Maximizing Network Throughput in Heterogeneous UAV Networks

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***Abstract*—In this paper we study the deployment of an Unmanned Aerial Vehicle (UAV) network that consists of multiple UAVs to provide emergent communication service for people who are trapped in a disaster area, where each UAV is equipped with a base station that has limited computing capacity and power supply, and thus can only serve a limited number of people. Unlike most existing studies that focused on homogeneous UAVs, we consider the deployment of heterogeneous UAVs where different UAVs have different computing capacities. We study a problem of deploying K heterogeneous UAVs in the air to form a temporarily connected UAV network such that the network throughput – the number of users served by the UAVs, is maximized, subject to the constraint that the number of people served by each UAV is no greater than its service capacity. We then propose a novel $O(\sqrt{\frac{s}{K}})$-approximation algorithm for the problem, where s is a given positive integer with $1 \leq s \leq K$, e.g., $s = 3$. We also devise an improved heuristic, based on the approximation algorithm. We finally evaluate the performance of the proposed algorithms. Experimental results show that the numbers of users served by UAVs in the solutions delivered by the proposed algorithms are increased by 25% than state-of-the-arts.**

***Index Terms*—UAV communication networks, UAV deployment problem, heterogeneous UAVs, approximation algorithms.**

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I. INTRODUCTION

TERRESTRIAL LTE base stations usually are statically deployed. However, this static deployment limits their usage in key 5G and 5G Beyond applications with surging traffic demands at some hotspot locations (e.g., battlefields and concerts). In addition, the deployed base stations may have been destroyed in natural disasters, e.g., earthquakes, tsunamis, flooding, etc. Emergent communication service are definitely needed for rescue teams to rescue people trapped in disaster areas [9], [19].

The employment of Unmanned Aerial Vehicles (UAVs) or drones, e.g., DJI Matrice 300 RTK UAVs, has gained great attention in public safety communications [5], [9], [20], [22], [25], [27], [35], [37], [38], [45]. By installing an LTE base station on a UAV, the UAV can provide wireless communication service to ground users in the air [3], [26]. The LTE base station usually consists of two modules: SkyRAN and SkyCore, where SkyRAN provides wireless connectivity to ground users, while SkyCore is responsible for user mobility, management, control functions, and routing [26], [34]. In addition, some mobile operators, e.g., AT&T and Verizon, conducted experiments about UAVs with mounted LTE base stations [26]. A UAV communication network that consists of multiple UAVs can be easily deployed to provide emergent communication service in a disaster area, see Fig. 1. Both rescue teams and the people trapped can communicate with each other by leveraging the deployed UAV network.

In spite of the aforementioned promising applications of UAV networks, there are many challenges to realize these applications. Particularly, since the payload of each UAV usually is very limited, e.g., the maximum payload of a DJI Matrice 300 RTK UAV is only 2.7 kg [7], many functions in the SkyCore module must run in a low-end, light-weight server with a very resource-constrained CPU and a small-capacity battery, where the server is mounted on the UAV [3]. This could significantly increase the processing (control and data plane) latency of its traffic, thereby reducing network throughput [26]. Thus, a UAV usually needs to restrict the number of users it can serve, i.e., there is a *service capacity*

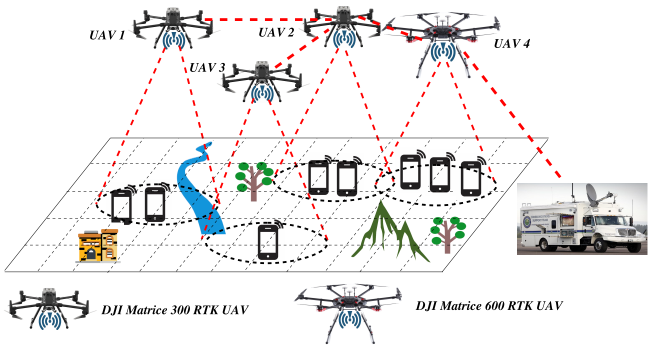


Fig. 1. A heterogeneous UAV network can provide communication service to people who are trapped in a disaster area, where UAVs 1, 2, and 3 are DJI Matrice 300 RTK, while UAV 4 is DJI Matrice 600 RTK and it is connected to the Internet through the relay of an emergency communication vehicle.

on each UAV [40], [46], e.g., 200 users. Otherwise, if a UAV serves too many users, each of the users may experience a very long service delay, e.g., a few seconds, and the network throughput also significantly decreases [26].

A. Motivation

The deployment of resource-constrained UAV networks recently has attracted a lot of attentions [10], [21], [30], [32], [39], [40], [41], [42], [46]. Most existing studies assumed that the UAVs are *homogeneous*. Different from these existing studies, in this paper we consider the deployment of *heterogeneous* UAVs. There are two major reasons for employing heterogenous UAVs. The first reason is that the UAVs owned by a rescue team usually are used for multiple disasters (e.g., earthquakes, flooding, tsunamis, etc.), not only for a single disaster. Therefore, the rescue team needs to purchase different types of UAVs for the usages in different disaster scenarios. The second reason is that the UAVs owned by the rescue team may be purchased at different time periods. Some UAVs bought a few years ago may not be available in the current market, while recently purchased UAVs, even made by the same company, have different payloads and battery capacities. For example, consider two popular UAVs for emergency communications: DJI Matrice 600 RTK UAV and DJI Matrice 300 RTK UAV. The former has a maximum payload of 5.5 kg [6] but it is out of production line now, while the latter has a maximum payload of 2.7 kg only and is available in the market [7]. In addition, heterogeneous UAVs are widely used in real post-disaster emergency communications. For example, in the Luding earthquake of China in 2022, pterosaur-2H UAVs and double-tailed scorpion TB UAVs were used in the disaster area to provide communication service [8], [29].

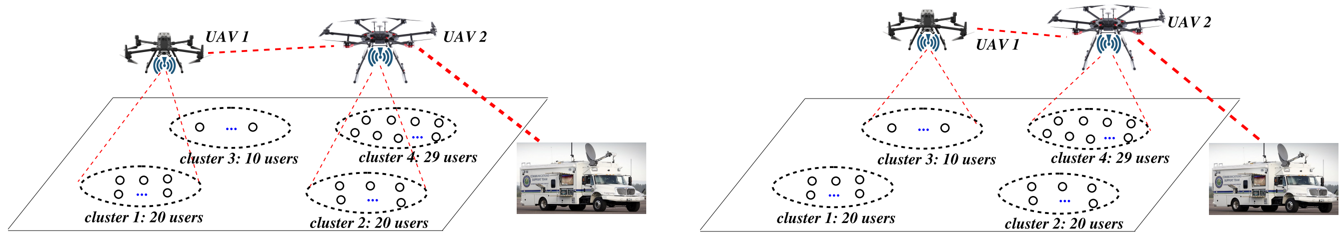
Due to different maximum payloads and energy capacities on different UAVs, the base stations mounted on different UAVs may be different too. The base station on a DJI Matrice 600 RTK UAV may be more powerful than the one on a DJI Matrice 300 RTK UAV, in terms of computing capability and/or battery capacity, thus the former is able to serve more users, i.e., has a larger *service capacity*. Fig. 1 illustrates such a heterogeneous UAV network.

B. Novelty

In this paper, we consider the deployment of a UAV network that consists of multiple heterogeneous UAVs in a disaster area, so as to provide emergent communication service to ground users who are trapped in the area. We study a novel *maximum connected coverage problem*, which is to deploy K heterogeneous UAVs to serve users such that the number of users served by the deployed UAVs is maximized, subject to that (i) the number of users served by each UAV is no greater than its service capacity; (ii) the data rate of each user served by a UAV is no less than his/her minimum data rate requirement; and (iii) the UAV communication network must be connected as the data from the users served by one UAV must be sent to the users served by another UAV, e.g., the communications between trapped people and rescue teams.

A potential solution to the maximum connected coverage problem is that, the to-be-deployed K UAVs are assumed to be homogeneous and their uniform service capacity is assumed as the average service capacity of the original heterogeneous UAVs, K hovering locations of the UAVs then are identified, by applying one of existing algorithms in [10], [21], [30], [40], [42], and [46]. Finally, the K original UAVs with different service capacities are deployed at the K chosen hovering locations in a greedy way. That is, assume that the service capacities of the K UAVs are sorted in non-increasing order. The kth UAV is deployed at one of the K locations with the maximum new increased number of served users, while ensuring that the location was not deployed by any UAV previously, where $1 \leq k \leq K$. For example, assume that $K(=2)$ UAVs need to be deployed to serve four clusters of users, where there are 20, 20, 10, 29 users in the four clusters, respectively, and the service capacities of the two UAVs are 10 and 30 users, respectively, see Fig. 2(a). The average service capacity of the two UAVs is 20 $(= \frac{10+30}{2})$ users. Existing algorithms for the homogeneous UAV deployment may identify two hovering locations above clusters 1 and 2, since 40 users will be served if the UAVs were homogeneous, see Fig. 2(a). The two original heterogeneous UAVs are deployed at the two hovering locations, respectively. It can be seen that only 30 $(= 10 + 20)$ users will be served by the two deployed UAVs, since the service capacity on UAV 1 is 10 users only. In contrast, Fig. 2(b) shows that $39(= 10 + 29)$ users will be served in the optimal deployment with heterogeneous UAVs. It can be seen from the example in Fig. 2 that, less users will be served if we apply the exiting algorithms for the homogeneous UAV deployment to the scenario with heterogeneous UAVs. New algorithms for the heterogeneous UAV deployment are desperately needed.

