Fair Communications in UAV Networks for Rescue Applications

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***Abstract*—We study the deployment of an unmanned aerial vehicle (UAV) network to provide urgent communications to people trapped in a disaster zone, where each UAV is an aerial base station in the air. Unlike most existing studies that assumed that each user communicates with a UAV directly, we introduce Device-to-Device (D2D) communications, in which a user within the communication range of a UAV can serve as a hotspot (e.g., WiFi hotspot), and provide communication services to his nearby users who are out of the communication range of any UAV. More users thus can have the communication service provided by the UAV network. To ensure that the users within and out of the communication ranges of deployed UAVs have *fair* communication quality, we study a novel UAV deployment and resource allocation problem under the D2D communication model, which is to deploy K given UAVs in the top of a disaster zone, allocate the bandwidth of each UAV to its served users, allocate the bandwidth of each hotspot to his served users, determine the data rate of each user, and find the routing paths for data transmissions, such that the accumulative utility of all users is maximized. We also propose a novel $(1-1/e-\epsilon)$-approximation algorithm `algMaxUtility` for the problem, where e is the base of the natural logarithm, and ϵ is a given constant with $0 < \epsilon < 1-1/e$. We finally evaluate the performance of the algorithm. Experimental results show that accumulative utility by the algorithm is up to 18% larger than those by existing algorithms. In addition, more than 16% users are served in the deployed UAV network by the proposed algorithm.**

***Index Terms*—Approximation algorithm, Device-to-Device (D2D) communication, submodular function, unmanned aerial vehicle (UAV) communication networks, utility maximization.**

I. Introduction

It IS reported that there were more than 7000 severe disaster events in the world from 2000 to 2019, such as Haiti earthquake in 2010, the Wenchuan earthquake in 2008, Hurricane Katrina in 2005, etc. [1]. Millions of people lost their lives and the economic losses in the disasters were as high as U.S. $3 trillion. When a disaster occurs, the first priorities are to search and rescue trapped people and get them out of the disaster area. However, the trapped people may not be able to communicate with rescue teams, since some telecommunication infrastructures have already been destroyed by the disaster [2]. In addition, it usually takes a long time, e.g., several days, to repair the destroyed telecommunication infrastructures. In this scenario, a temporary communication network is urgently needed.

The utilization of multiple unmanned aerial vehicles (UAVs) to build an emergent communication network has drawn a lot of attentions, due to unique advantages of UAVs [3], [4], [5]. Benefiting from hardware miniaturization technologies, UAVs are able to be equipped with lightweight base station devices, thus work as aerial base stations to provide wireless communication services in the air [6]. In addition, UAVs are very flexible and can be quickly deployed, which make them desirable in unexpected disaster events [7]. For example, the UAV "Wing Loong" was deployed to provide emergency communications to the trapped people in the disaster zone after a severe flooding in the summer of 2021 at Henan province, China [8]. Furthermore, UAVs are able to offer better wireless communication services in the air, due to their higher height than terrestrial base stations [9].

Considerable efforts have been devoted to the deployment of UAV wireless communication networks. Most of the existing studies assumed that a ground user communicates with a UAV directly [10], [11], [12], [13], [14], [15], [16], [17]. For example, Fig. 1(a) shows that three UAVs are deployed to serve users in the disaster area, where seven users $u_1, u_2, \ldots, u_7$ are within the service area of the three UAVs, while the other three users u_8, u_9, and u_{10} are out of the service area, thus cannot access the Internet.

Note that there may be limited number of available UAVs just after a disaster and they may not be able to serve all users in the disaster area, since the disaster area may be very

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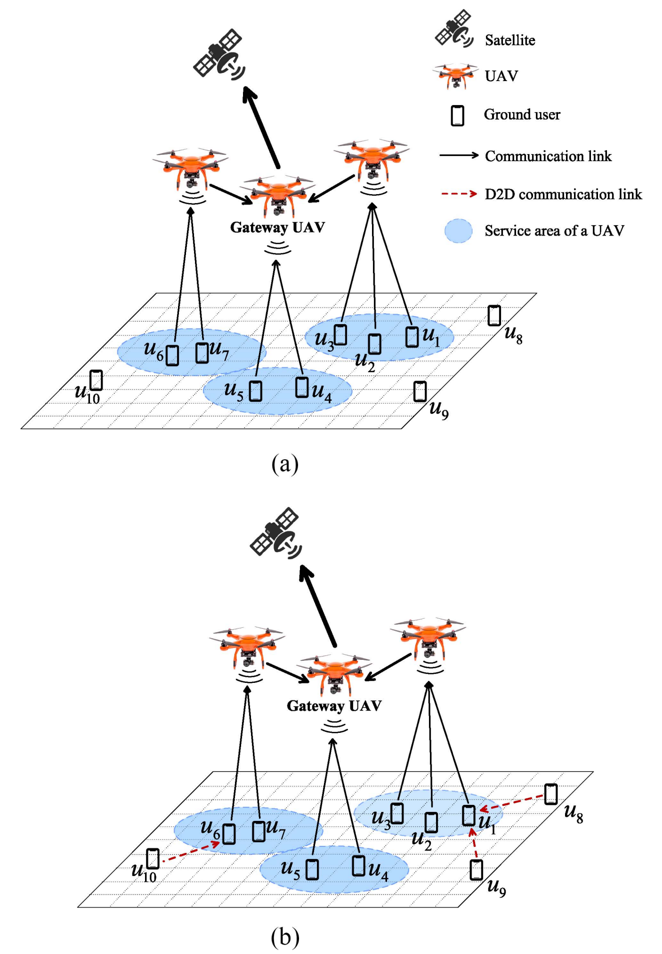


Fig. 1. Comparison between a UAV network without D2D communication and another UAV network with D2D communication. (a) UAV network without D2D communication. (b) UAV network with D2D communication.

large [18]. Moreover, it may take several days to purchase new UAVs and install new base stations on them. Thus, a critical problem is to quickly deploy available UAVs to serve as many users as possible, especially within the first 72 golden hours after a disaster. Then, some users may not be within the communication range of any UAV, and cannot send their information to the rescue team, e.g., see users u_8, u_9, and u_{10} in Fig. 1(a). Then, they may have already lost their lives when the rescue team finds them, as it may take a long time for the rescue team to locate them.

To further improve the coverage of a UAV network and provide communication services to as many users as possible, in this article we introduce the utilization of Device-to-Device (D2D) communication, in which a user having cellular service can serve as a hotspot, e.g., WiFi hotspot, to provide communication services to other users in his/her proximity [19]. For example, Fig. 1(b) shows that user u_1 serves as a hotspot to both users u_8 and u_9, and user u_6 serves as another hotspot to user u_{10}. It can be seen that more users can access the Internet with the D2D communication, and casualties thus can be reduced.

In this article, we study a novel *UAV deployment and resource allocation problem* under the D2D communication model. Specifically, the problem is to deploy K given UAVs in the top of a disaster zone, allocate the bandwidth of each UAV to its served users, allocate the bandwidth of each hotspot to his/her served users, determine the data rate r_j of each user u_j, and find the routing paths for data transmissions, such that the accumulative utility $\sum_{j=1}^{n} \mu(r_j)$ is maximized. The utility $\mu(r_j)$ measures the communication satisfaction of user u_j with a data rate r_j, and the function $\mu(r_j)$ has the diminishing return property that the marginal return of user u_j becomes smaller when his/her data rate r_j is larger [20], e.g., $\mu(r_j) = \log_2(r_j + 1)$. By adopting the utility function, different users have fair communication quality from the UAV network. Otherwise, the users within the transmission ranges of UAVs will have much higher data rates than the other users out of the UAV transmission ranges.

The considered problem poses many challenges.

1) Where to deploy the K UAVs in the air, as there are many candidate hovering locations.
2) Since the total bandwidth of each UAV is limited, which users should be directly served by UAVs and how to allocate the limited bandwidth of UAVs to the users?
3) Which users should act as hotspots and how to allocate the limited hotspot bandwidth to the users that cannot be directly served by UAVs?
4) How to determine the data rate r_j of each user u_j and its routing path such that the accumulative utility is maximized. In this article, we propose a novel $(1 - 1/e - \epsilon)$-approximation algorithm `algMaxUtility` to address the challenges, where e is the base of the natural logarithm, and ϵ is a given constant with $0 < \epsilon < 1 - 1/e$.

Notice that although the D2D communication technique was adopted in the traditional terrestrial cellular networks to extend their wireless coverage [21], [22], since the locations of base stations in the networks are fixed and will not change, existing studies usually considered only the resource allocation and routing problem. In contrast, in a disaster area, the hovering locations of aerial base stations, i.e., UAVs, are unknown, and we need to deploy multiple UAVs in the air, allocate bandwidth resource, and find routing paths. Therefore, existing algorithms for the traditional cellular networks with D2D communication cannot be applied to the problem in this article.

