results of different methods in Fig. 2. The number of deployed emergency centers are 7, 8, and 7 for Load-balancing, Cluster-Voronoi, and Tour-splitting, respectively, the corresponding total costs of which are 7.4375, 8.4449, and 7.4988, respectively. We can see that the required number of emergency centers obtained by our proposal is fewer than that of the Cluster-Voronoi. Moreover, although the numbers of emergency centers are the same, the cruise cost of our proposal is smaller than that of the Tour-splitting since the sub-tours are split based on the delay threshold in the Tour-splitting.

Then, we investigate the average system performance. Each value in the following figures is the average result by applying each algorithm to 20 randomly generated instances with the same network size. Let Ideal define the optimal values derived by (10) under the ideal assignment.

In Fig. 3, we present the total cost as a function of the number of GUs. As expected, the total cost is approximately proportional to the number of GUs since the number of required emergency centers would grow to support the in-

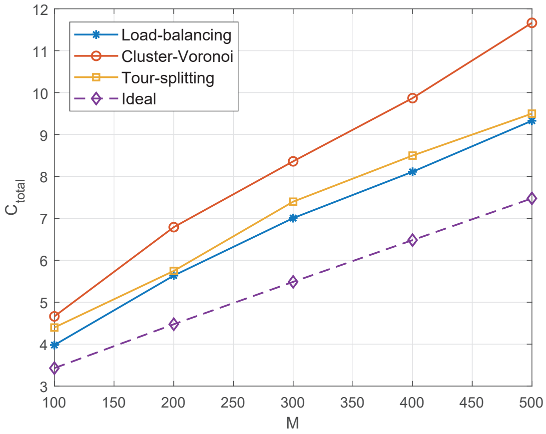


Fig. 3. The total cost as a function of the number of GUs.

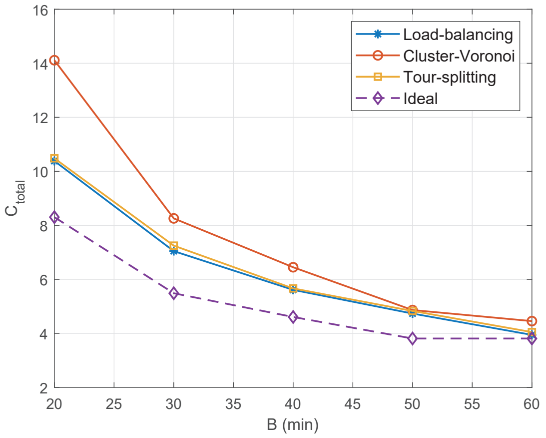


Fig. 4. The total cost as a function of the delay threshold, $M = 300$.

creasing number of GUs within the bound of delay. The total cost of our proposal is about 17.14% and 4.62% less than those of the Cluster-Voronoi and the Tour-splitting on average, respectively. The gap between our proposal and the Ideal is 19.22% in average.

Fig. 4 gives the total cost as a function of the delay threshold. The total cost of our proposal is 13.64% on average less than that of the Cluster-Voronoi. Our proposed load-balancing scheme slightly outperforms the Tour-splitting, which can save 1.84% cost on average. In addition, the performance of our proposal approaches that of the Ideal as the delay threshold extends, the gap is 3.4% when $B = 60$ min. The reason is that the process of adding a new emergency center is unnecessary to execute when the bound of delay is relatively loose.

V. Conclusion

In this paper, we investigated the multi-UAV-assisted emergency communications, where UAVs are dispatched to serve all the ground users while satisfying the given delay threshold. Aiming at minimizing the total cost consisting of deployment cost and cruise cost, the deployment of the emergency centers and the trajectories of the UAVs were jointly optimized. Since the formulated task is a combinatorial optimization problem, which is NP-hard, we first adopted the continuous paradigm to replace the complex combinatorial quantities, based on which the number of required emergency centers is estimated. Then, we proposed a load-balancing deployment and path planning algorithm based on clustering and equitable region partitioning to solve the optimization task. Numerical results validated that our proposal can complete the mission at less cost than the compared algorithms. Moreover, the performance of our proposal is close to the optimal, especially when the delay threshold is loose relative to the number of users.