The heterogeneous UAV deployment problem is very challenging, since the objective of the problem, i.e., serving more users, conflicts with the network connectivity constraint, which is explained as follows. On one hand, to serve as many users as possible, the UAVs should be deployed over locations with high-density users. However, such locations may be far away from each other. The resulting UAV network may not be connected. On the other hand, to ensure the connectivity of deployed UAVs, the UAVs should not be deployed too far



(a) A UAV deployment by existing algorithms for homogenous UAVs (b) the optimal deployment with heterogeneous UAVs

Fig. 2. A comparison between a UAV deployment by existing algorithms for homogeneous UAVs and the optimal deployment with heterogeneous UAVs, where the service capacities on UAVs 1 and 2 are 10 and 30 users, respectively.

away from each other, since the communication range between any two UAVs is limited, e.g., a few hundred meters. Then, the total coverage area of the two UAVs may be overlapping, i.e., some users can be served by the two UAVs simultaneously. In addition, since different UAVs have different service capacities, the UAVs with large service capacities should be deployed over the places with high-density users, while the UAVs with low service capacities may be more likely to act as relays between the UAVs with large service capacities. However, existing studies in [10], [21], [30], [40], [42], and [46] for homogeneous UAVs deployment does not consider the different UAV service capacities, and a UAV with a low service capacity may be deployed to serve ground users, while a UAV with a large service capacity may serve as a relay in their delivered solutions.

The novelty of this paper lies in not only incorporating the heterogeneous service capacities of different UAVs into consideration, but also devising a novel approximation algorithm and an improved heuristic for the heterogeneous UAV deployment problem. Specifically, both the proposed algorithms deliver $O(\sqrt{\frac{s}{K}})$-approximate solutions, where K is the number of UAVs, s is a given positive integer with $1 \leq s \leq K$, e.g., $s = 3$. Notice that the approximation ratio $O(\sqrt{\frac{s}{K}})$ is better when the value of s is larger, this however incurs a longer running time.

C. Contributions

The main contributions of this paper are summarized as follows. We first formulate a novel maximum connected coverage problem for deploying a heterogeneous UAV network. We then devise an approximation algorithm for the problem and its approximation ratio is $O(\sqrt{\frac{s}{K}})$, followed with an improved heuristic algorithm, where s is a given positive integer. We finally evaluate the algorithm performance and our experimental results show that the number of users served by the proposed algorithms are up to 25% larger than those by existing algorithms.

The organization of this paper is as follows. Section II introduces the system model and defines the problem precisely. Section III and IV propose a novel approximation algorithm and an improved heuristic for the problem, respectively. Section V evaluates the performance of the proposed algorithms empirically. Section VI reviews related studies, and Section VII concludes this paper.

II. Preliminaries

In this section, we first introduce the system and channel models. We then figure out the maximum number of users served by UAVs, assuming that UAVs have already been deployed. We finally define the problem precisely.

A. System Model

The deployed communication infrastructures in a disaster, e.g., an earthquake, a debris flow, or a flooding, might no longer function any more, due to the damages or power outage caused by the disaster. To evacuate people trapped in a disaster area, it is important to provide a temporarily emergent communication network for them. A promising solution is to deploy a UAV communication network.

Fig. 1 illustrates that a UAV network of four UAVs above a disaster area act as aerial base stations to provide communication service (e.g., LTE or WiFi) to people on the ground. There is at least one of the UAVs serving as the *gateway UAV*, which means that the UAV is connected to the Internet with the help of satellites or emergency communication vehicles. With the help of the UAV network, a person who is trapped in the disaster area can communicate with a nearby UAV, using his/her smartphone to send/receive critical information, such as voice and video, to/from the rescue team.

We treat the disaster zone as a 3-dimensional space with length α, width β, and height γ, e.g., $\alpha = \beta = 3$ km and $\gamma = 500$ m. Assume that there are n users $u_1, u_2, \ldots, u_n$ in the disaster area, and let $U = \{u_1, u_2, \ldots, u_n\}$. Each user $u_i \in U$ has a minimum data rate requirement r_i^{min}, e.g., 2 kbps, if the user is served by a UAV base station. Denote by $(x_i, y_i, 0)$ the coordinate of a user u_i with $1 \leq i \leq n$. Assume that locations of the n users are given, where the location information can be derived by applying an existing target detection method [12], [14], [15] for the photos/vidoes taken by UAV on-board cameras.

We consider the employment of K (≥ 2) *heterogeneous* UAVs to provide communication service (e.g., LTE or WiFi) to affected people in the disaster area. Each UAV is equipped with a base station to serve as an aerial base station in the air [3]. Due to different maximum payloads and energy capacities on different UAVs, the base stations equipped on different UAVs have different capabilities. For example, since the maximum payload (i.e., 5.5 kg) [6] of a DJI Matrice 600 RTK UAV is larger than the payload (i.e., 2.7 kg) [7] of a DJI Matrice 300 RTK UAV, the base station on the former may be more powerful, in terms of computing ability and/or battery capacity, thus is able to serve more users than the one on the latter UAV.

Denote by C_k the *service capacity* on the kth UAV with $1 \leq k \leq K$, which means that the UAV can provide communication service to at most C_k users simultaneously, e.g., $C_k = 100$ users. Notice that the service capacities of different UAVs usually are different. Following existing studies [4], [18], [21], [40], [43], [46], we assume that all UAVs hover at the same altitude H_{uav} to provide communication service to ground users, where H_{uav} is the optimal altitude for the maximum coverage from the air and the value of H_{uav} can be calculated by the algorithms in [2] and [42], e.g., $H_{uav} = 300$ meters. On the other hand, a ground user will receive a weaker signal from a UAV if the UAV hovers at a higher or lower altitude than the optimal altitude H_{uav}, which was both analytically and empirically validated in [2].

Since the base stations mounted on the K UAVs may have different capabilities, the transmission powers of the base stations on the UAVs are different, too. Denote by P_t^k the transmission power of the base station on the kth UAV with $1 \leq k \leq K$.

For the sake of convenience, we divide the plane at altitude H_{uav} into equal size squares with a given side length λ, e.g., $\lambda = 50$ meters. Assume that both the length α and width β of the disaster area are divisible by the side length λ. Thus, the UAV hovering/service plane at altitude H_{uav} are partitioned into $m = \frac{\alpha}{\lambda} \times \frac{\beta}{\lambda}$ grids. Let $v_1, v_2, \ldots, v_m$ be the center locations of the m grids, respectively. Also, let $V = \{v_1, v_2, \ldots, v_m\}$. Assume that no more than one UAV can hover in a grid to avoid UAV collisions [46], i.e., two or more UAVs are not allowed to hover in the same grid.

B. Wireless Channel Models

We adopt similar UAV-to-user and UAV-to-UAV wireless channel models as those in [2], [40], and [46]. For the sake of convenience, we briefly introduce them as follows. On one hand, UAV-to-user wireless channels are so complicated as there may be obstacles, e.g., a building, between a UAV in the air and a user on the ground. Following existing studies, the UAV-to-user wireless channels are composed of Line-of-Sight (LoS) links and Non-Line-of-Sight (NLoS) links [2], [46]. Specifically, the pathloss $PL_{i,j}$ between a ground user u_i and a UAV deployed at an aerial hovering location v_j is $PL_{i,j} = P_{LoS} \cdot L_{LoS} + P_{NLoS} \cdot L_{NLoS}$, where P_{LoS} is the LoS link probability and can be calculated by the method in [2], $P_{NLoS} = 1 - P_{LoS}$, L_{LoS} and L_{NLoS} are the average pathlosses for LoS and NLoS links, respectively. In addition, $L_{LoS} = 20 \log_{10} \frac{4\pi f_c d_{ij}}{c} + \eta_{LoS}$, $L_{NLoS} = 20 \log_{10} \frac{4\pi f_c d_{ij}}{c} + \eta_{NLoS}$, where $20 \log_{10} \frac{4\pi f_c d_{ij}}{c}$ is the free space passloss, f_c is the carrier frequency, d_{ij} is the Euclidean distance between nodes u_i and v_j, c is the velocity of light, η_{LoS} and η_{NLoS} are the average shadow fadings in LoS and NLoS wireless connections, respectively.

The signal-to-noise ratio (SNR) received by user u_i from the UAV at location v_j then is $SNR_{ij} = 10^{\frac{P_t^j + g_t^j - PL_{i,j} - P_N}{10}}$, where P_t^j and g_t^j are the transmission power and antenna gain of the base station on the UAV, and P_N is the noise power. The average data rate r_{ij} of user u_i from the UAV at hovering location v_j then is $r_{ij} = B_w \log_2(1 + SNR_{ij})$, where B_w is the channel bandwidth allocated to user u_i, e.g., $B_w = 180\ kHz$ when the OFDMA technique is used [28], [40].

Assume that the kth UAV at altitude H_{uav} can communicate with a ground user if their Euclidean distance is no greater than a given communication range R_{user}^k, where $1 \leq k \leq K$. This indicates that the communication coverage radii R_{user}^ks of different UAVs may be different, due to their different transmission powers and/or antenna gains.

On the other hand, UAV-to-UAV wireless channels can be modelled as the free space path loss [2], since there are usually no obstacles between any two UAVs in the air. We assume that any two UAVs can communicate with each other if their Euclidean distance is no more than a given communication range R_{uav}. The wireless connectivity technique among UAVs may be WiFi 802.11ad, FSO (Free Space Optics), or mmWave, where high bandwidth is available [34]. For example, WiFi 802.11ad offers a high bandwidth with 2 GHz and a reasonable communication range, e.g., 1 km. Notice that the value of R_{user}^k usually is smaller than R_{uav} [21], i.e., $R_{user}^k \leq R_{uav}$.

C. Problem Definition

A UAV network is presented by an undirected graph $G = (U \cup V, E)$, where U is the set of n to-be-served users in the disaster area, V is the set of the m candidate UAV hovering locations at altitude H_{uav}. There is an edge (v_j, v_k) in the edge set E between two hovering locations v_j and v_k if their Euclidean distance is no more than the UAV communication range R_{uav}, and there is an edge (u_i, v_k) in E between a ground user u_i and a UAV hovering location v_k if their distance is no more than the communication coverage radius R_{user}^k of the UAV.