The contributions of this article are summarized as follows.

1) Unlike most existing studies where users communicate with UAVs directly, in this article we introduce D2D communication into the UAV network, such that more users can access the Internet via the relay of hotspot users. We study a novel UAV deployment and resource allocation problem in a UAV network with D2D communication, which is to deploy multiple UAVs, allocate bandwidths of UAVs and hotspots, determine the data rate of each user and find its routing path for data transmission, such that the accumulative utility $\sum_{j=1}^{n} \mu(r_j)$ of all users is maximized.
2) We then devise an approximation algorithm `algMaxUtility` for the problem.

3) Finally, we evaluate the performance of the proposed algorithm through experimental simulations. Experimental results show that accumulative utility by the proposed algorithm is up to 18% larger than those by existing algorithms. In addition, more than 16% users are served in the deployed UAV network by the proposed algorithm.

The remainder of this article is organized as follows. Section II reviews related studies. Section III introduces system models and defines the UAV deployment and resource allocation problem precisely. Section IV proposes a novel approximation algorithm for the problem. Section V evaluates the algorithm performance. Finally, Section VI concludes this article.

II. Related Work

The deployment of UAVs to provide emergent communication services to ground users has received many attentions, when a user communicates with a deployed UAV directly [7], [10], [11], [12], [13], [14], [15], [17], [23]. For example, Xu et al. [23] proposed a $[(1 - 1/e)/\sqrt{K}]$-approximation algorithm for the problem of maximizing the throughput of ground users by deploying a limited number of UAVs, subject to the constraints on the capacity of each UAV and the connectivity of the deployed UAV network. Kimura and Ogura [7] studied a distributed 3-D deployment method which consists of two key parts. They first estimated user density by utilizing data from on-ground sensors. Then, the 3-D position of each UAV is determined by invoking a distributed push-sum algorithm, such that the number of covered users is maximized. Zhao et al. [17] investigated two problems, one is to cover users in a given area with the minimum number of UAVs and the other is to cover as many users as possible by deploying a given number of UAVs while maintaining the connectivity of the UAV network. For the former problem, they first deploy enough UAVs to ensure that each user can be served, followed by removing redundant UAVs. For the latter problem, they designed a distributed control algorithm by considering the distribution of user densities, the safe distance between different UAVs, and the avoidance from obstacles. Mozaffari et al. [14] studied a problem of deploying multiple UAVs to provide the maximum coverage for ground users, by deriving the downlink coverage probability as a function of UAV altitude, transmit power, and antenna gain, assuming that all UAVs use the same carrier frequency. Alzenad et al. [10] studied a problem of finding the service location in the sky for a UAV to cover the maximum number of ground users. They then minimized the transmission power of the UAV, while ensuring the maximum coverage of users. Lyu et al. [13] studied a problem of deploying the minimum number of UAVs to cover a given area without the UAV network connectivity constraint, and solved the problem by a method of spiral deployment. Bor-Yaliniz et al. [11] studied the optimal 3-D placement problem of a single UAV for the maximum throughput of ground users in different scenarios and obtained a near-optimal solution with the help of an interior-point optimizer. Mozaffari et al. [15] investigated a problem of deploying UAVs in the sky and allocating ground users to the deployed UAVs, so that the total transmission power of the UAVs is minimized, while maintaining the minimum data rate requirement of each user. Liu et al. [12] proposed a method based on the deep reinforcement learning (DRL) to dispatch a given number of UAVs to fairly cover users in an area for a period.

We notice only a very few studies that introduce D2D communications into UAV networks, where a user can communicate with a UAV in the air directly, or send his data to another user and the latter user forwards the data to the UAV serving him. Liu et al. [24] considered a scenario in which a single UAV has been deployed in the sky and studied the problem of extending coverage and improving user data rates in UAV networks with multihop D2D communications. They first proposed the shortest-path-routing algorithm to find D2D routing paths for the users out of the communication range of the UAV, then designed an algorithm for maximizing the sum of data rates of source nodes by optimally distributing transmission power of the UAV. Wang et al. [25] studied a problem of optimizing the trajectory of a single UAV and the transmit power of ground devices to maximize network throughput, where the UAV serves a relay between separated devices without direct links while the devices with direct links can communicate with each other (i.e., D2D communication). Zhong et al. [26] extended the study in [25] to the case with multiple UAVs.

Unlike the studies in [24] and [25] that considered only a single UAV, in this article we consider the deployment of multiple UAVs, which is applicable to large-scale disaster areas. On the other hand, although Zhong et al. [26] considered the deployment of multiple UAVs, the users within the communication range of UAVs do not serve as hotspots to other users out of the communication range of any UAV, which however is taken into account in this article. This indicates that more users will be served in the solution delivered by the proposed algorithm in this article.

III. Preliminaries

In this section, we first introduce the network model, then present the channel models, bandwidth allocation strategies, and finally define the problem.

A. Network Model

We consider an area that is being suffered from a natural disaster, e.g., an earthquake or a mudslide, where communication infrastructures may have been destroyed already. The trapped people in the disaster area then are unable to send their information to rescue teams [5]. In this scenario, it is critical for the rescue teams to obtain information of them. A temporary communication network thus needs to be deployed as quickly as possible.

We consider the deployment of multiple UAVs to form an emergent network in the top of the disaster area, which can provide communication services to the ground users [see Fig. 1(b)].

We model the disaster area as a 3-D space with its length L, width W, and height H, e.g., $L = W = 3$ km, $H =$ 500 m.

Assume that there are n ground users $u_1, u_2, \ldots, u_n$ in the disaster area. Let U be the set of the n users, i.e., $U = \{u_1, u_2, \ldots, u_n\}$. Also, assume that the user locations are known, for example, by detection from photographs taken by a UAV with onboard cameras and GPS modules [23], [27]. Denote by $(x_j, y_j, 0)$ the coordinate of a user u_j with $1 \le j \le n$.

Assume that K given UAVs hover at the same optimal hovering altitude h for the maximum coverage area, and most existing studies adopted such an assumption [17], [28], where the value of h can be calculated by the algorithm in [9], e.g., $h = 300$ m. Since there are infinite number of candidate hovering locations for the UAVs at altitude h, for the sake of convenience, we divide the plane h into m equal grids with their side length being γ, e.g., $\gamma = 50$ m, where $m = (L/\gamma) \times (W/\gamma)$, assuming that both the length L and width W of the disaster area are divisible by γ. The center of each grid is considered as a candidate UAV hovering location, and at most one UAV can hover at the grid center to avoid collisions between different UAVs. Denote by $v_1, v_2, \ldots, v_m$ the center locations of the m grids, respectively. The set of candidate UAV hovering locations then is $V = \{v_1, v_2, \ldots, v_m\}$.

In order to access the Internet, assume that one of the K UAVs can communicate with the satellite [29], and the UAV is referred to the *gateway UAV* [see Fig. 1(b)]. The other $(K-1)$ UAVs can connect to the Internet with the relay of the gateway UAV. Once all the UAVs connect to the Internet, they can provide communication services to the ground users. A ground user can access the Internet by directly communicating with a UAV, or via the relay of other ground users, i.e., D2D communications, e.g., WiFi. For example, in Fig. 1(b), user u_1 communicates with a UAV directly, while both users u_8 and u_9 access the Internet via the relay of user u_1.

We assume that the K UAVs are initially co-located at a rescue center close to the disaster area. There is a server located in the rescue center and it can communicate with the gateway UAV by equipping with a wireless module. A UAV scheduling algorithm can first run in the server and the server then sends the hovering locations of different UAVs to the gateway UAV, and the gateway UAV further forwards the hovering locations of other UAVs.

B. Channel Models

In the following, we model the D2D, UAV-to-device, and UAV-to-UAV wireless channels, respectively.

1) Device-to-Device Channel Model: Consider two ground users u_j and u_k, assume that user u_k serves as a D2D hotspot, e.g., WiFi hotspot. The signal-to-noise ratio SNR_{jk} from user u_j to hotspot u_k [31] is modeled as $\mathrm{SNR}_{jk} = [(P_{\mathrm{d2d}}\ g_{\mathrm{d2d}})/P_N](c/[4\pi f_{\mathrm{d2d}}])^2[1/(d_{jk}^{\sigma})]$, where P_{d2d} and g_{d2d} are the transmission power and antenna gain of user u_k for D2D communications, respectively, P_N is the power of the Gaussian white noise, c is the speed of light, f_{d2d} is the radio frequency of the D2D transmission (e.g., $f_{\mathrm{d2d}} = 2.4$ GHz for the WiFi communication [30]), d_{jk} is the Euclidean distance between users u_j and u_k, σ is the path-loss exponent and its typical value is 3. Denote by R_{d2d} the maximum D2D communication distance between two users, e.g., $R_{\mathrm{d2d}} = 50$ m. That is, the two users can communicate with each other, if their distance is no greater than R_{d2d}.

