NOMA-Based UAV-Aided Networks for Emergency Communications

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Abstract: High spectrum efficiency (SE) requirement and massive connections are the main challenges for the fifth generation (5G) and beyond 5G (B5G) wireless networks, especially for the case when Internet of Things (IoT) devices are located in a disaster area. Non-orthogonal multiple access (NOMA)-based unmanned aerial vehicle (UAV)-aided network is emerging as a promising technique to overcome the above challenges. In this paper, an emergency communications framework of NOMA-based UAV-aided networks is established, where the disasters scenarios can be divided into three broad categories that have named emergency areas, wide areas and dense areas. First, a UAV-enabled uplink NOMA system is established to gather information from IoT devices in emergency areas. Then, a joint UAV deployment and resource allocation scheme for a multi-UAV enabled NOMA system is developed to extend the UAV coverage for IoT devices in wide areas. Furthermore, a UAV equipped with an antenna array has been considered to provide wireless service for multiple devices that are densely distributed in disaster areas. Simulation results are provided to validate the effectiveness of the above three schemes. Finally, potential research directions and challenges are also highlighted and discussed.

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I. INTRODUCTION

The fifth generation (5G) and beyond 5G (B5G) wireless networks face challenges in terms of high spectrum efficiency (SE) requirement and massive connections [1]. In particular, when Internet of Things (IoT) devices are located in a disaster area, the base stations (BSs) may be damaged, and thus cannot provide reliable services to users. Due to its flexibility and mobility, unmanned aerial vehicles (UAVs) act as flying BSs that can be rapidly deployed to provide wireless coverage to a disaster area. On the other hand, non-orthogonal multiple access (NOMA) is considered as a prominent candidate to improve SE as well as to support massive connectivity of IoT devices [2]. Compared with the conventional orthogonal multiple access (OMA), NOMA enables multiple users to share the same physical resources (time/frequency/code) by employing superposition coding (SC) at the transmitters and successive interference cancellation (SIC) at the receivers, and thus achieves better spectrum utilization [2].

Recently, NOMA-based UAV-aided networks have attracted much attention in both academia and industry [3]-[7]. In [3], a stochastic geometry method was studied in multiple-input multiple-output (MIMO)-NOMA assisted UAV networks to model the locations of users and interference sources, in which the closed-form expressions of the outage probability and the ergodic rate were derived both for line-of-sight (LoS) and non-line-of-sight (NLoS) scenarios. In [4], the trajectory of UAV and precoding vectors at the BS were jointly optimized in UAV-assisted NOMA networks to maximize the sum rate of all users. A low-complexity mechanism was proposed in [5] for maximizing the number of users with satisfied quality- of-service (QoS) experience in a NOMA-based UAV system, where the placement design, admission control and power allocation were jointly optimized. In [6], a max-min rate optimization was studied in a UAV-enabled NOMA system, and the problem was solved by a path-following algorithm under the constraints of total power, bandwidth, flight altitude and antenna beamwidth. In [7], an aerial-ground (AG)-NOMA scheme with perfect and statistical channel state information (CSI) was proposed for investigating the achievable rates of the ground users (GU), in which the closed-form expressions for the optimal SIC policy, power allocation, GU rate and feasibility conditions were derived. Although excellent research now exists on NOMA-based UAV networks, very few works have been focused on NOMA-based UAV-aided networks for emergency communications [8]. In [8], a distributed SIC- free NOMA (DSF-NOMA) scheme was proposed for a UAV-assisted emergency communication in the heterogeneous IoT to satisfy the communication requirements of the surviving users and devices. Simulation results demonstrated that the DSF-NOMA scheme achieved better performance compared with the orthogonal frequency division multiple access (OFDMA) scheme. However, an emergency communications architecture for NOMA-based UAV networks is missing in the aforementioned research works.

In this paper, an emergency communications framework of NOMA-based UAV-aided networks is established, where the disasters scenarios are divided into three categories, namely, emergency areas, wide areas and dense areas. First, a UAV is employed as a data collector to gather information from IoT devices in emergency areas. To maximize the total uplink throughput and prevent buffer overflow in IoT devices, a deep- Q-learning (DQL)-based path planning scheme is designed, where the data transmission requirements priorities of IoT devices, the uncertain channel state information (CSI) and the wireless coverage of the UAV are jointly taken into account. Then, for the case that IoT devices are distributed over wide geographical areas, a multi-UAV enabled NOMA system is established to extend the UAV coverage for IoT devices. To maximize the total achievable rate at IoT devices, a total achievable rate optimization problem with the constraints of the minimum rate constraint, maximum transmit power and user scheduling is studied, where the interference between UAVs is considered. Finally, a UAV equipped with an antenna array has been considered, where multi-beams are generated to provide wireless service for multiple devices that are densely distributed in disaster areas. To improve the sum rate of IoT devices while guaranteeing the QoS of devices, a sum rate maximization problem is investigated, in which the UAV path planning, beam pattern and transmit power are jointly optimized.