In this paper, we consider a *maximum connected coverage problem* in G, which is to choose K hovering locations $v_1, v_2, \ldots, v_K$ among the m candidate hovering locations in V ($K \leq m$), deploy K UAVs to the K chosen locations, respectively, and assign users to the K deployed UAVs, such that the number of users served by the UAVs is maximized, subject to following constraints that (i) each user $u_i \in U$ is served by at most one UAV within its communication range R_{user}^k and the data rate is no less than its minimum data rate requirement r_i^{min}; (ii) the number of users served by the kth UAV is no greater than its service capacity C_k with $1 \leq k \leq K$; and (iii) the deployed UAV communication network is connected.

We note that users in a disaster zone may move around. In this scenario, an optimal deployment of UAVs may become sub-optimal sometimes later. We thus may need to re-deploy the UAVs by adopting the similar strategy in [40]. Specifically, after every fixed time period, e.g., 2 minutes, we invoke the proposed algorithms in Section III to find the updated optimal deployment locations for the K UAVs, where the most recent user location information can be detected and predicted from the photos taken by the on-board cameras of the UAVs [14],

[15]. If the number of served users under the previous UAV deployment locations is only slightly worse than the one under this new UAV deployment locations, e.g., no more than 5% smaller, the K UAVs do not fly to their new deployment locations, since users may experience interrupted service due to frequent changes of the network topology. Otherwise (the previous number of served users is at least 5% smaller than the new number), the K UAVs fly to their new deployment locations.

D. The Optimal Assignment of Users With Given Deployed UAVs

Given K hovering locations $v_1, v_2, \ldots, v_K$, assume that the kth UAV with service capacity C_k has already been deployed at location v_k in the air with $1 \le k \le K$. We here consider a *maximum assignment problem*, which is to assign users in U to the K deployed UAVs such that the number of users served by the UAVs is maximized, subject to the constraint that the number of users served by the UAV at location v_k is no greater than the service capacity C_k on the UAV. This problem serves as a subproblem of the maximum connected coverage problem in the previous Section II-C. There are two major differences between the two problems. The first one is that the K UAVs have been deployed in the former, while the to-be-deployed locations of the K UAVs are unknown in the latter, and the second one is that the deployed UAV communication network may be disconnected in the former, whereas the deployed UAV network must be connected in the latter.

We now propose an optimal algorithm for the maximum assignment problem, which will serve as a subroutine of the proposed algorithm for the maximum connected coverage problem. Given a set S of K hovering locations $v_1, v_2, \ldots, v_K$ with $|S| = K$, assume that the kth UAV with service capacity C_k has already been deployed at location v_k with $1 \le k \le K$. A flow graph $G' = (\{s\} \cup U \cup S \cup \{t\}, E')$ is first constructed, where nodes s and t are the source and sink nodes in the flow graph G', respectively. There is a directed edge $\langle s, u_i \rangle$ in E' from s to each user $u_i \in U$ with a capacity of one. There is a directed edge $\langle u_i, v_k \rangle$ in E' from each user $u_i \in U$ to each location $v_k \in S$ if their Euclidean distance is no more than the communication range R^k_{user} of the kth UAV, and the data rate r_{ik} of user u_i is no less than its minimum data rate r_i^{min}. The capacity on edge $\langle u_i, v_k \rangle$ is one. Finally, there is a directed edge $\langle v_k, t \rangle$ in E' from each location $v_k \in S$ to sink node t, and the edge capacity on it is the service capacity C_k of the UAV deployed at location v_k. Fig. 3 illustrates the construction of the flow graph G' with $C_1 = 1$ and $C_2 = 2$.

Having constructed the flow graph G', we find an integral maximum flow in G' from s to t, by applying the algorithm in [1]. We obtain a feasible solution to the maximum assignment problem from the flow, where a user u_i is assigned to the UAV at location v_k if the flow of edge $\langle u_i, v_k \rangle$ is one. For example, Fig. 3 shows that user u_1 is assigned to the UAV at location v_1, and both users u_3 and u_4 are assigned to the UAV at location v_2. However, user u_2 is not served by any UAV. Notice that the number of served users is equal to the value of the flow.

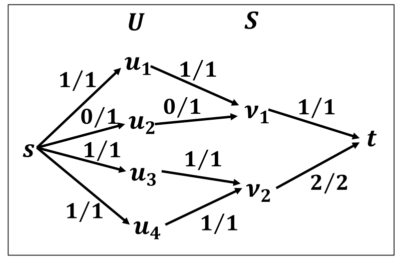


Fig. 3. An illustration of the construction of a flow graph G', where the numbers before and after a virgule '/' next to each edge mean the flow and capacity of the edge, respectively, the capacities of two UAVs are $C_1 = 1$ and $C_2 = 2$, respectively, and the value of the maximum flow is 3.

Lemma 1: Given a set U of users, a set S of K hovering locations $v_1, v_2, \ldots, v_K$, the kth UAV with service capacity C_k has already been deployed at location v_k in S with $1 \le k \le K$. There is an algorithm for the maximum assignment problem in G, which delivers an optimal solution in time $O(Kn^2)$, where $K = |S|$ and $n = |U|$.

Proof: The proof is contained in Section I of the supplementary file. □

E. Notions of Submodular Functions and Matroids

Let N be a set of finite elements and f be a function with $f : 2^N \mapsto \mathbb{R}^{\ge 0}$. For any two subsets A and B of N with $A \subseteq B$ and any element $e \in N \setminus B$, f is *submodular* if $f(A \cup \{e\}) - f(A) \ge f(B \cup \{e\}) - f(B)$ [11], and f is *monotone submodular* if $f(A) \le f(B)$.

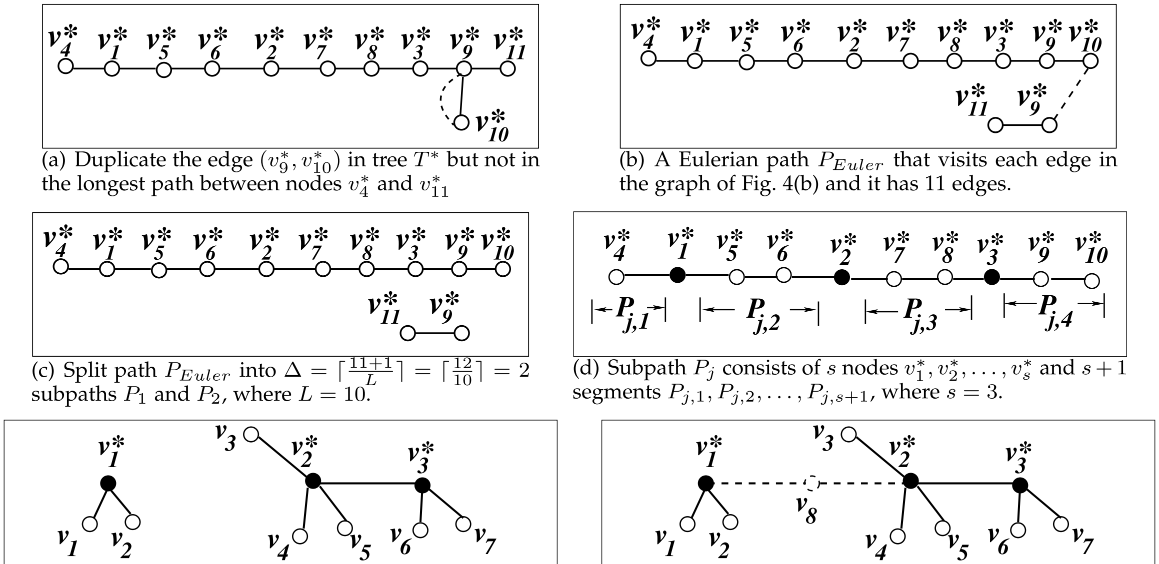
A *matroid* $\mathcal{M}$ is a pair $(N, \mathcal{I})$, where N is a set of elements and $\mathcal{I}$ is a family of subsets of N with the following three properties [11]: (i) $\emptyset \in \mathcal{I}$; (ii) the hereditary property: for any two sets A and B with $A \subseteq B \subseteq N$, if $B \in \mathcal{I}$, then $A \in \mathcal{I}$; and (iii) the augmentation property: for any two sets A and B in $\mathcal{I}$, if A contains more elements than B (i.e., $|A| > |B|$), then there is an element $e \in A \setminus B$ such that $B \cup \{e\}$ is contained in $\mathcal{I}$, too.

III. Algorithms for the Maximum Connected Coverage Problem

In this section, we study the maximum connected coverage problem in a large-scale disaster area. In this case, we choose the hovering locations of the K UAVs carefully, such that not only the number of users served by the deployed UAVs is maximized, but also the communication network formed by the UAVs is connected. We propose a novel $O(\sqrt{\frac{s}{K}})$-approximation algorithm for the problem with time complexity $O(K^2 n^2 m^{s+1})$, where s is a given positive integer, K is the number of UAVs, n is the number of users in the disaster area, and m is the number of candidate hovering locations. It can be seen that the approximation ratio $O(\sqrt{\frac{s}{K}})$ is larger if the value of s is larger, which however incurs a longer running time.

A. Basic Idea of the Approximation Algorithm

Assume that, in an optimal solution of the problem, the K UAVs are deployed at K hovering locations $v_1^*, v_2^*, \ldots, v_K^*$,



(a) Duplicate the edge (v_9^*, v_{10}^*) in tree T^* but not in the longest path between nodes v_4^* and v_{11}^*

(b) A Eulerian path P_{Euler} that visits each edge in the graph of Fig. 4(b) and it has 11 edges.

(c) Split path P_{Euler} into $\Delta = \lceil \frac{11+1}{L} \rceil = \lceil \frac{12}{10} \rceil = 2$ subpaths P_1 and P_2, where $L = 10$.

(d) Subpath P_j consists of s nodes $v_1^*, v_2^*, \ldots, v_s^*$ and $s+1$ segments $P_{j,1}, P_{j,2}, \ldots, P_{j,s+1}$, where $s = 3$.

