Resource Allocation for Multi-UAV Aided IoT NOMA Uplink Transmission Systems

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Resource Allocation for Multi-UAV Aided IoT NOMA Uplink Transmission Systems

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Abstract—UAV communication is a promising technology for Internet of Things (IoT) systems. In this paper, we combine UAV communication and non-orthogonal multiple access (NOMA) for constructing high capacity IoT uplink transmission systems, where UAVs are used as aerial base stations for collecting data from IoT nodes while NOMA is invoked for uplink transmission. We aim to maximize the system capacity by jointly optimizing the subchannel assignment, the uplink transmit power of IoT nodes and the flying heights of UAVs. We commence by proposing an efficient subchannel assignment algorithm relying on the classic K-means clustering method and matching theory. Then, we determine both the distributed uplink transmit power of IoT nodes and flying heights of UAVs based on successive optimization approach. An alternative optimization algorithm is also proposed for finding the near-optimal solutions. Finally, numerical results demonstrate the superiority of our proposed scheme.

Index Terms—UAV communication, NOMA, Internet of Things, uplink transmission, resource allocation.

I. INTRODUCTION

A. Motivations

Unmanned aerial vehicle (UAV) communication is an emerging technology for the fifth generation (5G) networks and beyond [1]–[3]. On one hand, UAVs can be quickly and efficiently deployed to support existing cellular networks and enhance ground users’ quality-of-service (QoS) by establishing line-of-sight (LoS) links. On the other hand, given the popularization of civilian UAVs, they are also expected to be important users of the future network. With their inherent attributes such as high mobility, low cost and flexible deployment, UAVs can be beneficially applied to some key potential applications in next generation wireless networks. To elaborate a little further, UAVs can be used as aerial base stations (ABSs) for providing reliable uplink and downlink communications for ground users [4]. They can also act as airborne relays for connecting the dead zone users with the terrestrial BSs and enlarging the communication coverage [5]. Moreover, their ability to provide LoS connections can mitigate the signal blockage and shadowing, thus greatly improving the spectrum efficiency. A range of new compelling applications are also being developed for further tapping the potentials of UAVs in wireless communications.

The Internet of Things (IoT), which leads to massive connections between physical things such as vehicles, wearable devices and various sensors, is a key component of future networks [6]. However, in many application scenarios, the reliable transmission between IoT devices remains a challenge since IoT devices cannot support long distance transmission due to their power constraints. Fortunately, UAVs are expected to provide effective solutions. UAVs can flexibly navigate to the IoT devices, collect the data and then efficiently transmit the data to other IoT devices or directly to the data center. The high probability of LoS connections is capable of improving the transmission efficiency as well as decreasing the transmit power of the IoT devices, thereby prolonging their service life.

Despite the considerable benefits of applying UAVs to IoT systems, the limited cruise time of UAVs presents as a bottleneck. Existing UAVs typically have an endurance time of less than one hour. Therefore, improving the transmission efficiency is of utmost importance. Non-orthogonal multiple access (NOMA) is a promising technology for the future network, it has superior spectrum efficiency by allowing simultaneous transmissions of different users within the same channel, which relies on the superposition coding (SC) at the transmitters and the successive interference cancellation (SIC) at the receivers [7], [8]. The combination between UAVs and NOMA technology will bring about predictable benefits. Therefore, in this work, a multi-UAV aided NOMA system is established for the uplink transmission of IoT applications. Specially, UAVs are used as flying BSs to collect data from various IoT nodes and NOMA is assumed for the uplink transmission between the UAVs and the IoT nodes for promoting spectrum efficiency. And we propose a staged optimization algorithm for joint optimizing the subchannel assignment, the uplink transmit power of IoT nodes and the flight heights of UAVs.
B. Related Works