The remainder of this paper is organized as follows. In the next section, an emergency communications framework of NOMA-based UAV-aided networks is first presented. Then, a DQL-based path planning scheme is studied to avoid data overflow in IoT devices. In addition, a multi-UAV enabled NOMA system is designed to extend the wireless coverage of the UAV. Subsequently, a joint three-dimension (3D) trajectory and power allocation scheme is established to maximize the sum rate of IoT devices while guaranteeing the

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QoS of devices. Finally, potential research directions and challenges are discussed, and then the conclusions are given in the final section.

II. Emergency Communications Framework of NOMA-Based UAV Networks

The emergency communications framework of NOMA-based UAV-aided networks can be described as follows:

- Scenario 1: In the scenario with IoT devices distributed in an area where unexpected and sudden disasters occur, the UAV is dispatched to gather real-time data from IoT devices and sends it to the control station for further processing and analysis. To avoid data overflow in IoT devices, a real-time trajectory planning of UAV is designed, in which the data transmission requirements priorities of IoT devices and the wireless coverage of UAV are jointly considered.
- Scenario 2: In the scenario with IoT devices that are dispersed over a wide geographical area, multi-UAVs can be deployed to extend the wireless coverage and provide wireless service for IoT devices. In this case, the UAV deployment and interference management are properly designed to maximize the total achievable rate of IoT devices.

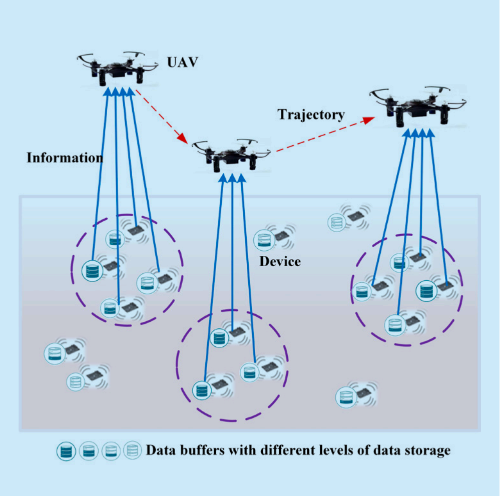

Fig. 1. *Illustration of a UAV-enabled uplink NOMA network.*

- Scenario 3: In the scenario with ultra-dense device deployment, a UAV mounted with an antenna array is dispatched as a flying BS to disseminate data towards IoT devices. With the help of the multi-beam and NOMA, multiple devices can be served simultaneously in a high-throughput communications system. In this case, UAV's path planning, beam pattern and transmit power are jointly optimized to maximize the sum rate of all IoT devices.

In the follow sections, these key scenarios of NOMA-based UAV networks for emergency communications are analyzed in detail.

III. Path Planning of the UAV for Uplink NOMA Systems

When the IoT devices located in an area where unexpected and sudden disasters occur, it is crucial to gather data from specific areas and send it to the control station for further processing and analysis. In this section, we consider a scenario where an UAV acts as a data collector to collect data from multiple IoT devices. To overcome the inherent latency and improve the system throughput, a UAV-enabled uplink NOMA system is established. Besides, since the data transmission requirements are changing over time, the trajectory planning of UAV should be appropriately designed, which is discussed in this section.

3.1 System description and problem formulation

The system is shown in Figure 1. We consider an uplink NOMA communication system wherein a UAV flying at a constant altitude is deployed to collect information from a certain number of IoT devices periodically. Those IoT devices $\mathcal{K} \triangleq \{k = 1, 2, \cdots, K\}$ are randomly distributed on the ground and send their sensory data to the UAV via NOMA transmission. For simplicity, we assume that the UAV and all devices are equipped with a single antenna and the horizontal location of IoT device k is $z_k = (x_k, y_k, 0)$. The flight period of UAV is given as T, which is divided into N time slots. The duration of each time slot $\delta = \frac{T}{N}$ is chosen to be sufficiently small so that the UAV can be considered to be static in each time slot. The location of UAV at slot $n \in \{1, \cdots, N\}$ is $z_u[n] = (x_u[n], y_u[n], h_u[n])$. It is assumed that the UAV communication channel is dominated by LoS links, and the channel gain from the UAV to the kth device at slot n is $h_k[n]$ [9]. The coverage radius of UAV is R_{cov}. At each slot, the update of UAV's position is synchronized at its flying speed $v[n] \in [0, v_{\max}]$ and flying angel $\theta[n] \in [0, 2\pi]$, where $v_{\max}$ is the maximum flying speed. Since IoT devices are used to sense and collect data in real time from the physical surrounding environment, the amount of data stored in the buffer will vary over time. $\lambda_k[n]$ represents data accumulation rate of the IoT device k at slot n, which obeys Poisson distribution. $Q_k[n] = \frac{\lambda_k[n] l_k[n]}{l_{\max}}$ denotes the data transmission requirement priority of device k at slot n where $l_k[n]$ is the current data buffer length and $l_{\max}$ is the maximum storage. Since the data storage capacity is limited, the UAV should collect data in time to prevent data overflow. We use $N_o[n]$ to denote the number of devices with data over flow.