(e) A $\frac{1}{3}$-approximate solution with nodes $v_1, v_2, \ldots, v_7$, and $v_1^*, v_2^*, \ldots, v_3^*$ of the L nodes in P_j

(f) Place a relay node v_8 to obtain a connected UAV network

Fig. 4. An illustration of the basic idea of the proposed algorithm.

respectively. Let $V^* = \{v_1^*, v_2^*, \ldots, v_K^*\}$. Recall that in the maximum connected coverage problem, the induced subgraph $G[V^*]$ by V^* is connected. Denote by T^* a spanning tree of $G[V^*]$, where T^* consists of the K nodes in V^* and $K-1$ edges. Let P^* be the longest path in tree T^*, e.g., the path between nodes v_4^* and v_{11}^* in Fig. 4(a). A Eulerian path P_{Euler} can be obtained by duplicating the edges in T^* but not in path P^*, see Fig. 4(a) and Fig. 4(b). The number of edges in the Eulerian path P_{Euler} is no more than $2(K-1) - D^*$, where D^* is the number of edges in path P^* with $D^* \geq 1$.

For any positive integer L with $L \geq s$ (the optimal value of L will be calculated later in Section III-D), the Eulerian path P_{Euler} can be split into Δ subpaths (or segments) $P_1, P_2, \ldots, P_\Delta$, such that the number of nodes in each subpath P_j is equal to L with $1 \leq j \leq \Delta - 1$, and the number of nodes in the last subpath P_Δ is no greater than L, where

$$\Delta = \lceil \frac{2K - 2 - D^* + 1}{L} \rceil \leq \lceil \frac{2K-2}{L} \rceil, \quad \text{as } D^* \geq 1, \tag{1}$$

see Fig. 4(c). It can be seen that there is one subpath P_j among the Δ subpaths such that the number of users served by the UAVs in P_j is no less than $\frac{1}{\Delta}$ of the number of users served by the UAVs in tree T^*.

Consider any s nodes $v_1^*, v_2^*, \ldots, v_s^*$ in subpath P_j, where the s nodes can be found by enumerating all possible candidates. It can be seen that P_j consists of the s nodes and $s+1$ segments $P_{j,1}, P_{j,2}, \ldots, P_{j,s+1}$, see Fig. 4(d). Denote by p_i the number of nodes in segment $P_{j,i}$ with $1 \leq i \leq s+1$. For example, Fig. 4(d) shows that $p_1 = 1$, $p_2 = p_3 = p_4 = 2$ with $s = 3$. Let D be the sum of nodes in the $s+1$ segments, i.e., $D = \sum_{i=1}^{s+1} p_i = L - s$, where there are L nodes in P_j.

The **basic idea** of the proposed algorithm is that, we observe that the L nodes in subpath P_j form a feasible solution to a submodular maximization problem, subject to the constraints of $\alpha(=2)$ matroids $\mathcal{M}_1$ and $\mathcal{M}_2$, where $\mathcal{M}_1$ and $\mathcal{M}_2$ will be introduced later in Section III-B and Section III-C, respectively. We then can obtain a $\frac{1}{\alpha+1}$ $(= \frac{1}{3})$ approximate solution V' with L nodes, by applying the algorithm in [11], where the s nodes $v_1^*, v_2^*, \ldots, v_s^*$ must be contained in V'. Assume that $V' = \{v_1, v_2, \ldots, v_D, v_1^*, v_2^*, \ldots, v_s^*\}$, e.g., see Fig. 4(e) with $D = L - s = 10 - 3 = 7$. It can be seen that the number of users served by the UAVs deployed at locations in set V' is no less than $\frac{1}{3}$ of the number of users served by the UAVs in P_j, thus no less than $\frac{1}{3\Delta}$ of the number of users served by the UAVs in the optimal solution T^*, where $\Delta \leq \lceil \frac{2K-2}{L} \rceil$ following Eq. (1).

Notice that the induced subgraph by $G[V']$ may be disconnected, e.g., see Fig. 4(e). We then place extra relaying nodes to obtain a connected UAV subnetwork, such that the nodes in V' are contained in the subnetwork. Fig. 4(f) shows that node v_8 is added as a relay node between nodes v_1^* and v_2^*. Notice that the number of nodes in the connected subnetwork must be no greater than K.

In the following, we first define matroids $\mathcal{M}_1$ and $\mathcal{M}_2$ in Sections III-B and Section III-C, respectively, where the definition of $\mathcal{M}_2$ depends on the value of L, and the $s+1$ numbers $p_1, p_2, \ldots, p_{s+1}$. We then calculate the optimal values of L and $p_1, p_2, \ldots, p_{s+1}$ in Section III-D. We finally describe the approximation algorithm in Section III-E.

B. Definition of Matroid $\mathcal{M}_1$

Let X be the set of K UAVs, i.e., $X = \{1, 2, \ldots, K\}$. Given the K UAVs in X and m hovering locations in V, we construct a set N of $K \times m$ elements, where N is the Cartesian product of sets X and V, i.e., $N = \{< k, v_j > \mid 1 \leq k \leq K, \ \forall v_j \in V\}$. It can be seen that an element $< k, v_j >$ in N indicates that the kth UAV with service capacity C_k will be deployed at location v_j.

Given any subset A of N, denote by $f(A)$ the number of users served by the UAVs in A, which can be calculated by invoking the algorithm in Section II-D. For example, assume that $A = \{< 1, v_1 >, < 2, v_2 >\}$, which means that UAVs 1 and 2 are deployed at locations v_1 and v_2, respectively. Following the study in [24], function $f(A)$ is **submodular**.

We define a set system $\mathcal{M}_1 = (N, \mathcal{I}_1)$ on set N, where $\mathcal{I}_1$ is a family of subsets of N such that, for each set $A \in \mathcal{I}_1$ ($A \subseteq N$), the number of pairs in A sharing the *same UAV* is no greater than one. In other words, each UAV cannot be placed at more than one location. For example, $A_1 = \{< 1, v_1 >\}$ is contained in $\mathcal{I}_1$, while $A_2 = \{< 1, v_1 >, \ < 1, v_2 >\}$ is not contained in $\mathcal{I}_1$ as UAV 1 cannot be deployed at the two different locations v_1 and v_2. The proof for the claim that $\mathcal{M}_1$ is a matroid is similar to the one for Lemma 2 in [23] at page 10, omitted.

C. Definition of Matroid $\mathcal{M}_2$

Consider any s nodes $v_1^*, v_2^*, \ldots, v_s^*$ in subpath P_j, where there are L nodes in P_j, see Fig. 4(d). Subpath P_j consists of the s nodes and $s+1$ segments $P_{j,1}, P_{j,2}, \ldots, P_{j,s+1}$. Recall that there are p_i nodes in segment $P_{j,i}$ with $1 \le i \le s+1$.

For any node v_l in P_j, denote by d_l the minimum number of hops in P_j between node v_l and nodes in the set $\{v_1^*, v_2^*, \ldots, v_s^*\}$. For example, Fig. 4(d) shows that the shortest hop between node v_5^* and nodes in set $\{v_1^*, v_2^*, v_3^*\}$ is only one. Let $h_{max} = \max\{p_1, p_{s+1}, \max_{i=2}^{s}\{\lceil \frac{p_i}{2} \rceil\}\}$, where h_{max} means the maximum shortest hops between nodes in P_j and nodes in the set $\{v_1^*, v_2^*, \ldots, v_s^*\}$. For example, in Fig. 4(d), we know that $p_1 = 1$, $p_2 = p_3 = 2$, and $p_4 = 2$ with $s = 3$. Then, $h_{max} = 2$.

For each integer h with $0 \le h \le h_{max}$, denote by Q_h the number of nodes in P_j that are at least h hops away from the nodes in set $\{v_1^*, v_2^*, \ldots, v_s^*\}$. For example, Fig. 4(d) shows that $Q_0 = 10$ since all the ten nodes in P_j are at least zero hop away from the nodes in $\{v_1^*, v_2^*, v_3^*\}$, $Q_1 = 7$ since the seven nodes $v_4^*, v_5^*, \ldots, v_{10}^*$ are at least one hop away from the nodes in $\{v_1^*, v_2^*, v_3^*\}$, and $Q_2 = 1$ since only node v_{10}^* is at least two hops away from the nodes in $\{v_1^*, v_2^*, v_3^*\}$.

We now formally define the value of Q_h with $0 \le h \le h_{max}$. Initially, $Q_0 = L$.

When $1 \le h \le h_{max}$, we then have

$$Q_h = \max\{p_1 - (h-1), 0\} + \sum_{i=2}^{s} \max\{p_i - 2(h-1), 0\} + \max\{p_{s+1} - (h-1),\ 0\},\ 1 \le h \le h_{max}. \quad (2)$$

Considering the L nodes in P_j, we define a family $\mathcal{I}_2$ of subsets of V, such that for any subset V' in $\mathcal{I}_2$, the shortest hop between any node in V' and the nodes in $\{v_1^*, v_2^*, \ldots, v_s^*\}$ is no more than h_{max}, and there are no more than Q_h nodes in V' that are at least h hops away from the nodes in set $\{v_1^*, v_2^*, \ldots, v_s^*\}$, where $0 \le h \le h_{max}$. We later show that $\mathcal{M}_2 = (V, \mathcal{I}_2)$ is a matroid, see Lemma 1 in the supplementary file.

D. Calculate the Optimal Values of L and $p_1, p_2, \ldots, p_{s+1}$

Consider any feasible solution V' in matroid $\mathcal{M}_2$, the induced subgraph by $G[V']$ may not be connected, see Fig. 4(e). We need to place extra relay nodes to ensure that the resulting graph become connected, so that nodes in V' are contained in the subnetwork. The number of deployed UAVs in the connected subnetwork is no greater than

$$\begin{aligned} g(L, p_1, p_2, \ldots, p_{s+1}) &= s + \sum_{i=2}^{s} p_i + \frac{p_1(p_1+1)}{2} \\ &\quad + \sum_{i=2}^{s} \frac{p_i^2 + 2p_i + (p_i \bmod 2)}{4} + \frac{p_{s+1}(p_{s+1}+1)}{2}, \end{aligned} \quad (3)$$

and its proof is contained in Lemma 2 of the supplementary file.

To serve more users, the value of L should be as large as possible. However, the number $g(L, p_1, p_2, \ldots, p_{s+1})$ of deployed UAVs should be no greater than K UAVs.