Following the Shannon theory, the link capacity C_{jk}^{d2d} from user u_j to hotspot u_k is

$$C_{jk}^{\mathrm{d2d}} = B_{jk}^{\mathrm{d2d}} \log_2\left(1 + SNR_{jk}\right) \tag{1}$$

where B_{jk}^{d2d} is the bandwidth allocated to u_j by u_k, and the value of B_{jk}^{d2d} is to be determined later. Denote by B_{hotspot} the bandwidth allocated to each hotspot, e.g., $B_{\mathrm{hotspot}} = 20$ MHz [30]. Since each hotspot may serve multiple users, the sum of bandwidths allocated to the users by the hotspot should be no greater than his total bandwidth B_{hotspot}, i.e., $\sum_{u_j \in N_{\mathrm{users}}(u_k)} B_{jk}^{\mathrm{d2d}} \le B_{\mathrm{hotspot}}$, where $N_{\mathrm{users}}(u_k)$ is the set of users served by the hotspot u_k.

2) UAV-to-Device Channel Model: Consider a UAV at a hovering location v_i at altitude h and a ground user u_j. Following the existing study in [9], the path loss between the UAV and the user is a Line-of-Sight (LoS) loss if there are no obstacles between them. Otherwise, the path loss is a Non-Line-of-Sight (NLoS) loss. We can dispatch some UAVs to detect whether there are some obstacles between the UAV and the user, e.g., sending some sample signals, before we deploy a UAV network in the air to serve users. In addition, we can adopt the method used in work [32] to capture the signal strengths between ground users and different UAV hovering locations. We model the channel model under the two scenarios as follows.

On the one hand, if there are no obstacles between the ground user u_j and the UAV at location v_i, then the signal-to-noise ratio $\mathrm{SNR}_{ji}^{\mathrm{LoS}}$ from user u_j to the UAV at location v_i is modeled as $\mathrm{SNR}_{ji}^{\mathrm{LoS}} = [(P_t g_t)/P_N](c/[4\pi f_{\mathrm{uav}} d_{ji}])^2(1/\eta_{\mathrm{LoS}})$, where P_t is the transmission power of the UAV, g_t is the antenna gain, f_{uav} is the radio frequency, e.g., $f_{\mathrm{uav}} = 4.7$ GHz [33], d_{ji} is the Euclidean distance between user u_j and the UAV at location v_i, η_{LoS} is the average shadow fading for the LoS link. Denote by R_{u2d} the maximum communication range between a UAV and a user, e.g., $R_{\mathrm{u2d}} = 800$ m. That is, a user can communicate with a UAV directly, if their Euclidean distance is no greater than R_{u2d}. Following the Shannon theory, the link capacity C_{ji}^{u2d} from user u_j to the UAV hovering at location v_i under the LoS scenario is

$$C_{ji}^{\mathrm{u2d}} = B_{ji}^{\mathrm{u2d}} \log_2\left(1 + \mathrm{SNR}_{ji}^{\mathrm{LoS}}\right) \tag{2}$$

where B_{ji}^{u2d} is the bandwidth allocated to user u_j by the UAV at location v_i, and the value of B_{ji}^{u2d} is to be determined later.

On the other hand, if there are some obstacles between user u_j and the UAV at location v_i, then the wireless link between them experiences NLoS losses. The signal-to-noise ratio $\mathrm{SNR}_{ji}^{\mathrm{NLoS}}$ from user u_j to the UAV at location v_i is modeled as $\mathrm{SNR}_{ji}^{\mathrm{NLoS}} = [(P_t g_t)/P_N](c/[4\pi f_{\mathrm{uav}} d_{ji}])^2(1/\eta_{\mathrm{NLoS}})$, where η_{NLoS} is the average shadow fading for the NLoS link. Notice that the value of η_{NLoS} is much larger than the value of η_{LoS}. For example, the values of η_{NLoS} and η_{LoS} are 20 and 1 dB, respectively, in an urban environment [9]. The link capacity C_{ji}^{u2d} from user u_j to the UAV hovering at location v_i under the NLoS link scenario then is

$$C_{ji}^{\text{u2d}} = B_{ji}^{\text{u2d}} \log_2\left(1 + \text{SNR}_{ji}^{\text{NLoS}}\right). \tag{3}$$

By combining (2) and (3), we have

$$C_{ji}^{\text{u2d}} = \begin{cases} B_{ji}^{\text{u2d}} \log_2\left(1 + \text{SNR}_{ji}^{\text{LoS}}\right), & \text{if the link from user } u_j \text{ to the UAV at location } v_i \text{ is LoS} \\ B_{ji}^{\text{u2d}} \log_2\left(1 + \text{SNR}_{ji}^{\text{NLoS}}\right), & \text{if the link from user } u_j \text{ to the UAV at locations } v_i \text{ is NLoS.} \end{cases} \tag{4}$$

Since each UAV serves multiple ground users, the sum of bandwidths allocated to the users served by the UAV at location v_i should be no greater than its total bandwidth B_{uav}, i.e., $\sum_{u_j \in N_{\text{users}}(v_i)} B_{ji}^{\text{u2d}} \leq B_{\text{uav}}$, where $N_{\text{users}}(v_i)$ is the set of users served by the UAV at location v_i.

3) UAV-to-UAV Channel Model: The UAV-to-UAV channels are mainly dominated by LoS links. Then, the path loss between two UAVs can be modeled as the free-space propagation loss [9]. Denote by R_{uav} the maximum communication range between two UAVs, e.g., $R_{\text{uav}} = 5$ km. That is, two UAVs can communicate with each other if their Euclidean distance is no greater than R_{uav}.

We represent the UAV network as an undirected graph $G = (V \cup U, E)$, where V is the set of candidate UAV hovering locations and U is the set of ground users. In addition, there is an edge (v_i, v_j) in E between two UAV hovering locations v_i and v_j in V if their Euclidean distance is no greater than the maximum UAV communication range R_{uav}, there is an edge (v_i, u_k) in E between a hovering location v_i in V and a user u_k in U if their distance is no greater than their maximum communication range R_{u2d}, and there is an edge (u_k, u_l) in E between two users u_k and u_l in U if their distance is no more than their maximum communication range R_{d2d}.

C. Bandwidth Allocations

Since bandwidth resources are limited, there may be serious interferences among different UAVs and/or among different users, especially when there are a large number of users, we introduce bandwidth allocation strategies as follows.

1) Bandwidth Allocation for Hotspots: On the one hand, it can be seen that if more users serve as hotspots by relaying the data from their nearby users, more users will be served or obtain higher data rates. However, if too many users serve as hotspots, since the wireless bandwidth resources for acting as hotspots may be very limited, two nearby hotspots may use the same spectrum segment, and there will be serious data transmission interferences. In the following, we allocate the available spectrum segments to hotspots such that the number of users served by the hotspots is maximized while ensuring that there are no communication interferences between any two hotspots.

Denote by U' the candidate hotspot set, where a user u_i' is in set U' if its residual energy is no less than a given energy threshold, e.g., 30% of energy.

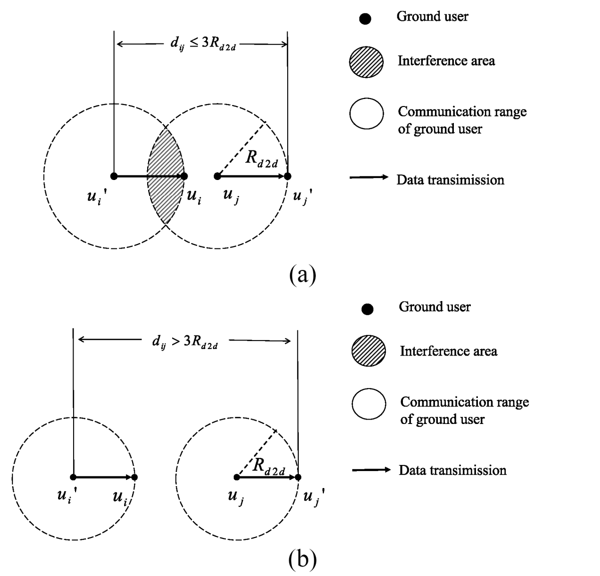


Fig. 2. Interferences elimination between nearby hotspots. (a) Distance between hotspots u_i' and u_j' is no greater than $3R_{\text{d2d}}$. (b) Distance between hotspots u_i' and u_j' is larger than $3R_{\text{d2d}}$.