The UAV adopts the NOMA technique [10] to achieve low latency massive access, and hence the achievable rates at slot n is

$$R[n] = \sum_k r_k[n] = \log_2\left(1 + \sum_k \frac{p_k[n] h_k[n]}{\sigma^2}\right), \tag{1}$$
$$\forall k, \| z_k - z_u[n] \| \leq R_{cov},$$

where σ^2 denotes the variance of additive white Gaussian noise (AWGN). Here, we assume that the transmit power of IoT devices are fixed. To maximize the uplink throughput, the flight control of the UAV (i.e., the UAV deployment) is optimized by considering the coverage radius constraints. Since the data transmission requirements priorities of the IoT devices are dynamic and uncertain and the CSI is imperfect, the proposed optimization problem cannot be modeled as a deterministic optimization problem. As a result, the flight control of the UAV is intractable and impractical. Given the fact that deep-Q-learning (DQL) [11] can handle sophisticated state space and time-varying environment, a path planning algorithm based on DQL is developed to solve this problem.

3.2 DQL-based path planning of the UAV for uplink NOMA systems

Based on Q-learning, DQL is an efficient reinforcement learning (RL) method that enables the agent to find an optimal policy to maximize the average long-term cumulative reward through the Q-table. Besides, DQL uses deep neural network (DNN) as a function approximator to estimate the action-value function so as to circumvent the curse-of-dimensionality of Q- learning. The state space, action space and reward function of agent are defined as follows:

- State space $\mathbf{s}[n]$: The state space of the agent consists of the location of the UAV, the relative positions between the target device and the UAV, the number of IoT devices with data over flow and the number of times that the UAV tries to fly out of the restricted area. Here, we assume that the IoT device with the highest priority (i.e.,

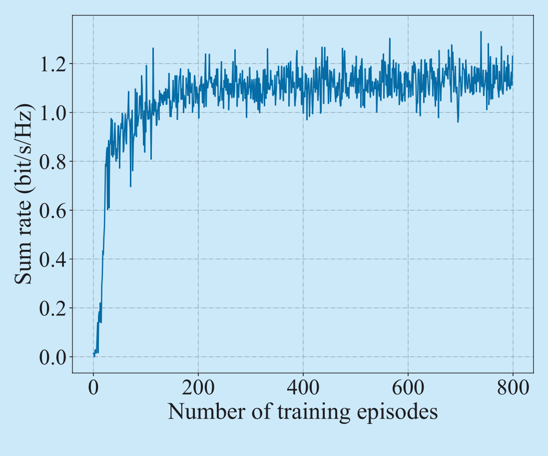

Fig. 2. *An example of convergence behaviors of the proposed DQL- based algorithm.*

the highest service requirements) is chosen as the target, and its location is known by the UAV.

- Action space $\mathbf{a}[n]$: The action space includes the flying speed and flying angle of the UAV. To improve the accuracy of the flight control, both flying speed and angle are uniformly discretized into 8 values. According to the observed state, the UAV flies to a waypoint that serves the target and the other devices within the coverage area of the UAV.
- Reward function $R[n]$: The UAV gets the reward for improving the uplink throughput of the network which is calculated by (1) as well as flying close to the target device. On the other hand, the UAV gets penalties for flying out of bounds and buffer over flows in IoT devices.

At each time slot, based on the observed state $\mathbf{s}[n]$, the UAV interacts with the environment by executing action $\mathbf{a}[n]$ and receives reward. Then, the long-term reward is updated and maximized through the parameters of the neural network updated iteratively from its interactions with the environment. Finally, the UAV achieves a path planning strategy to solve the proposed problem.

3.3 Simulation results

In this section, numerical results are provided to evaluate the performances of our proposed DQL-based algorithm. We assume that 100 IoT devices are distributed in a $400 \times 400\text{m}^2$ area, where the data accumulation rate $\lambda_k(t)$ is randomly assigned from {4, 6,10,18} and the maximum storage $l_{\max}$ is set to 5000 packets. The coverage radius of the UAV is 20 m, and the maximum flying speed $v_{\max}$ is 40m/s. The flight altitude of the UAV h_u is set to 100 m. The received signal noise ratio (SNR) at a reference distance of 1 m is 40 dB. Our simulation runs are performed with Tensor flow 2.1.0 and Python 3.7.