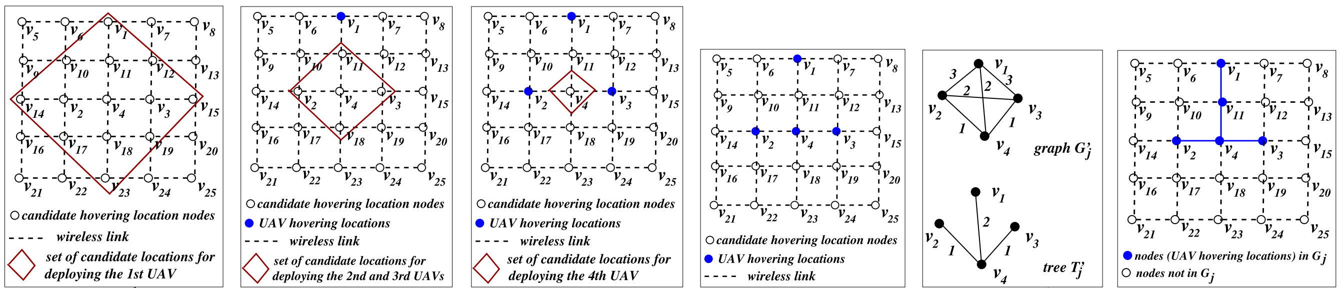
In the following, we calculate the optimal values of L and $p_1, p_2, \ldots, p_{s+1}$. Denote by L_{max} the maximum value of L, and denote by $p_1^*, p_2^*, \ldots, p_{s+1}^*$ the optimal numbers of $p_1, p_2, \ldots, p_{s+1}$, respectively, subject to the constraint that $g(L_{max}, p_1^*, p_2^*, \ldots, p_{s+1}^*)$ is no greater than K.

We calculate the maximum value of L_{max} by binary search. It can be seen that $s \le L_{max} \le K$. Given a guess L of L_{max}, following Eq. (3), the number $g(L, p_1, p_2, \ldots, p_{s+1})$ of deployed UAVs depends on the values of L, and $p_1, p_2, \ldots, p_{s+1}$. Denote by $p_1^L, p_2^L, \ldots, p_{s+1}^L$ the optimal values of $p_1, p_2, \ldots, p_{s+1}$, respectively, for the fixed L, such that the number $g(L, p_1, p_2, \ldots, p_{s+1})$ of deployed UAVs is minimized, where $\sum_{i=1}^{s+1} p_i^L = L - s$, $0 \le p_i^L \le L - s$ with $1 \le i \le s+1$. We calculate the values of $p_1^L, p_2^L, \ldots, p_{s+1}^L$ as follows.

Given the value of L, we later show that, when the number $g(L, p_1^L, p_2^L, \ldots, p_{s+1}^L)$ of deployed UAVs is minimized, the difference of p_1^L and p_{s+1}^L is no greater than one, i.e., $|p_1^L - p_{s+1}^L| \le 1$, and the difference of p_i^L and $p_{i'}^L$ is also no greater than one, i.e., $|p_i^L - p_{i'}^L| \le 1$ with $2 \le i, i' \le s$, see Section II in the supplementary file. Without loss of generality, we assume that $p_2^L \ge p_3^L \ge \cdots \ge p_s^L$. Then, $p_2^L - p_s^L \le 1$. Assume that there are j integers among the $s-2$ integers $p_2^L, p_3^L, \ldots, p_{s-1}^L$ so that they are larger than p_s^L by one. Let $p = p_s^L$. Then, $p_2^L = p_3^L = \cdots = p_{j+1}^L = p+1$ while $p_{j+2}^L = p_{j+3}^L = \cdots = p_s^L = p$. Since the difference of p_1^L and p_{s+1}^L is no greater than one, let $p_1^L = \lfloor \frac{L - s - \sum_{i=2}^{s} p_i^L}{2} \rfloor = \lfloor \frac{L-s-(s-1)p-j}{2} \rfloor$, and $p_{s+1}^L = \lceil \frac{L-s-(s-1)p-j}{2} \rceil$.

It can be seen that the value of p is in the interval $[0, L-s]$ and the value of j is in the interval $[0, s-2]$. Then, we can calculate the minimum number $g(L, p_1^L, p_2^L, \ldots, p_{s+1}^L)$ of deployed UAVs and the values of $p_1^L, p_2^L, \ldots, p_{s+1}^L$, by considering all combinations of p and j.

The algorithm for calculating L_{max} and $p_1^*, p_2^*, \ldots, p_{s+1}^*$ is presented in `Algorithm 1`. It can be seen that the time for finding the optimal value L_{max} and the optimal numbers $p_1^*, p_2^*, \ldots, p_{s+1}^*$ is only $O(s^2 K \log K)$.



(a) the set $V^1_{feasible}$ of feasible locations for deploying the 1st UAV (b) the 1st UAV is deployed at location v_1 (c) the 2nd and 3rd UAVs are deployed at locations v_2 and v_3, respectively (d) the nodes in set V_j', where the 4th UAV is deployed at location v_4 (e) graph G_j' and an MST T_j' in G_j' (f) graph G_j, where V_j is the set of nodes in G_j

Fig. 5. An illustration of the execution of the approximation algorithm, where $K = 5$, $L_{max} = 4$, $s = 1$ and $V_j^* = \{v_4\}$.

Algorithm 1 Calculate the Maximum Value of L_{max} and the Optimal Numbers $p_1^*, p_2^*, \ldots, p_{s+1}^*$

Input: The number K of UAVs and the value of s
Output: The values of L_{max} and $p_1^*, p_2^*, \ldots, p_{s+1}^*$

```
Let L_max ← s; /* an initial value of L_max */
Let L_lb ← s, L_ub ← K; /* L_lb and L_ub are lower and upper
    bounds on L_max, respectively */
while L_lb + 1 < L_ub do
    Let L ← ⌊(L_lb + L_ub)/2⌋; /* L is a guess of L_max */
    Let g(L, p_1^L, p_2^L, ..., p_{s+1}^L) ← +∞;
    for 0 ≤ p ≤ L − s, 0 ≤ j ≤ s − 2 do
        if (s − 1)p + j ≤ L − s then
            /* Ensure that the sum of p_2, p_3, ..., p_s, i.e., (s−1)p+j,
               is no greater than L − s; */
            Set p_2 = p_3 = ··· = p_{j+1} = p + 1, p_{j+2} = p_{j+3} =
                ··· = p_s = p, p_1 = ⌊(L−s−(s−1)p−j)/2⌋, and p_{s+1} =
                ⌈(L−s−(s−1)p−j)/2⌉;
            Calculate the number g(L, p_1, p_2, ..., p_{s+1}) of deployed
                UAVs by Eq. (3);
            if g(L, p_1, p_2, ..., p_{s+1}) < g(L, p_1^L, p_2^L, ..., p_{s+1}^L)
            then
                Let p_i^L ← p_i with 1 ≤ i ≤ s + 1;
            end if
        end if
    end for
    if g(L, p_1^L, p_2^L, ..., p_{s+1}^L) ≤ K then
        Let L_lb ← L; /* updated lower bound on L_max */
        Let L_max ← L and p_i^* ← p_i^L with 1 ≤ i ≤ s + 1;
    else
        Let L_ub ← L; /* updated upper bound on L_max */
    end if
end while
return the values of L_max and p_1^*, p_2^*, ..., p_{s+1}^*.
```

E. Approximation Algorithm

Given a positive integer s, the proposed algorithm first calculates the optimal values of L_{max} and $p_1^*, p_2^*, \ldots, p_{s+1}^*$, by invoking Algorithm 1 in Section III-D.

For any subset V_j^* of V with s nodes, the proposed algorithm finds a connected subgraph G_j of G, where $1 \leq j \leq \binom{m}{s}$, $m = |V|$ and $\binom{m}{s}$ is the number of different ways of choosing s nodes from set V with m nodes. The solution to the problem then is the subgraph G_{j^*} among the $\binom{m}{s}$ subgraphs such that the number of served users is maximized and the number of nodes in the subgraph is no greater than K, where $1 \leq j^* \leq \binom{m}{s}$. In the following, we show how to find a connected subgraph G_j.

For any subset V_j^* of V with s nodes in V, let $V_j^* = \{v_1^*, v_2^*, \ldots, v_s^*\}$. We define a submodular maximization problem, subject to the constraints of $\alpha(= 2)$ matroids $\mathcal{M}_1$ and $\mathcal{M}_2$, where $\mathcal{M}_1$ was defined in Section III-B, while $\mathcal{M}_2$ was defined in Section III-C by replacing L with L_{max} and replacing p_i with p_i^* $(1 \leq i \leq s+1)$. For example, Fig. 5(a) shows the set V of candidate hovering locations. Assume that there are $K = 5$ UAVs, and $s = 1$. Then, $L_{max} = 4$, $p_1^* = 1$, $p_2^* = 2$ by invoking Algorithm 1. By the definition of matroid $\mathcal{M}_2$ in Section III-C, we have $h_{max} = 2$, $Q_0 = 4, Q_1 = 3, Q_2 = 1$, following Eq. (2). In addition, assume that $V_j^* = \{v_4\}$. Then, a subset V_j' is contained in matroid $\mathcal{M}_2$, if every node in V_j' is no more than $h_{max} = 2$ hops away from v_4, and there are no more than Q_h nodes that are at least h hops away from v_4, where $0 \leq h \leq 2$.

We find an approximate solution V_j' with no more than L_{max} nodes to the submodular maximization problem under the constraints of matroids $\mathcal{M}_1$ and $\mathcal{M}_2$ as follows.

For the sake of convenience, we assume that $C_1 \geq C_2 \geq \cdots \geq C_K$, where C_k is the service capacity of the kth UAV with $1 \leq k \leq K$. The proposed algorithm consists of L_{max} iterations, and in the kth iteration we deploy the kth UAV with service capacity C_k at a hovering location, where $L_{max} \leq K$.