To eliminate interferences, two close hotspots should use different spectrum segments. For example, Fig. 2(a) shows that two hotspots u_i' and u_j' and their Euclidean distance is less than $3R_{\text{d2d}}$, where hotspot u_i' serves user u_i, hotspot u_j' serves user u_j, and R_{d2d} is the maximum communication range of D2D communication. It can be seen that if hotspots u_i' and u_j' use the same spectrum segment, there are communication interferences at user u_i, when hotspot u_i' sends data to user u_i, and user u_j sends its data to its hotspot u_j', since u_i are within the communication areas of both hotspot u_i' and user u_j at the same time.

On the other hand, we claim that there are no communication interferences between two hotspots u_i' and u_j', even if they use the same spectrum segment, when their Euclidean distance is strictly larger than $3R_{\text{d2d}}$ [see Fig. 2(b)]. We prove the claim in Section 1 of the supplementary file.

To allocate the available spectrum resources to hotspots, we construct an auxiliary graph $G_{hs} = (U' \cup U, E)$, where U' is the set of candidate hotspots with $U' \subseteq U$. There is an edge (u_i', u_j') in E between two candidate hotspots u_i' and u_j', if their Euclidean distance is no greater than $3R_{\text{d2d}}$, where the edge (u_i', u_j') indicates that there may be communication interferences between hotspots u_i' and u_j' if they use the same spectrum segment. In addition, there is an edge (u_i', u_l) in E between a candidate hotspot u_i' in U' and a user u_l in U, if their Euclidean distance is no greater than R_{d2d}, where the edge (u_i', u_l) means that hotspot u_i' can serve user u_l.

Assume that there are q orthogonal spectrum segments $f_1, f_2, \ldots, f_q$ available for the D2D communications, e.g., $q = 3$ orthogonal spectrum segments for the WiFi communications [30]. Consider two users in U', assume that they are chosen as hotspots. It can be seen that they cannot be allocated the same spectrum if they are neighbors in graph G_{hs}; otherwise (they are not neighbors), they can use the same spectrum segment.

We choose the sets of hotspots that use spectrum segments $f_1, f_2, \ldots, f_q$ one by one. We first choose a subset U_1^{hs} of users in U' that serve as hotspots and they use the first spectrum segment f_1. We use a greedy strategy to find the subset U_1^{hs} as follows. Initially, $U_1^{hs} = \emptyset$. We find a candidate user u_i' in $U' \setminus U_1^{hs}$ such that it is not a neighbor of any node in U_1^{hs} and the number of increased served users is maximized. We then add user u_i' to U_1^{hs} and remove the users served by u_i' from graph G_{hs}. We continue the procedure until every node in $U' \setminus U_1^{hs}$ is a neighbor of some node in U_1^{hs}. Having obtained the subset U_1^{hs}, we remove the nodes in U_1^{hs} and their incident edges from graph G_{hs}. The findings of subsets $U_2^{hs}, U_3^{hs}, \ldots, U_q^{hs}$ for spectrum segments $f_2, f_3, \ldots, f_q$ are similar to that of U_1^{hs}, omitted. Denote by U^{hs} the set of hotspot users, i.e., $U^{hs} = \bigcup_{j=1}^{q} U_j^{hs}$. Let n_{hs} be the number of hotspots, i.e., $n_{hs} = |U^{hs}|$.

We notice that the energy consumption of a hotspot user may be larger than that of a nonhotspot user, due to larger network traffic. Then, a user can serve as a hotspot if his residual energy is no less than a given energy threshold, e.g., 30% of energy. On the other hand, when the residual energy of a hotspot user falls below the energy threshold, he becomes a nonhotspot user. We can rechoose the set of hotspot users and invoke the proposed algorithm to redeploy UAVs and reallocate bandwidth resource.

2) Bandwidth Allocation for UAVs: Following existing studies [28], assume that the orthogonal frequency-division multiple access (OFDMA) technique is adopted and different UAVs use different spectrum segments, due to the rich bandwidth resource in 5G and beyond. Denote by B_{uav} the bandwidth available for each UAV. Following the 3GPP standard, $B_{\text{uav}} = 50$ MHz [33].

Table I lists the notations used in this article.

TABLE I
NOTATIONS AND THEIR DESCRIPTIONS

Notations	Descriptions
U	the set of n users $u_1, u_2, \ldots, u_n$
K	the number of UAVs
h	the hovering altitude of the K UAVs
V	the set of m candidate hovering locations $v_1, v_2, \ldots, v_m$ in the air
S	the set of hovering locations for the K UAVs
SNR_{jk}	the signal-to-noise ratio from user u_j to hotspot u_k
B_{jk}^{d2d}	the bandwidth allocated to user u_j by hotspot u_k
C_{jk}^{d2d}	the link capacity from user u_j to hotspot u_k
R_{d2d}	the maximum communication distance between a user and a hotspot
$B_{hotspot}$	the total bandwidth of each hotspot
SNR_{ji}^{LoS}	the signal-to-noise ratio from user u_j to the UAV at location v_i if the link is LoS
SNR_{ji}^{NLoS}	the signal-to-noise ratio from user u_j to the UAV at location v_i if the link is NLoS
B_{ji}^{u2d}	the bandwidth allocated to user u_j by the UAV at location v_i
C_{ji}^{u2d}	the link capacity from user u_j to the UAV hovering at location v_i
R_{u2d}	the maximum communication range between a UAV and a user
B_{uav}	the total bandwidth of each UAV
R_{uav}	the maximum communication range between two UAVs in the air
$U' (\subseteq U)$	the set of users whose amounts of residual energy are no less than a given energy threshold
q	the number of spectrum segments $f_1, f_2, \ldots, f_q$ for D2D communications
U_j^{hs}	the set of hotspots that use spectrum segment f_j
U^{hs}	the set of hotspots, i.e., $U^{hs} = \cup_{j=1}^{q} U_j^{hs}$
r_j	the data rate of user u_j
$\mu(r_j)$	the utility of user u_j with a data rate r_j
$N_{users}(v_i/u_k)$	the set of users within the communication range of the UAV at v_i or hotspot u_k
$N_{hotspots}(u_j)$	the set of hotspots within the communication range of user u_j
$N_{uav}(u_j)$	the set of UAVs within the communication range of user u_j
f_{ji} (or f_{jk})	the sum of data rates in the link from user u_j to the UAV at location v_i (or hotspot u_k)

D. Problem Definition

In this article, we consider the deployment of a UAV network to provide communication services to ground users in a disaster area. Since the bandwidth resources for communications are limited, some users have good wireless communication quality with some UAVs, e.g., LoS links, while the other users experience poor communication quality due to long distances to the UAVs or obstacles between the users and the UAVs. However, it is important to provide good communication services to all users, since every user is urgent to send his/her data to the rescue teams.

To measure the communication satisfaction of each user u_j, we introduce a utility function $\mu(r_j)$, which is defined as an increasing, twice-differentiable and strictly concave function, where r_j is the data rate of user u_j to be determined. For example, $\mu(r_j) = \log_2(r_j+1)$ [34]. The utility function characterizes the diminishing return property, which means that the marginal return of user u_j becomes smaller when his/her data rate r_j is larger [20]. The accumulative utility of all ground users then is $\sum_{j=1}^{n} \mu(r_j)$.

In this article, we consider a *UAV deployment and resource allocation problem*, which is to deploy K UAVs in the top of a disaster zone, allocate the bandwidth of each UAV to its served users, allocate the bandwidth of each hotspot to his/her served users, determine the data rate r_j of each user u_j, and find routing paths for data transmissions, such that the accumulative utility $\sum_{j=1}^{n} \mu(r_j)$ is maximized. This is, the objective is to

$$\text{maximize} \quad \sum_{j=1}^{n} \mu(r_j) \tag{5}$$

subject to the following constraints.

1) Find K hovering locations in V to deploy the K UAVs, respectively.
2) The sum of bandwidth allocated to users by each deployed UAV at location v_i is no greater than its total available bandwidth B_{uav}, i.e., $\sum_{u_j \in N_{\text{users}}(v_i)} B_{ji}^{\text{u2d}} \leq B_{\text{uav}}$.