As shown in Figure 2, we can observe that the sum rate initially increases with the number of training episodes, and then converges to a stable value after 200 iterations. Then, the performance of the proposed algorithm in terms of the average data buffer length and the average number of devices with data over flow are shown in Figure 3. It is observed that the average data buffer length converges to 0.3 when the number of training episodes is 200. At the same time, the number of IoT devices whose data over flow occurred drops from 25 to nearly 0. This is due to the fact that the UAV achieves the flight control by using the trained DNN. Specifically, the IoT devices with high data transmission requirements are accurately covered by the UAV. As a result, the IoT devices can upload data in a timely manner to

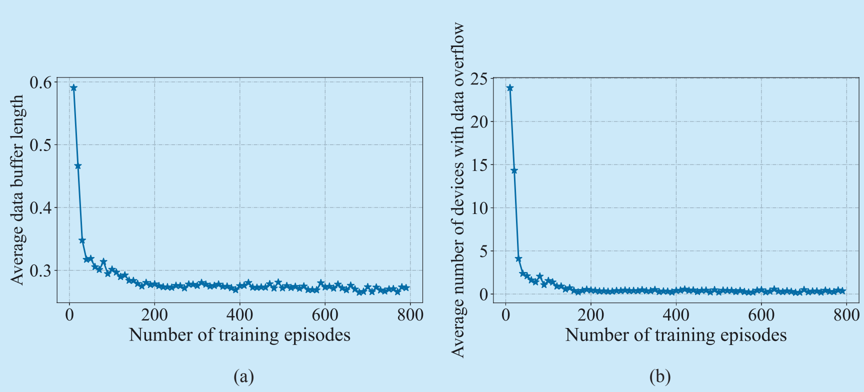

Fig. 3. *The training curves of the proposed DQL-based algorithm (a) Average data buffer length; (b) Average number of devices with data over flow.*

reduce the average data storage of the system, and thereby prevent a buffer over flow. Thus, the throughput of the uplink NOMA communication system can be optimized through a proper management of the proposed DQL-based algorithm with the consideration of the data transmission requirements priorities of IoT devices.

3.4 Discussion

In this scenario, the trajectory design of the uplink NOMA communication network is designed to maximize the uplink throughput under the fixed transmit power. To further reduce the inter-user interference and guarantee the user fairness, the transmit power should be also optimized. Therefore, a joint trajectory planning and power allocation problem can be further investigated, in which the data transmission requirements of the IoT devices, the imperfect CSI and the wireless coverage radius of the UAV are considered. In this case, the optimization problem becomes more complex, and an effective resource allocation scheme should be designed, which needs further exploration.

IV. Minimum Throughput Maximization for Multi-UAV Enabled NOMA Networks

When the IoT devices are deploying in a wide area, it is inefficient to employ single UAV for data transmission due to the communication delay. Therefore, in this scenario, multiple UAVs can be exploited to extend the wireless coverage of IoT devices and to disseminate data towards IoT devices. To improve the transmission performance in multi-UAV enabled NOMA networks, an achievable rate maximization problem is studied. In addition, since the interference between UAVs can severely degrade the system performance, a joint UAV deployment and resource allocation scheme is designed, which is discussed in this section.

4.1 Problem formulation

We consider a multi-UAV enabled NOMA network as shown in Figure 4. M UAVs are employed to provide reliable wireless access to K IoT devices. The IoT devices can be grouped into M clusters through the K-means algorithm, and each cluster is served by one UAV. For any cluster $m \in \mathcal{M} = \{1, \cdots, M\}$, we use NOMA scheme to support massive access, where all devices share the same subcarrier. The UAVs and IoT devices are equipped with

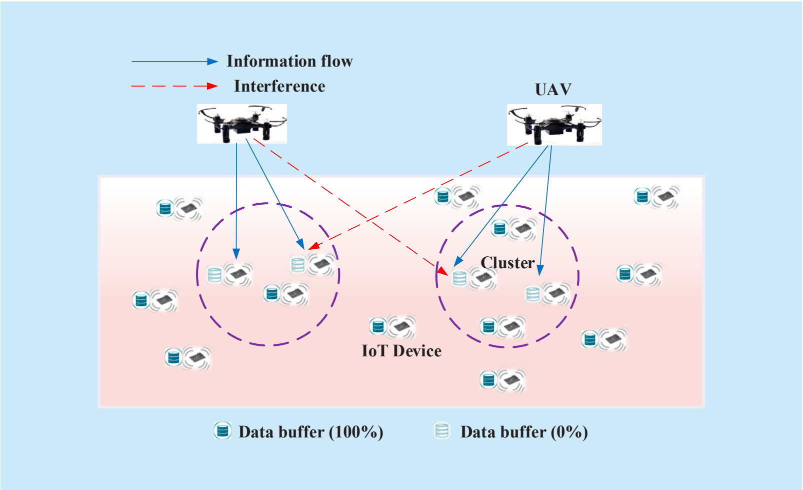

Fig. 4. *Illustration of a multi-UAV enabled NOMA network with UAV deployment and resource scheduling.*