Assume that before the kth iteration, UAVs $1, 2, \ldots, k-1$ have already been deployed at hovering locations $v_1, v_2, \ldots, v_{k-1}$, respectively, i.e., $V_j' = \{v_1, v_2, \ldots, v_{k-1}\}$. Also, denote by n_{k-1} the number of users served by the deployed $k-1$ UAVs, which can be calculated by invoking the algorithm in Section II-D that considers the connections between users and deployed UAVs.

In the kth iteration, we deploy the kth UAV at a hovering location v_k such that the increased number of users served by the UAV in maximized. Specifically, denote by $V^k_{feasible}$ the set of nodes in $V \setminus V_j'$ such that the set $\{v_l\} \cup V_j'$ is contained in matroid $\mathcal{M}_2$, where v_l is in $V \setminus V_j'$, i.e., $V^k_{feasible} = \{v_l \mid (\{v_l\} \cup V_j') \in \mathcal{M}_2,\ v_l \in V \setminus V_j'\}$. For example, Fig. 5(a) shows the set $V^1_{feasible}$ of candidate hovering locations for deploying the first UAV, which is the set of nodes within two hops away from v_4. For each hovering location $v_l \in V^k_{feasible}$ that has not been deployed a UAV in the first $k-1$ iterations, we calculate the number $n_{k,l}$ of users served the k UAVs $1, 2, \ldots, k$, assuming that the kth UAV is deployed at location v_l. We then identify the location v_k in $V^k_{feasible}$ such that the new increased number of users served is maximized, i.e., $v_k = \arg\max_{v_l \in V^k_{feasible}} \{n_{k,l} - n_{k-1}\}$, where n_{k-1} is the number of users served by the deployed first $k-1$ UAVs in the first $k-1$ iterations. For example, Fig. 5(b) shows that the first UAV is deployed at location v_1. The procedure continues until the hovering locations for UAVs $1, 2, \ldots, L_{max}$ are found, where $L_{max} \le K$. The set of hovering locations for the L_{max} UAVs then is $V'_j = \{v_1, v_2, \ldots, v_{L_{max}}\}$. For example, Fig. 5(b) shows the set of candidate locations for deploying the second and third UAVs, which is the set of nodes within one hop away from v_4 (since there should be no more than $Q_2 = 1$ node that is two hops away from v_4 and the first UAV has already been deployed at node v_1 that is exactly two hops away from v_4). Then, assume that the second and third UAVs are deployed at locations v_2 and v_3, respectively, see Fig. 5(c). We finally consider set of candidate hovering locations for deploying the fourth UAV. Since there are already three nodes in V'_j that are at least one hop away from v_4 (i.e., $V'_j = \{v_1, v_2, v_3\}$), to ensure that the fourth UAV is deployed at a location v so that $V'_j \cup \{v\}$ is still contained in matroid $\mathcal{M}_2$, the fourth UAV can be deployed at only location v_4, which is zero hop away from itself. The set of hovering locations for the $L_{max} = 4$ UAVs then is $V'_j = \{v_1, v_2, v_3, v_4\}$, see Fig. 5(d).

It must be mentioned that the s nodes $v^*_1, v^*_2, \ldots, v^*_s$ in V^*_j must be contained in V'_j, as only nodes in V^*_j are zero hop away from V^*_j itself, and the number of nodes in V'_j that are zero hop away from V^*_j is $Q_0 - Q_1 = s$.

Recall that the kth UAV is deployed at hovering location v_k with $1 \le k \le L_{max}$ and $V'_j = \{v_1, v_2, \ldots, v_{L_{max}}\}$. Notice that the induced subgraph $G[V'_j]$ by V'_j may not be connected, see Fig. 5(d). We construct a connected subgraph G_j of G such that the nodes in V'_j are contained in G_j as follows.

A weighted graph $G'_j = (V'_j, E'_j)$ is first constructed from set V'_j, where there is an edge (v_k, v_l) in E'_j between any two nodes v_k and v_l in V'_j, and its edge weight $w(v_k, v_l)$ is the minimum number of hops in G between them. A minimum spanning tree (MST) T'_j in G'_j is then found, see Fig. 5(e). Denote by q'_j the number of nodes in T'_j. For each edge (v_k, v_l) in tree T'_j, there is a corresponding shortest path $P_{k,l}$ in graph G between nodes v_k and v_l.

A *connected subgraph* G_j of G can be obtained from T'_j, which is the union of the $(q'_j - 1)$ shortest paths in G, i.e., $G_j = \{P_{k,l} \mid (v_k, v_l) \in T'_j\}$, see Fig. 5(f). Denote by V_j the set of nodes in G_j. Also, let $q_j = |V_j|$. If the number q_j of nodes in G_j is greater than K, then G_j is not a feasible solution to the problem. Otherwise ($q_j \le K$), we deploy UAVs at the location node in G_j as follows.

Following the construction of G_j, it can be seen that the nodes in V'_j are contained in G_j (i.e.,V'_j is a subset of V_j), where $V'_j = \{v_1, v_2, \ldots, v_{L_{max}}\}$ and the kth UAV with service capacity C_k has already been deployed at location node v_k with $1 \le k \le L_{max}$. We deploy UAVs $L_{max}+1, L_{max}+2, \ldots, q_j$ at nodes in $V_j \setminus V'_j$ in an arbitrary way, e.g., in a greedy way. For example, Fig. 5(f) shows that the fifth UAV is deployed at location v_{11}. The algorithm for the problem is presented in `Algorithm` 2.

Algorithm 2 Approximation Algorithm for the Maximum Connected Coverage Problem in a Disaster Area (`approAlg`)

Input: A set U of users, a set V of candidate hovering locations, and K UAVs with service capacities $C_1, C_2, \ldots, C_K$, respectively
Output: A solution to the maximum connected coverage problem
Calculates the optimal values of L_{max} and $p^*_1, p^*_2, \ldots, p^*_{s+1}$, by invoking the algorithm in Section III-D;
Let $Q_0 \leftarrow L_{max}$ and define Q_h by Eq. (2), $1 \le h \le h_{max}$;
Let $n^* \leftarrow 0$; /* the maximum number of served users */
for each subset V^*_j of V with s nodes **do**
  Sort the K UAVs by their service capacities in decreasing order, and assume that $C_1 \ge C_2 \ge \cdots \ge C_K$;
  Let $V'_j \leftarrow \emptyset$; /* no UAVs are deployed initially */
  Let $n_0 \leftarrow 0$; /* no users are served initially */
  for $1 \le k \le L_{max}$ **do**
    Find the set $V^k_{feasible}$ of feasible location nodes for deploying the kth UAV, where $V^k_{feasible} \leftarrow \{v_l \mid (\{v_l\} \cup V'_j) \in \mathcal{M}_2,\ v_l \in V \setminus V'_j\}$;
    Deploy the kth UAV at a location node v_k in $V^k_{feasible}$ such that the increased number of users served by the UAV in maximized, i.e., $v_k \leftarrow \arg\max_{v_l \in V^k_{feasible}} \{n_{k,l} - n_{k-1}\}$;
    Let $V'_j \leftarrow V'_j \cup \{v_k\}$;
  end for
  Construct a graph $G'_j = (V'_j, E'_j)$, where there is an edge $(v_k, v_l) \in E'_j$ between any two nodes v_k and v_l in V'_j, and its edge weight $w(v_k, v_l)$ is the minimum number of hops between v_k and v_l in G;
  Find a Minimum Spanning Tree (MST) T'_j in G'_j;
  Construct a connected subgraph G_j of G, where $G_j = \{P_{k,l} \mid (v_k, v_l) \in T'_j\}$ and $P_{k,l}$ is the shortest path in G between nodes v_k and v_l. Let V_j be the set of nodes in G_j and $q_j = |V_j|$;
  if $q_j \le K$ **then**
    Deploy UAVs $L_{max}+1, L_{max}+2, \ldots, q_j$ at location nodes in $V_j \setminus V'_j$ in an arbitrary way;
    Calculate the number n^*_j of users served by the deployed UAVs in G_j;
    if $n^*_j > n^*$ **then**
      /* Find a better UAV deployment */
      Let $n^* \leftarrow n^*_j$ and $j^* \leftarrow j$;
    end if
  end if
end for
Assign users in U to the UAVs deployed in subgraph G_{j^*}, by invoking the algorithm in Section II-D;
return the deployment of UAVs in G_{j^*} and the assignment of users in U.

F. The Approximation Ratio Analysis

Theorem 1: Given a UAV network $G = (U \cup V, E)$ and K UAVs with service capacities $C_1, C_2, \ldots, C_K$, respectively, there is an approximation algorithm, i.e., `Algorithm` 2, for the maximum connected coverage problem with time complexity of $O(K^2 n^2 m^{s+1})$, and the approximation ratio of the algorithm is $\frac{1}{3\lceil \frac{2K-2}{L_1} \rceil} = O(\sqrt{\frac{s}{K}})$ and $L_1 = \lfloor \sqrt{4sK + 4s^2 - 8.5s} \rfloor - 2s + 2$, where n is the number of users in U ($n = |U|$) and m is the number of candidate hovering locations in V ($m = |V|$).

Proof: See the supplementary file. □

IV. An Improved Heuristic

Following Eq. (1), the performance of `Algorithm 2` is better when the value of L is larger. However, when the value of L is too large, the number of nodes in the connected subnetwork G_j found at Step 15 in `Algorithm 2` may be larger than the number K of available UAVs. On the other hand, recall that we estimated the upper bound $g(L, p_1, p_2, \ldots, p_{s+1})$ on the number of nodes in the connected subnetwork G_j with Eq. (3), and we can ensure that the number of nodes in G_j is no greater than K when its upper bound $g(L, p_1, p_2, \ldots, p_{s+1})$ is no more than K. Note that L_{max} is the largest integer such that $g(L, p_1, p_2, \ldots, p_{s+1}) \leq K$. However, the estimated upper bound $g(L, p_1, p_2, \ldots, p_{s+1})$ may be conservative and the actual number of nodes in G_j may be less than the upper bound. Then, even if we adopt a value of L larger than the value L_{max} found by `Algorithm 1`, we may still find a connected subnetwork G_j with no more than K nodes. In this section, we propose a heuristic to improve the algorithm performance as follows.