3) The sum of bandwidth allocated to users by each hotspot u_k is no greater than his/her total bandwidth B_{hotspot}, i.e., $\sum_{u_j \in N_{\text{users}}(u_k)} B_{jk}^{\text{d2d}} \leq B_{\text{hotspot}}$, where $u_k \in U^{hs}$.
4) The sum of data rates in each link from a user u_j to a UAV at location v_i is no more than the link capacity between them, i.e., $f_{ji} \leq C_{ji}^{\text{u2d}}$.
5) The sum of data rates in each link from user u_j to hotspot u_k is no more than the link capacity, i.e., $f_{jk} \leq C_{jk}^{\text{d2d}}$.
6) The flow reservation constrains that the sum of data rates transmitted by each user u_j is equal to the sum of data rates received by the user u_j plus its data rate r_j, i.e., $\sum_{u_k \in N_{\text{hotspots}}(u_j)} f_{jk} + \sum_{v_i \in N_{\text{uav}}(u_j)} f_{ji} = \sum_{u_k \in N_{\text{users}}(u_j)} f_{kj} + r_j$, where $N_{\text{hotspots}}(u_j)$ is the set of hotspots providing service to user u_j and $N_{\text{uav}}(u_j)$ is the set of UAVs providing service to u_j.

Notice that the variables in the problem include: the hovering locations of the K UAVs; the bandwidth B_{ji}^{u2d} allocated to a user u_j by the UAV at each location v_i; the bandwidth B_{ji}^{d2d} allocated to a user u_j by each hotspot u_i; the data rate r_j of user u_j; the sum f_{jk} of data rates transmitted by each user u_j to another user u_k or the UAV at location v_k.

Lemma 1: The UAV deployment and resource allocation problem is NP-hard.

Proof: The proof is contained in Section 2 of the supplementary file. ■

IV. Approximation Algorithm

In this section, we propose an approximation algorithm `algMaxUtility` for the UAV deployment and resource allocation problem.

Since the UAV deployment and resource allocation problem considered in this article is complicated, we first consider a simpler problem, in which we assume the set S of hovering locations for UAVs have already been found and $m_S (= |S|)$ UAVs have already been deployed at the hovering locations in S, respectively, where $m_S \leq K$. We focus on the resource allocation problem in Section IV-A and propose a near-optimal algorithm for it. On the other hand, in Section IV-B, we remove the assumption that the UAV hovering locations have already been found and devise an approximation algorithm for the original problem. Notice that the algorithm in Section IV-A serves as subroutine of the algorithm in Section IV-B.

A. Near-Optimal Algorithm for the Resource Allocation Problem

Given a set S of hovering locations, let $m_S = |S|$ with $m_S \leq K$. We assume that N_S UAVs have already been deployed at the hovering locations in S, respectively. We consider the resource allocation problem in this section, which is to allocate the bandwidth of each UAV to its served users, allocate the bandwidth of each hotspot to his/her served users, determine the data rate r_j of each user u_j, and find the routing path for the data transmission of each user u_j, such that the accumulative utility $\sum_{j=1}^{n} \mu(r_j)$ is maximized.

The basic idea behind the proposed algorithm for the problem is that we formulate the problem as a convex optimization problem. Then, a near-optimal solution to the convex optimization problem returns a near-optimal solution to the problem.

Denote by x_{ji} the fraction of bandwidth allocated to a user u_j by the UAV at a hovering location v_i in S, where $0 \leq x_{ji} \leq 1$. Then, the bandwidth B_{ji}^{u2d} allocated to user u_j by the UAV at hovering location v_i is $B_{ji}^{\text{u2d}} = x_{ji} \cdot B_{\text{uav}}$, where B_{uav} is the total bandwidth of each UAV. Similarly, denote by y_{jk} the fraction of bandwidth allocated to a user u_j by a hotspot u_k, where $0 \leq y_{jk} \leq 1$. Then, the bandwidth B_{jk}^{d2d} allocated to user u_j by hotspot u_k is $B_{jk}^{\text{d2d}} = y_{jk} \cdot B_{\text{hotspot}}$, where B_{hotspot} is the total bandwidth of each hotspot. Recall that r_j represents the data rate of each user u_j, and f_{jk} represents the sum of data rates transmitted from user u_j to another hotspot user u_k or the UAV at location v_k. We formulate the resource allocation problem as follows:

$$\textbf{P1:} \quad \max_{x_{ji},\, y_{jk},\, r_j,\, f_{jk}} \sum_{j=1}^{n} \mu(r_j) \tag{6}$$

subject to the following constraints:

$$\sum_{u_j \in N_{\text{users}}(v_i)} x_{ji} \leq 1, \qquad 1 \leq i \leq m_S \tag{7}$$
$$\sum_{u_j \in N_{\text{users}}(u_k)} y_{jk} \leq 1, \qquad 1 \leq k \leq n_{hs} \tag{8}$$
$$f_{ji} \leq C_{ji}^{\text{u2d}}, \qquad 1 \leq j \leq n,\ 1 \leq i \leq m_S \tag{9}$$
$$f_{jk} \leq C_{jk}^{\text{d2d}}, \qquad 1 \leq j \leq n,\ 1 \leq k \leq n_{hs} \tag{10}$$
$$r_j + \sum_{u_k \in N_{\text{users}}(u_j)} f_{kj} = \sum_{u_k \in N_{\text{hotspots}}(u_j)} f_{jk} + \sum_{v_i \in N_{\text{uav}}(u_j)} f_{ji}, \quad 1 \leq j \leq n \tag{11}$$
$$\sum_{v_i \in N_{\text{uav}}(u_j)} x_{ji} + \sum_{u_k \in N_{\text{hotspots}}(u_j)} y_{jk} \leq 1, \quad 1 \leq j \leq n \tag{12}$$
$$0 \leq x_{ji} \leq 1, \quad 1 \leq j \leq n,\ 1 \leq i \leq m_S \tag{13}$$
$$0 \leq y_{jk} \leq 1, \quad 1 \leq j \leq n,\ 1 \leq k \leq n_{hs} \tag{14}$$
$$r_j \geq 0, \quad 1 \leq j \leq n \tag{15}$$
$$f_{ji} \geq 0, \quad 1 \leq j \leq n,\ 1 \leq i \leq m_S \tag{16}$$
$$f_{jk} \geq 0, \quad 1 \leq j \leq n,\ 1 \leq k \leq n_{hs} \tag{17}$$

where (7) ensures that the sum of allocated bandwidth by the UAV at each location v_i to the users within its communication range $N_{\text{users}}(v_i)$ is no greater than its total bandwidth; (8) ensures that the sum of allocated bandwidth by each hotspot user u_k to the users within its communication range $N_{\text{users}}(u_k)$ is no greater than its total bandwidth; (9) ensures that the sum f_{ji} of data rates from user u_j to the UAV at location v_i is no more than the link capacity C_{ji}^{u2d}; (10) ensures that the sum f_{jk} of data rates between user u_j and hotspot u_k is no more than the link capacity C_{jk}^{d2d}; (11) indicates the flow reservation; and (12) implies that each user u_j cannot transmit its data to a UAV base station and a hotspot simultaneously, but be able to transmit in a time-division way.

It can be seen that the functions in (7)–(17) are linear, thus convex. However, the objective function in (6) is not convex, since function $\mu(.)$ is concave. We transform problem **P1** into

Algorithm 1 Near-Optimal Algorithm for the Resource Allocation Problem

Input: $|S|$ deployed UAVs in the air, n users $u_1, u_2, \ldots, u_n$ in U, a set U^{hs} of hotspot users with $U^{hs} \subseteq U$, the total bandwidth B_{uav} of each UAV, the total bandwidth B_{hotspot} of each hotspot, and an additive error $\alpha > 0$

Output: the fraction x_{ji} of bandwidth allocated to user u_j by the UAV at location v_i in S, the fraction y_{jk} of bandwidth allocated to user u_j by hotspot user u_k, the data rate r_j for each user v_j, and the transmission rate f_{jk} of each link, such that accumulative utility of all users is maximized.

1: Transform the original resource allocation problem **P1** into another convex optimization problem **P2**;
2: Obtain near-optimal values of x_{ij}, y_{kj}, data rate r_j, and transmission rate f_{jk} for problem **P2** by applying **CVXPY**;
3: **return** the values of x_{ji}, y_{jk}, data rate r_j of each user u_j, the transmission rate f_{jk} of each link, and the accumulative utility $\sum_{j=1}^{n} \mu(r_j)$.

another convex optimization problem **P2**

$$\textbf{P2:} \quad \min_{x_{ji},\ y_{jk},\ r_j,\ f_{jk}} \quad -\sum_{j=1}^{n} \mu\left(r_j\right) \tag{18}$$

subject to (7)–(17). Then, the objective function in problem **P2** is convex. In addition, the optimal solutions to problems **P1** and **P2** are identical, So it is a convex optimization problem with continuous variables. Following the study in [35], we can find a near-optimal solution to a convex optimization problem. Specifically, given a constant α with $\alpha > 0$, the algorithm in [35] finds a solution to the resource allocation problem **P1** such that the total utility of the solution is no more than α smaller than the maximum utility. The algorithm may be implemented with the help of a Python toolkit *CVXPY*, which adopts the interior-point method. The detailed algorithm is described in Algorithm 1.