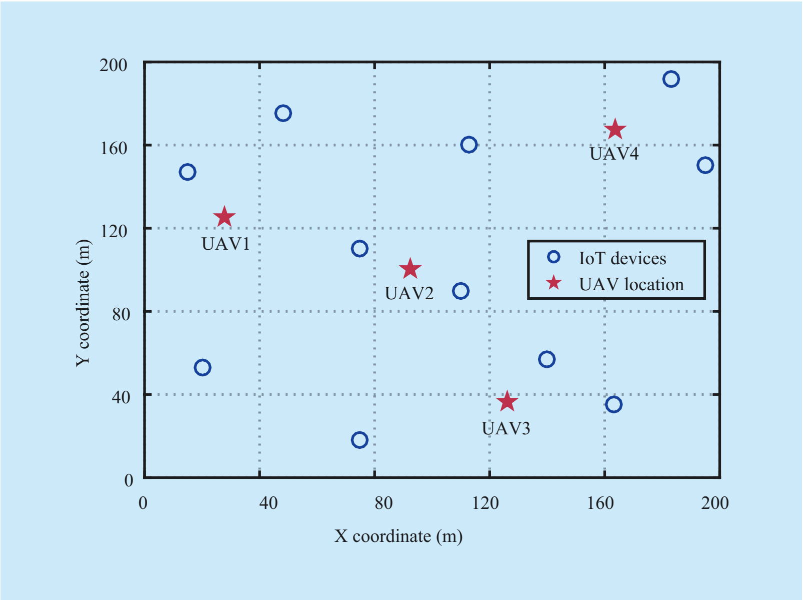

Fig. 5. *The locations of the UAVs in multi-UAV enabled NOMA networks with* $K = 11$ *IoT devices.*

single antenna. The location of the mth UAV is denoted by $z_m = (x_m, y_m, h_m)$, and the device $k_m \in \mathcal{K}_m = \{1, 2, \cdots, K\}$ served by the mth UAV is located at $z_{k_m} = (x_{k_m}, y_{k_m}, 0)$. To illustrate the user scheduling in the multi-UAV enabled NOMA system, we define a binary variable $\alpha_{k,m}$. In particular, $\alpha_{k,m}$ equaling 1 or 0 means that the device k_m is connected or not to the m th UAV. To ensure the reliability of transmission, the achievable rate of devices R_k should be larger than a threshold r_k. In order to satisfy the QoS requirements of all devices, the transmit power of the device k from the mth UAV is defined as $p_{k,m}$, and $\sum_{k \in \mathcal{K}_m} p_{k,m}$ is equal to the maximum transmit power P_{max}. To mitigate the intra-cluster interference, the SIC technique is applied for signal detection.

To improve the capacity and reliability of wireless network, we maximize the total achievable rate of devices by optimizing the user scheduling, the placement of UAVs and transmit power, where the intra-cluster interference, interference between UAVs, minimum rate requirements and maximum transmit power constraint are taken into consideration.

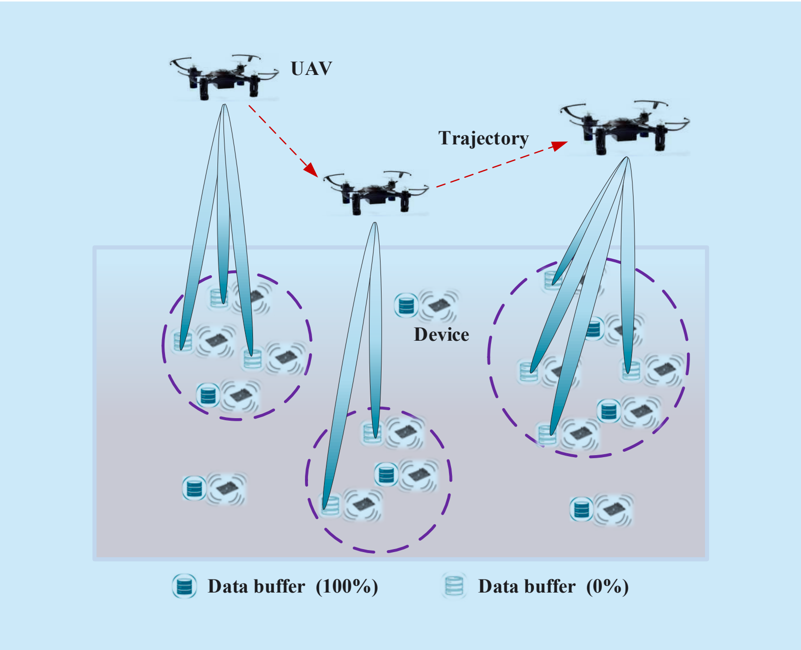

Fig. 6. *Illustration of a UAV-enabled NOMA network with multi-beams and power allocation.*

Due to the binary variable and the non-convex constraints, this problem is a mixed-integer non-convex optimization problem that is difficult to solve.