References

[1] Y. Sun, T. Wang, and S. Wang, "Location optimization and user association for unmanned aerial vehicles assisted mobile networks," *IEEE Trans. Veh. Technol.*, vol. 68, no. 10, pp. 10 056–10 065, Oct. 2019.

[2] D. H. Tran *et al.*, "UAV relay-assisted emergency communications in IoT networks: Resource allocation and trajectory optimization," *IEEE Trans. Wirel. Commun.*, vol. 21, no. 3, pp. 1621–1637, Mar. 2022.

[3] Y. Zhu and S. Wang, "Efficient aerial data collection with cooperative trajectory planning for large-scale wireless sensor networks," *IEEE Trans. Commun.*, vol. 70, no. 1, pp. 433–444, Jan. 2022.

[4] N. Zhao *et al.*, "UAV-assisted emergency networks in disasters," *IEEE Wirel. Commun.*, vol. 26, no. 1, pp. 45–51, Feb. 2019.

[5] Y. Lin, T. Wang, and S. Wang, "UAV-assisted emergency communications: An extended multi-armed bandit perspective," *IEEE Commun. Lett.*, vol. 23, no. 5, pp. 938–941, May 2019.

[6] Z. Chang *et al.*, "Trajectory design and resource allocation for multi-UAV networks: Deep reinforcement learning approaches," *IEEE Trans. Network Sci. Eng.*, 2022, 10.1109/TNSE.2022.3171600.

[7] M. Matracia, M. A. Kishk, and M. S. Alouini, "UAV-aided post-disaster cellular networks: A novel stochastic geometry approach," *IEEE Tran. Veh. Technol.*, vol. 72, no. 7, pp. 9406–9418, Jul. 2023.

[8] D. Kim *et al.*, "On theoretical trajectory planning of multiple drones to minimize latency in search-and-reconnaissance operations," *IEEE Trans. Mob. Comput.*, vol. 16, no. 11, pp. 3156–3166, Nov. 2017.

[9] Q. Guo *et al.*, "Minimizing the Longest Tour Time Among a Fleet of UAVs for Disaster Area Surveillance," *IEEE Trans. Mob. Comput.*, vol. 21, no. 7, pp. 2451–2465, Jul. 2022.

[10] Y. Zhu and S. Wang, "Learning-based cooperative aerial and ground vehicle routing for emergency communications," in *GLOBECOM'22*, Rio de Janeiro, Brazil, Dec. 2022.

[11] W. Xu *et al.*, "Minimizing the deployment cost of UAVs for delay-sensitive data collection in IoT networks," *IEEE/ACM Trans. Netw.*, vol. 30, no. 2, pp. 812–825, Apr. 2022.

[12] J. Carlsson *et al.*, "Solving min-max multi-depot vehicle routing problem," *Lectures Glob. Optim.*, vol. 55, pp. 31–46, 2009.

[13] A. Al-Hourani, S. Kandeepan, and A. Jamalipour, "Modeling air-to-ground path loss for low altitude platforms in urban environments," in *Proc. IEEE GLOBECOM'14*, Austin, TX, USA, Dec. 2014.

[14] J. Beardwood, J. H. Halton, and J. M. Hammersley, "The shortest path through many points," *Math. Proc. Cambridge Philos. Soc.*, vol. 55, no. 4, pp. 299–327, Oct. 1959.

[15] D. L. Applegate *et al.*, *The Traveling Salesman Problem: A Computational Study*. Princeton Univ. Press, 2006.

[16] K. Helsgaun, "General k-opt submoves for the Lin-Kernighan TSP heuristic," *Math. Program. Comput.*, vol. 1, no. 2-3, pp. 119–163, Jul. 2009.

[17] J. A. Hartigan and M. A. Wong, "Algorithm AS 136: A K-means clustering algorithm," *J. R. Stat. Soc. Ser. C.: Appl. Stat.*, vol. 28, no. 1, pp. 100–108, 1979.

[18] F. Aurenhammer, "Voronoi diagrams-a survey of a fundamental geometric data structure," *ACM Comput. Surv.*, vol. 23, no. 3, pp. 345–405, Sept. 1991.