B. Algorithm for the UAV Deployment and Resource Allocation Problem

We now remove the assumption that UAVs have been deployed and consider the original UAV deployment and resource allocation problem. The basic idea behind the proposed algorithm is to deploy the K UAVs in a greedy way, which is elaborated as follows.

Assume that the hovering locations $v_1, v_2, \ldots, v_k$ of k UAVs have been found. Let S_k be the set of the k hovering locations, i.e., $S_k = \{v_1, v_2, \ldots, v_k\}$. Initially, $k = 0$. The hovering location v_{k+1} of the $(k+1)$th UAV will be found in a greedy way. Specifically, for each candidate hovering location v_l in $V \setminus S_k$ with a nonempty set of ground users within the communication range of v_l, denote by $g(S_k \cup \{v_l\})$ the optimal accumulative utility by deploying $k+1$ UAVs in $S_k \cup \{v_l\}$. Also, denote by $\hat{g}(S_k \cup \{v_l\})$ the near-optimal accumulative utility by deploying the $k+1$ UAVs in $S_k \cup \{v_l\}$ with a given additive error α_{k+1}, which can be calculated by invoking Algorithm 1, where the value of α_{k+1} will be determined later. It can be seen that

$$g(S_k \cup \{v_l\}) \ \geq \ \hat{g}(S_k \cup \{v_l\}) \ \geq \ g(S_k \cup \{v_l\}) - \alpha_{k+1}. \tag{19}$$

The $(k+1)$th hovering location v_{k+1} then is a candidate hovering location v_l such that its accumulative utility $\hat{g}(S_k \cup \{v_l\})$ is maximized, i.e., $v_{k+1} = \arg\max_{v_l \in V \setminus S_k, N_{\text{users}}(v_l) \neq \emptyset} \{\hat{g}(S_k \cup \{v_l\})\}$, where $N_{\text{users}}(v_l)$ is the set of ground of users within the communication range of the UAV at hovering location v_l. The procedure continues until a set $S (= S_K)$ of K hovering locations is found.

We now discuss the value of α_{k+1}, where $1 \leq k+1 \leq K$. Given a multiplicative error ϵ with $0 < \epsilon < 1 - 1/e$, let $\delta = (\epsilon/[(K+1)(1-1/e)])$. We start by discussing the value of α_1, where $k = 0$. Notice that, for each candidate hovering location v_l, there is a ground user u_j within its communication range. Then, the optimal accumulative utility $g(\{v_l\})$ is no less than the utility of user u_j when the total bandwidth B_{uav} of the UAV at location v_l is allocated to user u_j. Therefore, $g(\{v_l\}) \geq \mu(r_{\min})$, where $r_{\min}$ is the minimum data rate of any user within the communication range of a UAV, and $\mu(r_{\min})$ is the utility with data rate $r_{\min}$. Let $\alpha_1 = \delta \cdot \mu(r_{\min})$. On the other hand, for $k > 0$, the value of α_{k+1} is set as $\alpha_{k+1} = \delta \cdot \hat{g}(S_k)$.

There is an important property for the settings of α_{k+1}. That is, for each k with $k = 0, 1, \ldots, K-1$, we have

$$g(S_k \cup \{v_l\}) \ \geq \ \hat{g}(S_k \cup \{v_l\}) \ \geq \ (1-\delta) \cdot g(S_k \cup \{v_l\}). \tag{20}$$

Specifically, following (22), we have

$$\begin{aligned} g(\{v_l\}) \geq \hat{g}(\{v_l\}) \ &\geq \ g(\{v_l\}) - \alpha_1 \\ &= g(\{v_l\}) - \delta \cdot \mu(r_{\min}) \\ &\geq g(\{v_l\}) - \delta \cdot g(\{v_l\}), \ \text{ as } \mu(r_{\min}) \leq g(\{v_l\}) \\ &= (1-\delta) \cdot g(\{v_l\}). \end{aligned} \tag{21}$$

We later show that the optimal utility $g(S_k)$ by deploying k UAVs at locations in S_k is no greater than the optimal utility $g(S_k \cup \{v_l\})$ by deploying $k+1$ UAVs at locations in $S_k \cup \{v_l\}$, i.e., $g(S_k) \leq g(S_k \cup \{v_l\})$. Then, following (22), we have

$$\begin{aligned} g(S_k \cup \{v_l\}) &\geq \hat{g}(S_k \cup \{v_l\}) \\ &\geq g(S_k \cup \{v_l\}) - \alpha_{k+1} \\ &= g(S_k \cup \{v_l\}) - \delta \cdot \hat{g}(S_k) \\ &\geq g(S_k \cup \{v_l\}) - \delta \cdot g(S_k), \ \text{ as } \hat{g}(S_k) \leq g(S_k) \\ &\geq g(S_k \cup \{v_l\}) - \delta \cdot g(S_k \cup \{v_l\}) \\ &= (1-\delta) \cdot g(S_k \cup \{v_l\}). \end{aligned} \tag{22}$$

This indicates that (20) holds.

The detailed algorithm for the UAV deployment and resource allocation problem is presented in Algorithm 1.

Notice that the people trapped in a disaster are likely to move around [36], [37]. We have proposed a solution to address the mobility issue in our recent work [23].

C. Algorithm Analysis

Theorem 1: Given K UAVs, a set V of candidate hovering locations, a set U of n users $u_1, u_2, \ldots, u_n$, a set U^{hs} of hotspot users with $U^{hs} \subseteq U$, the total bandwidth B_{uav} of each UAV, the total bandwidth B_{hotspot} of each hotspot, there is a $(1 - 1/e - \epsilon)$-approximation algorithm, i.e., Algorithm 2, for the UAV deployment and resource allocation problem, where ϵ is

Algorithm 2 Algorithm `algMaxUtility` for the UAV Deployment and Resource Allocation Problem

Input: K UAVs, a set V of candidate hovering locations, a set U of n users $u_1, u_2, \ldots, u_n$, a set U^{hs} of hotspot users with $U^{hs} \subseteq U$, the total bandwidth B_{uav} of each UAV, the total bandwidth B_{hotspot} of each hotspot, and a multiplicative error ϵ with $0 < \epsilon < 1 - 1/e$

Output: a set S of K hovering locations for the UAVs, the fraction x_{ij} of bandwidth allocated to user u_j by the UAV at location v_i in S, the fraction y_{kj} of bandwidth allocated to user u_j by hotspot user u_k, the data rate r_j for each user v_j, and the transmission rate f_{jk} of each link, such that accumulative utility of all users is maximized.

Let $S \leftarrow \emptyset$;
Let $\delta \leftarrow \frac{\epsilon}{(K+1)(1-1/e)}$;
Let $\alpha_1 \leftarrow \delta \cdot \mu(r_{\min})$;
for $k \leftarrow 1$ to K **do**
  For each candidate hovering location v_l in $V \setminus S$ with a non-empty set of ground users within the communication range of v_l, calculate values of x_{ji}, y_{jk}, data rate r_j of each user u_j, the transmission rate f_{jk} of each link, and the near-optimal accumulative utility $\hat{g}(S \cup \{v_l\})$, if k UAVs are deployed at hovering locations in $S \cup \{v_l\}$, by invoking `Algorithm 1` with the additive error α_k;
  Let $v_k = \arg\max_{v_l \in V \setminus S, N_{\text{users}}(v_l) \neq \emptyset} \{\hat{g}(S \cup \{v_l\})\}$;
  Let $S \leftarrow S \cup \{v_k\}$;
  Let $\alpha_{k+1} \leftarrow \delta \cdot \hat{g}(S)$;
end for
return the set S of K hovering locations, the values of x_{ij}, y_{kj}, data rate r_j of each user u_j, the transmission rate f_{jk} of each link, and the accumulative utility $\hat{g}(S)$ by deploying K UAVs at locations in S.

a given constant with $0 < \epsilon < 1 - 1/e$, and e is the base of the natural logarithm.

Proof: The proof is contained in Section 3 of the supplementary file. ■

V. Performance Evaluation

In this section, we study the performance of the proposed algorithm by comparing it with existing studies.

A. Experimental Environment

We consider a 3-D disaster area, and the length, width, and height of the area are 2 km, 2 km, and 500 m, respectively. The number n of users in the area is from 500 to 3000, and the human density follows the fat-tailed distribution [23], [38]. Fig. 3 shows a distribution example with 500 users.