To tackle this problem, we decompose the original problem into three sub-problems, i.e., the user scheduling, the mobility of the UAVs and transmit power control. In particular, we can obtain the suboptimal solutions through solving the subproblem with fixed transmit power $p_{k,m}$ and UAV locations z_m, the sub-problem with fixed user scheduling $\alpha_{k,m}$ and UAV locations z_m and the sub-problem with fixed user scheduling $\alpha_{k,m}$ and transmit power $p_{k,m}$. Specifically, when the transmit power $p_{k,m}$ and UAV locations z_m are fixed, we relax the binary variable $\alpha_{k,m}$ into a continuous variable which can take all values in [0,1]. Therefore, the problem can be reformulated as a linear program problem, which can be solved by the standard convex optimization techniques [12]. For the case that user scheduling $\alpha_{k,m}$ and UAV locations z_m are fixed, the problem remains non-convex. To solve this subproblem, we first transform the objective function into the difference of two convex functions, and then the difference of convex (DC) programming [13] is applied to convert the non-convex problem into a convex one that can be solved by the standard convex optimization techniques. Similarly, when the user scheduling $\alpha_{k,m}$ and transmit power $p_{k,m}$ are fixed, the optimization problem is reformulated as a non-convex single-variable optimization problem where transmit power $p_{k,m}$ is the optimization variable. To tackle it, the non-convex constraints are converted into convex ones via the successive convex approximation (SCA) technique [14], and hence the sub-problem can be solved by the standard convex optimization techniques. As a result, the suboptimal values of $\alpha_{k,m}$, $p_{k,m}$ and z_m can be achieved by solving the three sub-problems.

4.2 Simulation results

In this section, the performance of the proposed joint UAV deployment and resource allocation scheme is evaluated. We consider a multi-UAV enabled NOMA network with $M = 4$ UAVs and $K = 11$ IoT devices uniformly distributed within a $200 \times 200\text{m}^2$ area, where the UAVs are assumed to fly at a fixed altitude h = 100 m. The receiver noise power σ^2 is set to −110 dBm. The channel power gain at the reference distance $d_0 = 1\text{m}$ is set to be $\rho_0 = -60$ dB. The maximum transmit power of UAVs is assumed to be $P_{\max}$ = 0.1 W, and the minimum rate threshold r_k is set to 1 bit/s/Hz. As shown in Figure 5, in order to maximize the total achievable rate of IoT devices, the positions of UAVs lie within the center of devices that in the same cluster. In addition, to improve the communication performance as well as to reduce the interference between UAVs, the UAVs are geographically far away from each other. Therefore, the total achievable rate of all IoT devices can be maximized through a proper management of joint UAV deployment and resource allocation.

C. Discussion

In this scenario, we consider multiple UAVs as flying BSs to extend the coverage area of a multi-UAV enabled NOMA system. However, due to the constrained transmit power of the UAVs, the reliability requirements of devices cannot be guaranteed when the total number of users increases. To improve the system performance, device-to-device (D2D) communication can be employed to enable the UAVs to further extend the coverage of wireless networks at disaster areas. Therefore, an effective resource allocation scheme should be designed by optimizing the trajectory of UAVs and communication scheduling, which will be further studied.

V. Joint 3D Trajectory and Power Optimization

When the IoT devices are densely distributed in disaster areas, it is not efficient to employ a cluster of UAVs to provide wireless service for IoT devices due to the severe interference between UAVs. Alternatively, a UAV mounted with antenna array can be deployed as an access point and generates multi-beams to serve multiple users simultaneously, as shown in Figure 6. Thus, the beam pattern and transmit power are optimized to improve the QoS of users. In addition, since the coverage area of the UAV is limited by its deployment, the 3D trajectory of the UAV should be properly designed to extend its coverage, which is discussed in this section.

5.1 Problem formulation

We consider a UAV-enabled NOMA system consisting of K IoT devices and one UAV. The IoT devices are divided into Γ clusters according to the distance, and the UAV flies above Γ serving areas to communicate with K IoT devices periodically. It is assumed that a uniform planar array (UPA) with $M \times N$ array elements is equipped at the UAV, while the IoT devices are equipped with one antenna. To improve the system throughput, we employ the power-domain NOMA schemes such that all devices share the same subcarrier at different power level [2].