For any fixed value of L between L_{max} found by `Algorithm 1` and the number K of UAVs, we first find the optimal values $p_1^L, p_2^L, \ldots, p_{s+1}^L$ of $p_1, p_2, \ldots, p_{s+1}$ by invoking the pseudocodes from Step 5 to Step 15 in `Algorithm 1`, such that the value of $g(L, p_1, p_2, \ldots, p_{s+1})$ is minimized. Notice that the value of $g(L, p_1^L, p_2^L, \ldots, p_{s+1}^L)$ may be larger than K. We then find a connected subgraph G_L by invoking the pseudocodes from Step 3 to Step 24 in `Algorithm 2`. If the number of nodes in G_L is no greater than K, we may find a better solution than the one delivered by `Algorithm 2`. Denote by $L_{improved}$ the maximum value of L such that the number of nodes in the found connected subgraph G_L is no greater than K, where $L_{improved} \geq L_{max}$. We can find the value of $L_{improved}$ with a binary search. The improved heuristic algorithm for the problem is presented in `Algorithm 3`. It can be seen that the time complexity of `Algorithm 3` is only a factor of $O(\log K)$ larger than that of `Algorithm 2`.

Algorithm 3 Improved Heuristic Algorithm for the Maximum Connected Coverage Problem (`approAlgPlus`)

Input: A set U of users, a set V of candidate hovering locations, and K UAVs with service capacities $C_1, C_2, \ldots, C_K$, respectively
Output: A solution to the maximum connected coverage problem

Calculates the values of L_{max} and $p_1^*, p_2^*, \ldots, p_{s+1}^*$, by invoking the algorithm in Section III-D;
Let $L_{improved} \leftarrow L_{max}$; //$L_{improved}$ is the maximum value of L such that the number of nodes in the found connected subgraph is no greater than K.
Find a solution with L_{max} by invoking `Algorithm 2`, and let $n^*_{improved}$ be the number of served users in the solution;
Let $L_{lb} \leftarrow L_{max}$, $L_{ub} \leftarrow K + 1$; // L_{lb} and L_{ub} are lower and upper bounds on $L_{improved}$, respectively.
while $L_{lb} + 1 < L_{ub}$ **do**
  // A binary search of $L_{improved}$
  Let $L \leftarrow \lfloor \frac{L_{lb}+L_{ub}}{2} \rfloor$;
  Find the optimal values $p_1^L, p_2^L, \ldots, p_{s+1}^L$ of $p_1, p_2, \ldots, p_{s+1}$ by invoking the pseudocodes from Step 5 to Step 15 in `Algorithm 1`;
  Let $Q_0 \leftarrow L$ and define Q_h by Eq. (2), $1 \leq h \leq h_{max}$;
  Find a connected subgraph G_L by invoking the pseudocodes from Step 3 to Step 24 in `Algorithm 2`, and let n_L be the number of served users in G_L;
  if the number of nodes in G_L is no greater than K **then**
    Let $L_{lb} \leftarrow L$; // update the lower bound
    if $n_L > n^*_{improved}$ **then**
      // Find a better solution
      Let $n^*_{improved} \leftarrow n_L$;
      Let $L_{improved} \leftarrow L$;
    end if
  else
    Let $L_{ub} \leftarrow L$; // update the upper bound
  end if
end while
Find the solution with $L_{improved}$.

V. Performance Evaluation

In this section, we evaluated the performance of the proposed algorithms. In addition, we also investigated the impact of important parameters on the performance of the algorithms, including the number K of to-be-deployed UAVs, the value of parameter s, the number n of to-be-served users, the UAV service capacities, and the UAV communication range R_{uav}.

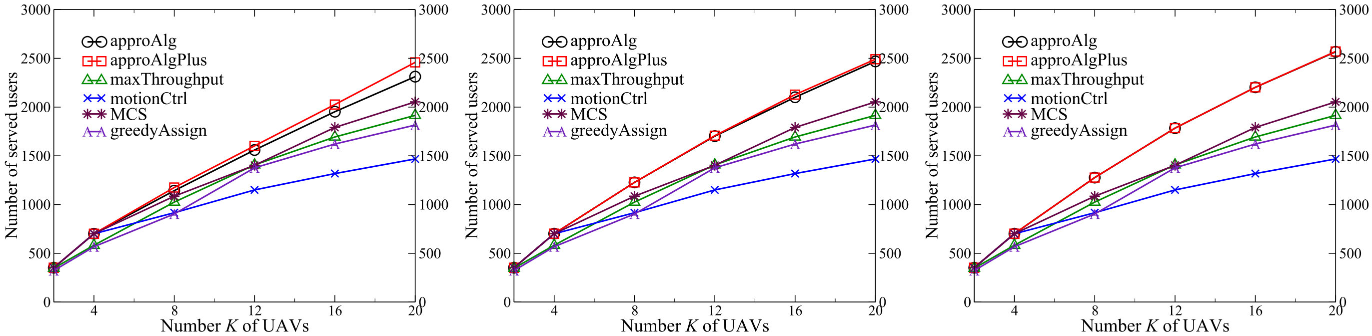
A. Experimental Environment

Consider a disaster zone with a 3×3 km^2 square [46], in which 1,000 to 3,000 users are located. The user density follows a fat-tailed distribution, i.e., many users are located at a small portion of places while a few users are sparely located at many other places in the disaster zone [31]. The number K of UAVs varies from 2 to 20. The service capacity C_k of the kth UAV is randomly chosen from an interval of $[C_{min}, C_{max}]$, where $C_{min} = 50$ users, $C_{max} = 300$ users [40], and $1 \leq k \leq K$. Each UAV hovers at an altitude $H_{uav} = 300$ m to provide communication service to ground users [2]. The UAV communication range is $R_{uav} = 600$ m, while the user communication range is $R^k_{user} = 500$ m [46].

In addition to the proposed algorithms `approAlg` and `approAlgPlus`, we consider four benchmark algorithms. (i) Algorithm `MCS` [17] finds a $\frac{1-1/e}{5(\sqrt{K}+1)}$-approximate solution to cover as many users as possible by deploying K UAVs. (ii) Algorithm `MotionCtrl` [46] proposes a motion control solution to cover the maximum number of users by deploying a connected UAV network that consists of K UAVs. (iii) Algorithm `greedyAssign` [16] first assigns each candidate hovering location a profit in a greedy way, then deploys a network consisting of K UAVs, such that the sum of profits in the network is maximized. (iv) Algorithm `maxThroughput` [40] finds a $\frac{1-1/e}{\sqrt{K}}$-approximation solution to a problem of placing K homogenous UAVs, so that the network throughput is maximized. All experiment simulations were run on a server with an Intel(R) Core(TM) i5-9500 CPU (2.9 GHz) and 8 GB RAM.

B. Algorithm Performance

We first study the performance of different algorithms by varying the number K from 2 to 20, when there are $n = 3,000$ users and the parameter s is 1, 2, and 3, respectively. Fig. 6(a) shows that the number of served users by each

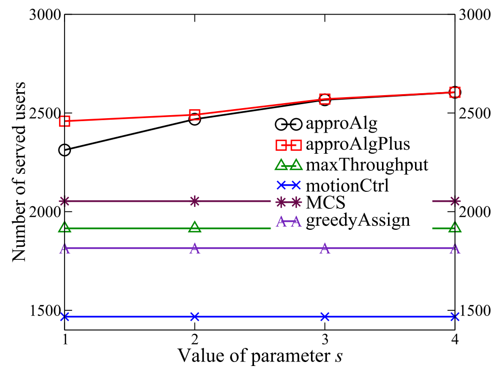


(a) value of parameter $s = 1$ (b) value of parameter $s = 2$ (c) value of parameter $s = 3$

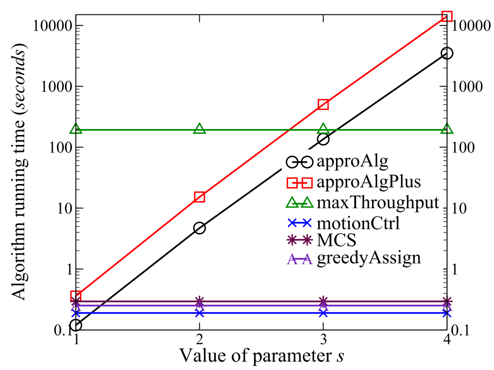
Fig. 6. The performance of different algorithms by increasing the number K of UAVs from 2 to 20, when there are $n = 3,000$ users, and $s = 1, 2,$ and 3, respectively.

algorithm increases with more UAVs deployed, when $s = 1$. It can be seen from Fig. 6(a) that the numbers of users served by both algorithms `approAlg` and `approAlgPlus` are up to 12% more than those by the other four algorithms when $K = 20$ UAVs. For examples, when $K = 20$, the numbers of users served by algorithms `approAlg`, `approAlgPlus`, `maxThroughput`, `MotionCtrl`, `MCS`, and `greedyAssign` are 2,312, 2,458, 1,915, 1,467, 2,053, 1,815, respectively. In addition, Fig. 6(a) demonstrates that the number of users served by algorithm `approAlgPlus` is only slightly larger than the number by algorithm `approAlg` when $K \leq 12$, while the number by algorithm `approAlgPlus` is significantly larger than the number by algorithm `approAlg` when $K > 12$. For example, when $K = 20$, the number of users served by algorithm `approAlgPlus` is 6% larger than the number by algorithm `approAlg`. On the other hand, both Fig. 6(b) and Fig. 6(c) show that the number of users served by both algorithm `approAlg` or `approAlgPlus` is larger when s is larger.