The number K of to-be-deployed UAVs varies from 2 to 10. The transmission power P_t of each UAV is 10 W, the antenna gain g_t is 5 dB, the power of Gaussian white noise P_N is -105 dB, and the maximum communication range R_{u2d} between a UAV and a ground user is 500 m [4]. In addition, following the 3GPP standard, the total bandwidth B_{uav} of each UAV is 50 MHz [33]. Furthermore, the average shadow fadings for LoS and NLoS links are $\eta_{\text{LoS}} = 1$ dB

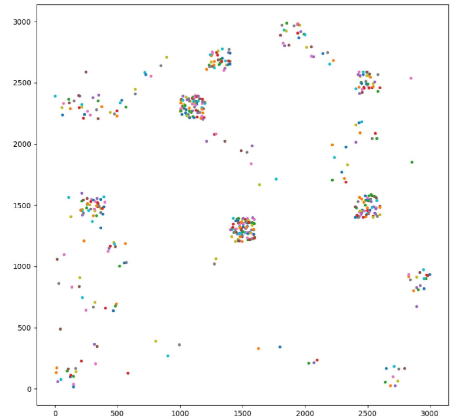


Fig. 3. There are 500 users distributed in a disaster area, and human density follows the fat-tailed distribution.

and $\eta_{\text{NLoS}} = 20$ dB, respectively [9]. Finally, the LoS probability of a user u_j served by a UAV at location v_i is $p_{ij}^{\text{LoS}} = (1/[1 + a \cdot \exp(-b(\theta - a))])$, where $a = 9.611725$, $b = 0.156082$, and θ is the elevation angle of user u_j for the UAV location v_i at altitude $h = 300$ m [9].

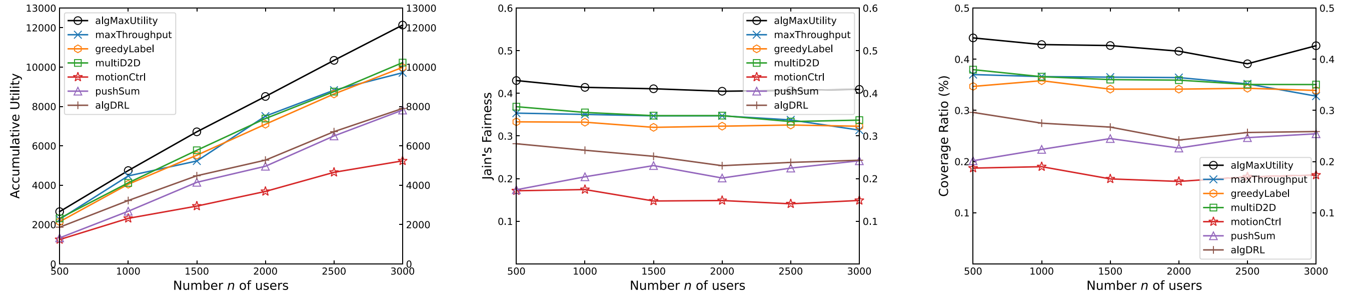
Recall that some users communicate with UAVs by the relay of hotspots, i.e., D2D communications. The transmission power P_{d2d} of each hotspot is 0.1 W, the antenna gain g_{d2d} is 10 dB, and the maximum transmission range of D2D communications is 50 m [15], [39]. Also, the total bandwidth of each hotspot is 20 MHz, respectively [30].

B. Benchmark Algorithms

To evaluate the performance of the proposed algorithm `algMaxUtility`, we consider five benchmark algorithms as follows.

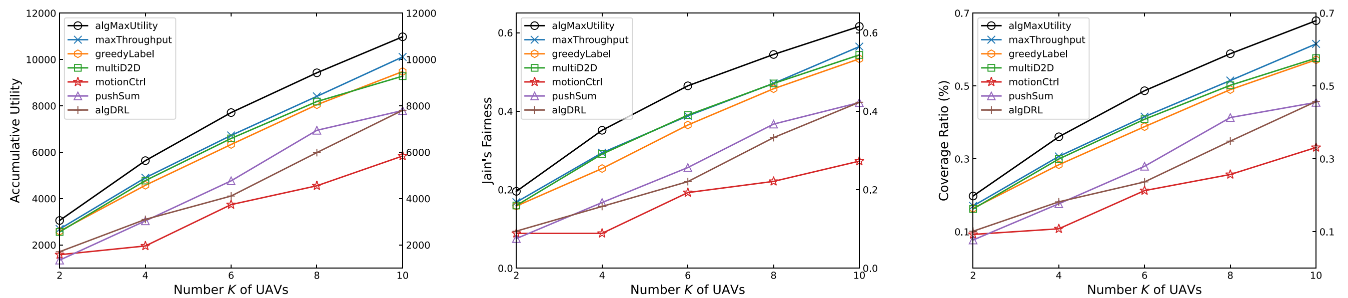
1) Algorithm `maxThroughput` [23] finds a $[(1 - 1/e)/\sqrt{K}]$-approximation solution to a problem of placing K UAVs, so that the network throughput, i.e., the sum of user data rates, is maximized.
2) Algorithm `greedyLabel` [40] first assigns each candidate hovering location a profit in a greedy way, then deploys a network with K UAVs, such that the sum of profits in the network is maximized.
3) Algorithm `multiD2D` [24] first uniformly deploys K UAVs in the top of the disaster area, then delivers a solution to assign the UAV transmission power to each user so that the sum of data rate is maximized, where a user out of the communication range of any UAV sends his data via a route with a minimum outage probability to another user served by a UAV.
4) Algorithm `motionCtrl` [17] proposes a motion control solution to cover the maximum number of users by deploying K UAVs.
5) Algorithm `pushSum` [7] proposes a distributed 3-D-deployment for downlinks to maximize the number of covered users by the deployed UAVs.
6) Algorithm `algDRL` [41] finds the hovering locations of the K UAVs by using the DRL.

Notice that the algorithms are implemented by the programming language Python 3.9, and all experiments are run on a



(a) (b) (c)

Fig. 4. Performance of different algorithms by increasing the number of to-be-served users n from 500 to 3000, when the number of UAVs $K = 5$ and the maximum communication range between a UAV and a ground is $R_{\text{u2d}} = 500$ m. (a) Accumulative utility. (b) Jain's fairness index. (c) Coverage ratio.



(a) (b) (c)

Fig. 5. Performance of different algorithms by varying the number K of UAVs from 2 to 10, when there are $n = 1500$ to-be-served users. (a) Accumulative utility. (b) Jain's fairness index. (c) Coverage ratio.

powerful server, which consists of an AMD Ryzen 7 5800X CPU with 8 cores and each core has a maximum turbo frequency of 3.8 GHz.

C. Performance Metrics

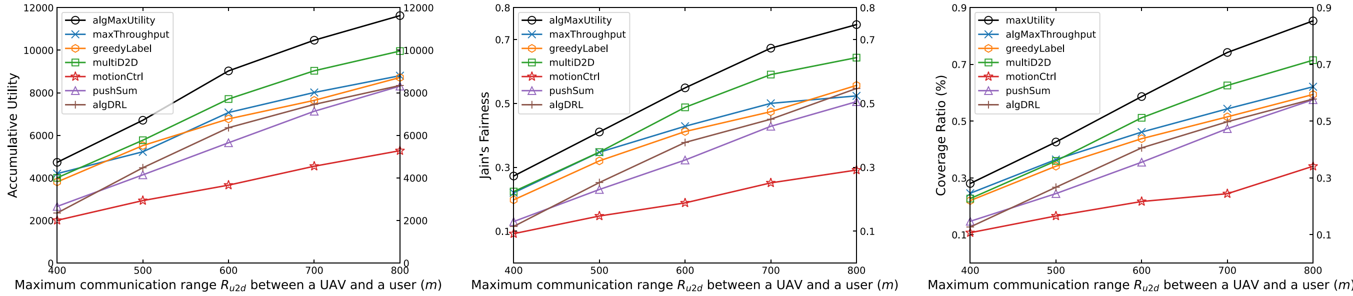
Assume that the data rates of the n users $u_1, u_2, \ldots, u_n$ in the disaster area are $r_1, r_2, \ldots, r_n$ in a deployed UAV network. Notice that the data rate of some users may be zero. To ensure that different users have *fair* communication service in the deployed UAV network, we use three different metrics to measure the performance of different algorithms: accumulative user utility, Jain's fairness index, and coverage ratio, which are defined as follows.