Define the 3D location of the UAV as $z_u = (x_u, y_u, h_u)$, and the coordinate of the device $k \in \{1, 2, \cdots, K\}$ as $z_k = (x_k, y_k, 0)$. The effective coverage area of the UAV is a circle with radius $h_u \tan\Theta$, where 2Θ denotes effective illumination angle. Thus, the horizontal distance between the UAV and devices $\| z_k - z_u \|$ should be less than or equal to the coverage radius $h_u \tan \Theta$. Besides, the beam pattern $\mathbf{E}(\theta, \phi)$ for the elevation θ and azimuth ϕ angles should be designed and optimized to improve the channel gain. To guarantee the QoS of users, the achievable rate of devices R_k should be larger than a rate threshold r_k. In addition, we define the transmit power from the UAV to device k as p_k, and $\sum_{k=1}^{K} p_k$ is equal to P_{max}.

To schedule the transmission of the UAV and guarantee the QoS of devices, the sum rate of all IoT devices can be maximized by sequentially optimizing the 3D position of the UAV, beam pattern $\mathbf{E}(\theta,\phi)$ and transmit power p_k, with the constraints of the maximum coverage radius of the UAV, minimum rate constraint, flight altitude restrictions and maximum transmit power constraint. However, this optimization problem is a mixed combinatorial and non-convex problem, and hence is extremely difficult to solve.

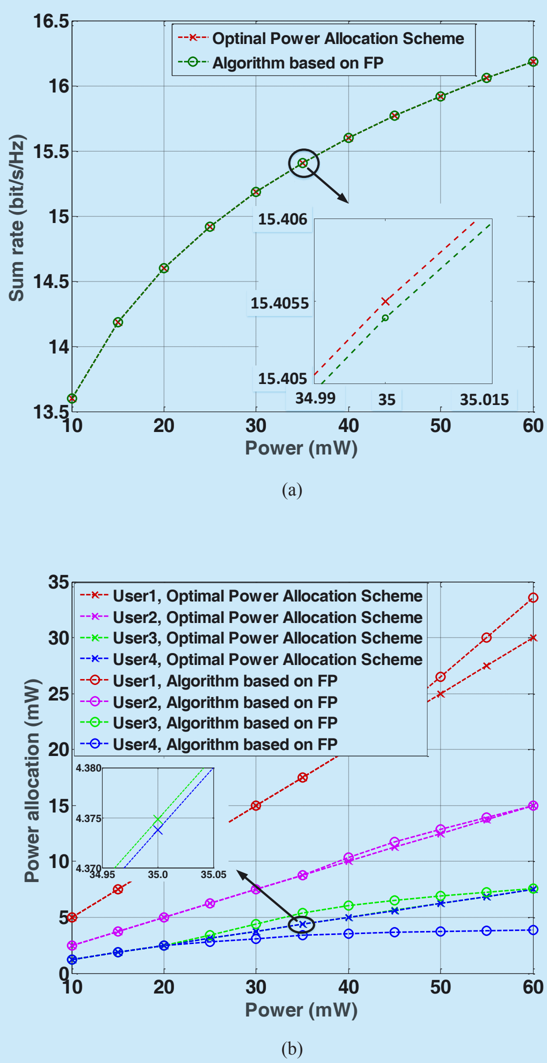

Fig. 7. *Performance of joint 3D trajectory and power optimization scheme: (a) Sum rate versus transmit power. (b) Power allocation of devices versus transmit power.*

To tackle this problem, we decompose the optimization problem into three sub-problems, and the suboptimal solutions can be calculated through solving the sub-problems sequentially. Specifically, when $\mathbf{E}(\theta,\phi)$ and p_k are fixed, the original problem is transformed into the problem of minimizing the total path loss, and the optimal value of h_u can be achieved by monotonic optimization theory. Then, with the solved h_u, the problem become a convex one, and the 2D location of the UAV can be calculated by the standard convex optimization techniques. When the 3D location of the UAV z_u and transmit power p_k are fixed, the problem can be reformulated into a beam pattern optimization problem. Note that the design of beam pattern $\mathbf{E}(\theta,\phi)$ considers the optimization of the array gain, side-lobe level (SLL) and beamwidth, which can be constructed into a multiobjective optimization problem with the variable $\boldsymbol{\beta}$ (i.e., the phases of the antenna elements). To solve this sub-problem effectively, the multiobjective evolutionary algorithm based on decomposition (MOEA/D) based algorithm [15] is applied to decompose this multiobjective optimization into a number of scalar sub-problems, which can be solved via an iteration process. When the 3D location of the UAV z_u and beam pattern $\mathbf{E}(\theta,\phi)$ are fixed, the problem becomes a non-convex transmit power optimization problem. To tackle this sub-problem, we first transform the constraints into convex functions by the logarithmic transformation, and then the fractional programming (FP) [16] and the Karush-Kuhn-Tucker (KKT) conditions [17] are applied to solve this subproblem, respectively. Since the UAV trajectory optimization problem can be constructed as a traveling salesman problem (TSP) to minimize the total flight distance, the branch and bound algorithm is developed to solve it.