We then deal with the tradeoff between the quality of the solution delivered by the proposed algorithms `approAlg` and `approAlgPlus` and their running times, by increasing the value of s from 1 to 4. Fig. 7(a) shows that the numbers of served users by both algorithms `approAlg` and `approAlgPlus` increase with the growth of parameter s, and the numbers are from 12% to 26% larger than those by the other four algorithms when s grows from 1 to 4. Furthermore, the gap between algorithms `approAlg` and `approAlgPlus` becomes smaller with the growth of s. Then, it can be seen from Fig. 6 and Fig. 7(a) that the number of users served by algorithm `approAlgPlus` is much larger than the number by algorithm `approAlg` when K is large (e.g., $K = 20$) and s is small (e.g., $s = 1$ or 2), whereas the number by algorithm `approAlgPlus` is only slightly larger than the number by algorithm `approAlg` when K is small or s is large. On the other hand, Fig. 7(b) plots that the running times of both algorithms `approAlg` and `approAlgPlus` also significantly increase with the growth of s, since their time complexity are $O(K^2 n^2 m^{s+1})$ and $O(K^2 n^2 m^{s+1} \log K)$, respectively. Notice that in the application of deploying a UAV communication network to people trapped in a disaster area, we need the best tradeoff between the quality of the delivered solution (i.e., the number of served users) and the algorithm running time. Fig. 6 and Fig. 7 indicate that we can find a good UAV deployment in a short time, e.g., within a few minutes, by either adopting algorithm `approAlg` with $s = 2$ or 3, or using algorithm `approAlgPlus` with $s = 1$ or 2. However, the running times of both algorithms `approAlg` and `approAlgPlus` with $s = 4$ usually are unacceptable, which are as high as about 58 minutes and 3.9 hours, respectively.



(a) Number of served users by different algorithms



(b) Running time of different algorithms

Fig. 7. The performance of different algorithms by increasing the parameter s from 1 to 4, when there are $n(= 3,000)$ users and $K(= 20)$ UAVs.

We also investigate the algorithm performance by varying the number n of to-be-served users from 1,000 to 3,000, when there are $K(= 20)$ UAVs and $s = 3$. Fig. 8 shows that

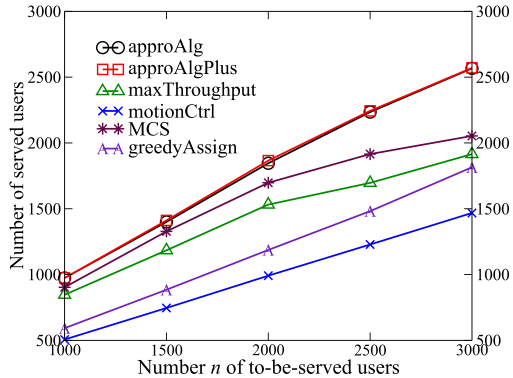


Fig. 8. The performance of different algorithms by varying the number n of to-be-served users from 1,000 to 3,000, when $K = 20$ UAVs and $s = 3$.

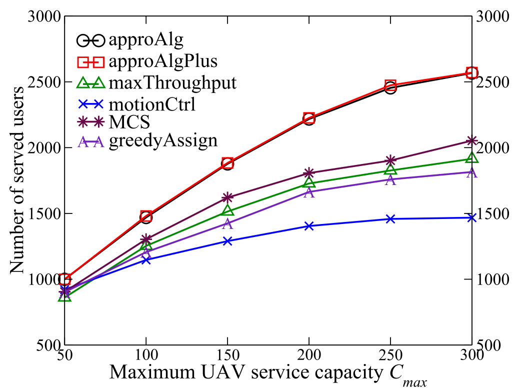


Fig. 9. The performance of different algorithms by varying the maximum UAV service capacity C_{max} from 50 to 300 users while fixing $C_{min} = 50$ users, when $n = 3,000$ users, $K = 20$ UAVs and $s = 3$.

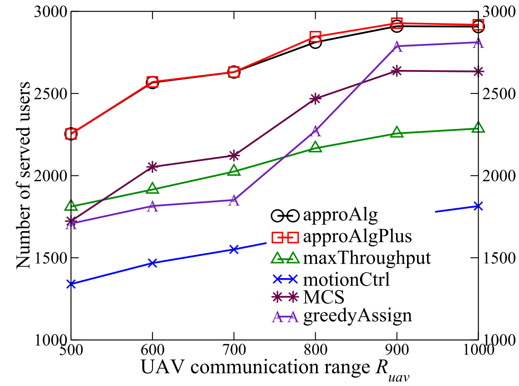


Fig. 10. The performance of different algorithms by varying the UAV communication range R_{uav} from 500 m to 1,000 m, when $n = 3,000$ users, $K = 20$ UAVs and $s = 3$.

the numbers of users served by both algorithms `approAlg` and `approAlgPlus` are about from 7% to 25% more than those by algorithms `maxThroughput`, `MotionCtrl`, `MCS`, and `greedyAssign` respectively, with the growth of n from 1,000 to 3,000. Fig. 8 demonstrated that more users will be served by all comparison algorithms when there are more to-be-served users in the disaster area.

We further evaluate the algorithm performance by varying the maximum UAV service capacity C_{max} from 50 to 300 users while fixing $C_{min} = 50$, where the service capacity of a UAV is randomly chosen from the interval $[C_{min}, C_{max}]$. Fig. 9 demonstrates that the numbers of users served by both algorithms `approAlg` and `approAlgPlus` are from 10% to 25% larger than those by the other four algorithms, when C_{max} increases from 50 to 300 users.

We finally study the algorithm performance by varying the UAV communication range R_{uav} from 500 m to 1,000 m. Fig. 10 shows that more users will be served by each of the six algorithms and the number of users served by both algorithms `approAlg` and `approAlgPlus` are from 3% to 24% larger than those by the other four algorithms.

VI. Related Work

The deployment of UAV networks recently has gained lots of attentions in public communications. Most existing studies considered the deployment of *homogeneous UAVs*. For example, Zhao et al. [46] studied a problem of deploying a connected UAV network that consist of K UAVs to serve as many as users as possible, and they proposed a motion control algorithm for their problem. Liu et al. [21] investigated a similar problem in [46], and proposed an algorithm based on the deep reinforcement learning technique. Yang et al. [42] considered the problem of the flying trajectory planning of multiple UAVs, so as to provide emergent communication service to ground people. Shi et al. [30] considered the problem of finding UAV flying trajectories during a given period, in order to minimize the average pathloss between UAVs and users. Su et al. [33] studied the problem for jointly finding locations and power allocation of UAVs and the beamforming of STAR-RIS, to maximize the sum-rate of the UAV network. Fahim and Gadallah [10] studied the deployment of a single UAV to serve as many ground devices as possible. Xu et al. [40] recently studied a problem of deploying a connected UAV network that consists of K homogeneous UAVs in the air for monitoring a disaster area, such that the sum of data rates of all users is maximized, subject to the constraint that the number of users served by each UAV is no greater than its service capacity. They proposed a $\frac{1-1/e}{\sqrt{K}}$-approximation algorithm, where e is the base of the natural logarithm.

There are several studies on finding a connected subgraph with no more K nodes in a graph such that the value of a given submodular function over the K found nodes is maximized. For instance, Kuo et al. [17] studied a problem of placing a connected wireless network that consists of K wireless routers such that the number of users served is maximized, and proposed a $\frac{1-1/e}{5(\sqrt{K}+1)}$-approximation algorithm. Khuller et al. [16] investigated a problem of finding a connected subgraph with K nodes in a graph, such that the number of neighbouring nodes of the found K nodes is maximized. They proposed a $\frac{1-1/e}{12}$-approximation algorithm. However, the proposed algorithm is not applicable to the problem in this paper. Huang et al. [13] studied a problem of placing a connected sensor network that consists of K sensors, such that the number of targets monitored by the placed sensors is maximized, by designing a $\frac{1-1/e}{8(\lceil 2\sqrt{2}\theta\rceil+1)^2}$-approximation algorithm, where $0 < \theta \leq 1$. Yu et al. [44] recently proposed an improved algorithm and the approximation ratio is improved to $\frac{1-1/e}{8(\lceil \frac{4}{\sqrt{3}}\theta \rceil+1)^2}$. It can be seen that both the approximation ratios $\frac{1-1/e}{8(\lceil 2\sqrt{2}\theta \rceil+1)^2}$ [13] and $\frac{1-1/e}{8(\lceil \frac{4}{\sqrt{3}}\theta \rceil+1)^2}$ [44] are between $\frac{1-1/e}{128}$ and $\frac{1-1/e}{32}$, as $0 < \theta \leq 1$. On the other hand, notice that there usually are tens or hundreds of UAVs to the deployed. In this case, the approximation ratio $\frac{1-1/e}{\sqrt{K}}$ in [40] usually is larger than those in [13] and [44], i.e., $\frac{1-1/e}{\sqrt{K}} \geq \frac{1-1/e}{32}$ when $K \leq 1,024$. However, the solutions in these studies are inapplicable to the heterogeneous UAVs deployment.

In addition, we noticed that Wang et al. [36] first surveyed the most recent network and protocol architectures of multi-UAV-based heterogeneous flying ad hoc networks (FANET), then proposed novel distributed gateway-selection algorithms in UAV networks, and finally conceived a UAV cloud-control system to improve the limited computational capabilities of resource constrained mobile UAVs. It can be seen that the work in [36] did not address the problem of deploying UAV networks. In contrast, in this paper we studied a problem of deploying a UAV network in the air above a disaster area to serve as many trapped people as possible. We think that the studies in [36] and in this paper investigated different issues in UAV networks, thus are complementary.

VII. Conclusion

Different from existing studies that considered only the deployment of homogenous UAV networks, in this paper, we investigated the problem of deploying a heterogenous UAV network in a disaster so as to maximize the network throughput. We proposed a performance-guaranteed approximation algorithm and a heuristic algorithm for the deployment problem of the heterogenous UAV network. Extensive experimental results demonstrated that the UAV network by the proposed algorithms served 25% more users than those by existing algorithms.

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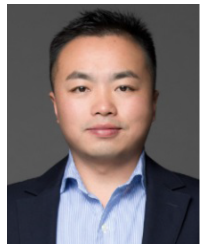

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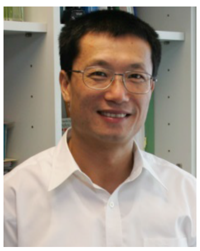

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