1) The *accumulative utility* of all users is $\sum_{j=1}^{n} \mu(r_j)$, where $\mu(r_j)$ is the utility of user u_j with a data rate r_j and $\mu(r_j) = \log_2(r_j + 1)$ [34].
2) The *Jain's fairness index* of the n users is defined as $([(\sum_{j=1}^{n} r_j)^2]/[n \cdot \sum_{j=1}^{n} r_j^2])$. It can be seen that the value of the index ranges from zero to one, and the value is one when the data rates of different users are equal.
3) The *coverage ratio* of the deployed UAV network is the ratio of the number of served users to the total number n of users in the disaster area.

D. Algorithm Performance

We first evaluate the algorithm performance by varying the number n of to-be-served users from 500 to 3000, when the number of UAVs is $K = 5$ and the maximum communication range between a UAV and a ground user is $R_{\text{u2d}} = 500$ m. Fig. 4(a) shows that the accumulative utility of all users by the proposed algorithm `algMaxUtility` is the largest one among the seven algorithms, which is about from 6% to 18% larger than those by the other six algorithms. For example, the accumulative utilities by the best two algorithms `algMaxUtility` and `MultiD2D` are about 12 100 and 10 200, respectively, when there are $n = 3000$ users in the disaster area. Fig. 4(a) also plots that the accumulative utility by each of the seven algorithms increases with the growth of the number n of to-be-served users, since the user density is larger and more users are within the coverage area of the deployed UAV network. Fig. 4(b) shows that the value of the Jain's fairness index by algorithm `algMaxUtility` is the largest one, which is about 18% larger than those by the other six algorithms. Furthermore, Fig. 4(c) demonstrates that more than 16% users are served in the deployed UAV network by algorithm `algMaxUtility` than the other six algorithms.

We then investigate the performance of different algorithms by varying the number K of UAVs from 2 to 10, when there are $n = 1500$ to-be-served users and the maximum communication range between a UAV and a ground is $R_{\text{u2d}} = 500$ m. Fig. 5(a) shows that the accumulative utility by each of the seven algorithms increases when more UAVs are deployed, as more users can be served. Fig. 5(a) also shows that the utility by algorithm `algMaxUtility` is from 10% to 18% larger than those by the other six algorithms. For example, the utility by algorithm `algMaxUtility` is 5600, while the utility by the other six algorithms is no greater than 4900, when $K = 4$ UAVs are deployed. Fig. 5(b) illustrates that the values of Jain's fairness index by different algorithms increase with



(a) (b) (c)

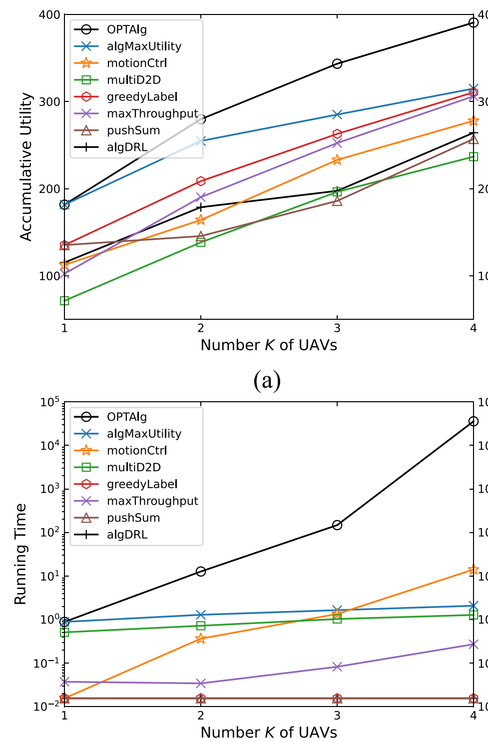
Fig. 6. Performance of different algorithms by increasing the maximum communication range R_{u2d} between a UAV and a ground user from 400 to 800 m, when $K = 5$ and $n = 1500$. (a) Accumulative utility. (b) Jain's fairness index. (c) Coverage ratio.

the growth of the number K of deployed UAVs, since more users are served by the deployed UAV network when K grows. Fig. 5(b) also plots that the value of the Jain's fairness index by algorithm `algMaxUtility` is at least 9% larger than those by the other algorithms. In addition, Fig. 5(c) demonstrates that the coverage ratio by algorithm `algMaxUtility` is about 11% larger than the other six algorithms. For example, the coverage ratios by algorithms `algMaxUtility`, `maxThroughput`, `multiD2D`, `greedyLabel`, `algDRL`, `pushSum`, and `motionCtrl` are 68%, 61%, 58%, 57%, 46%, 45%, and 33%, respectively, when $K = 10$ UAVs are deployed.

We finally study the performance of different algorithms by varying the maximum communication range R_{u2d} between a UAV in the air and a ground user from 400 to 800 m, when there are $K = 5$ UAVs and $n = 1500$ to-be-served users in the disaster area. Fig. 6(a) illustrates that the accumulative utilities by different algorithms increase with the increase of the R_{u2d}, since more users can be served when the maximum communication range R_{u2d} between a UAV and a ground user is larger, and the accumulative utility by algorithm `algMaxUtility` is from 12.5% to 17% larger than those by the other six algorithms. For example, the accumulative utilities by algorithms `algMaxUtility`, `multiD2D`, `maxThroughput`, `greedyLabel`, `algDRL`, `pushSum`, and `motionCtrl` are about 11 600, 9900, 8800, 8700, 8300, 8300, and 5300, respectively, when the maximum communication range R_{u2d} is 800 m. Fig. 6(b) shows that the value of Jain's fairness index by algorithm `algMaxUtility` is about 16.5% larger than those by the other six algorithms. In addition, Fig. 6(c) plots that more than 13% users are served by the deployed UAV network in the solution delivered by algorithm `algMaxUtility` than those by the other six algorithms.

E. Verification of the Theoretical Approximation Ratio

Recall that in Theorem 1 of Section IV-C, we showed that the theoretical approximation ratio of the proposed algorithm `algMaxUtility` is $1 - 1/e - \epsilon$, where e is the base of the natural logarithm and ϵ is a given constant with $0 < \epsilon < 1 - 1/e$, e.g., $\epsilon = 0.1$. Then, $1 - 1/e - \epsilon = 0.532$ with $\epsilon = 0.1$. To verify the theoretical approximation ratio, we compare with an optimal algorithm `OPTAlg`, which enumerates all possible hovering locations of the K UAVs. Fig. 7 shows the performance of different algorithms in a small network, by varying the number K of UAVs from 1 to 4, where there are only 100 users in a 500 m × 500 m disaster area. Fig. 7(a) demonstrates that the empirical approximation ratio of the accumulative utility by algorithm `algMaxUtility` to the one by the optimal algorithm `OPTAlg` is at least 0.8, which is much larger than its theoretical counterpart 0.532. This indicates that the theoretical approximation ratio 0.532 is very conservative. On the other hand, Fig. 7(b) shows that the running time of the optimal algorithm `OPTAlg` increases exponentially, which implies that algorithm `OPTAlg` is applicable to the scenario with only a small number of UAVs.



(a)

(b)

Fig. 7. Performance of different algorithms in a small network, where only 100 users are located in a 500 m × 500 m disaster area. (a) Accumulative utility. (b) Running time.

VI. Conclusion

In this article, we studied the deployment of a UAV network to provide urgent communications to people trapped in a disaster zone. Unlike most existing studies that assumed that each user communicates with a UAV directly, we introduced the D2D communications, in which a user within the communication range of a UAV can serve as a hotspot, and provide communication services to his nearby users who are out of the communication range of any UAV. To ensure that different users have fair communication service in the deployed UAV network, we investigated a novel UAV deployment and resource allocation problem, which is to deploy K given UAVs in the air, and allocate bandwidth resources, such that the accumulative utility of all users is maximized. We also proposed a novel $(1 - 1/e - \epsilon)$-approximation algorithm for the problem, where e is the base of the natural logarithm, and ϵ is a given constant with $0 < \epsilon < 1 - 1/e$. We finally evaluated the performance of the proposed algorithm. Experimental results showed that accumulative utility by the proposed algorithm is up to 18% larger than those by existing algorithms. In addition, more than 16% users are served in the deployed UAV network by the proposed algorithm.

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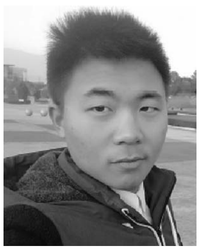

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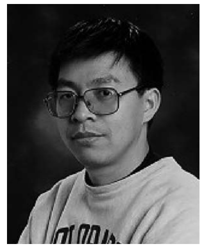

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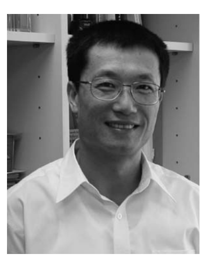

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