5.2 Simulation results

The performance of the joint 3D trajectory and power optimization scheme is analyzed in Figure 7. First, the sum rate of all IoT devices is investigated by comparing different power allocation schemes. We set the noise power $\sigma^2 = -110$ dBm, the mean square additional loss $\eta_{LoS} = 0.1$ dB, the path loss factor $\alpha = 2$, the maximum transmit power P_{max} = 80 mW, the minimum rate constraint of devices r_k = 1 bit/s/Hz, and the carrier frequency to 25 GHz. We assume that K = 4 IoT devices are distributed in a cluster, and the channel gains of four devices are $\|\mathbf{h}_1\| < \|\mathbf{h}_2\| < \cdots < \|\mathbf{h}_K\|$. The maximum effective illumination 2Θ, is set to 80° and the amplitude and spacing of the antenna array are set to 1 A and 5.5 mm, respectively. It is assumed that the minimum altitude h_{min} and maximum altitude h_{max} are set to 21 m and 120 m, respectively. As it can be seen in Figure 7(a), the sum rate increases rapidly to a certain transmit power, but thereafter rises slowly. In addition, it can also be observed that the sum rate performance of the FP-based algorithm is very close to that of the optimal power allocation scheme. Then, we also compare the power allocation of devices with different schemes in Figure 7(b). From Figure 7(b), we can see that the users with poor channel quality are allocated more power than the users with good channel quality. This is attributed to the fact that the weak devices allocated more transmit power can reduce the interference from other strong users according to the SIC technique. As a result, the sum rate of all IoT devices can be maximized through the proper management of the joint 3D trajectory design and power allocation.

5.3 Discussion

In this scenario, an antenna array mounted UAV is employing as a wireless access point to provide wireless service at the downlink in a NOMA-based UAV system. However, IoT devices are generally battery-powered, which may have limited energy storage. In this situation, the simultaneous wireless information and power transfer (SWIPT) technique can be exploited to prolong the lifetime of devices. Thus, the optimization problem can be modelled as an energy efficiency maximization problem. To tackle this problem, an efficient joint resource scheduling scheme should be properly designed.

VI. Open Research Issues and Challenges

In this article, the emergency communications framework of UAV-enabled NOMA-aided networks in disaster has been investigated. However, there are still some open research issues and challenges, which are highlighted as follows.

Energy supply: In the considered scenarios, an emergency communications framework of UAV-enabled NOMA networks is designed to provide network access for IoT devices. However, the battery-limited IoT devices usually suffer from the limitations in energy supply, especially in disaster. This challenge can be solved by the application of wireless power transfer (WPT) technique. Thus, an effective resource allocation scheme should be further analyzed with the consideration of downlink WPT and uplink wireless information transfer.

Secure communication: Secure communication is one of the key challenges for UAV-enabled NOMA networks due to the LoS channels and a higher transmit power allocated to the users with poor channel quality. Therefore, a secure UAV-enabled NOMA system should be further investigated to guarantee security of transmission. In addition, transmit beamforming with artificial noise (AN) should be properly designed to confuse the eavesdroppers.

Cellular-connected UAV: In this paper, we consider the scenarios where all the BSs are destroyed by disaster. In practice, the disaster areas may have some surviving BSs, and hence the UAVs can cooperate with the remaining BSs to offer the 3D communication coverage for ground users. However, since the UAV-BS channels are usually dominated by the LoS link, the UAVs may receive severe interference from the neighboring BSs. Thus, designing an effective interference mitigation scheme is very important for cellular-connected UAV networks.

VII. Conclusion

NOMA-based UAV-aided network is emerging as a promising technique to provide high spectrum efficiency and massive connections for IoT devices deployed in disaster areas. In this paper, an emergency communications framework of NOMA-based UAV-aided networks is established, where the disasters areas can be divided into three scenarios. First, a DQL-based path planning scheme has been established to gather information from IoT devices in emergency areas. Then, a multi-UAV enabled NOMA network has been investigated to extend the UAV coverage for IoT devices in wide areas. Furthermore, a joint 3D trajectory and power optimization scheme is designed to provide wireless service for IoT devices in densely distributed areas. Finally, some potential research directions and challenges have also highlighted and discussed.

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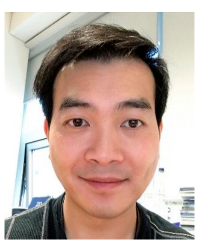

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