1) UAV communication: In literatures, UAV communication has been extensively studied for boosting the capacity and coverage of existing wireless networks [9]–[18]. Specially, Al-Hourani et al. and Yaliniz et al. investigated the two-dimensional and three-dimensional placement problems of a single UAV in [9] and [10], respectively. Their works showed that the optimal location of the UAV for realizing maximum coverage is closely related to the channel characteristics. A similar problem considering multi-UAV case was later studied in [11], where the circle packing theory was first introduced for determining the optimal locations of the UAVs. In [12], Mozaffari et al. analyzed the coverage and rate performances of UAV-based wireless communication in the presence of device-to-device communication links, where the average coverage probabilities were derived both in static UAV case and in mobile UAV case. A multi-UAV aided wireless network was investigated by Wu et al. in [13], where the user scheduling, the UAV’s trajectory and the UAV’s power were jointly optimized for maximizing the user’s throughput in a downlink transmission system. Additionally, the trajectory design problem of UAV was also studied in [14], where Zeng et al. built the energy consumption model of UAV as a function of UAV’s flying speed, direction and acceleration, and they proposed a horizontal trajectory design paradigm for jointly optimizing the communication throughput as well as UAV’s energy consumption. Prior to our work, UAVs have been introduced for IoT applications in [16] and [17]. In [16], Motlagh et al. gave a comprehensive survey on the UAV-aided IoT services, they also introduced an envisioned UAV-based architecture for delivering value-added IoT services from the sky. As for [17], Mozaffari et al. introduced UAVs for collecting data form IoT devices, where the UAV’s mobility, the UAV-device association, the uplink power control were jointly designed for a time-varying IoT network. They also derived the optimal mobility pattern of UAVs based on the activation process of IoT devices. It shall be mentioned that all these works were conducted in orthogonal multiple access (OMA) systems while our work is operated in a NOMA system, thus our work considers a much more complicated regarding the device-UAV association and the power control.

2) NOMA: NOMA is known to simultaneously serve multiple users by separating users in the power domain and the code domain. The theories and principles of NOMA were first introduced in [7], [19], while in [20], Ding et al. evaluated the performance of NOMA in a cellular downlink network with randomly deployed users, showing that NOMA has a better outage performance than OMA techniques as well as superior ergodic sum rate performance. Later the power allocation and user pairing in NOMA were studied in [21]–[24]. Specifically, Chen et al. proposed an enhanced proportional fair scheduling scheme, which consists of user selection and greedy consecutive subband assignment, for uplink NOMA user scheduling with contiguous resource allocation [21]. The matching theory was introduced for user scheduling by Di et al. in [22], where the authors modeled users and subchannels as two sets of players and proposed a many-to-many two-side matching algorithm for user scheduling and subchannel assignment. Their algorithm was guaranteed to coverage to a pair-wise stable matching after a limited number of iterations. Moreover, in [25], Fang et al. proposed a sub-optimal power allocation scheme based on the difference of convex functions programming approach, showing that their scheme achieved superior energy efficiency. It is worth mentioning that there are quite a few recent studies that have considered using NOMA for improving the performance of UAV-enabled system. For instance, in [26], Sharma et al. considered using UAV as flying BSs and served two ground users with NOMA, and they analyzed the outage performance. Later in [27], Nasir et al. considered a more user case and studied a max-min rate optimization problem for jointly optimizing the power allocation, bandwidth allocation, UAV altitude and antenna beamwidth. Liu et al. proposed an effective scheme for jointly optimizing the placement and power allocation of UAVs in a NOMA-UAV network, showing that the total downlink rate has been greatly improved [28]. In [29], Zhao et al. introduced a comprehensive framework for realizing effective UAV-base station cooperation for UAV-assisted NOMA networks. Relying on joint UAV trajectory and NOMA precoding optimization, it is substantially beneficial in terms of yielding large throughput of the system. However, all these efforts considered a single UAV case, while the relevant problems regarding multi-UAV enabled NOMA systems still remain unsolved, which is the main focus of our work.

C. Contributions and Organization

Our main contributions are listed as follows:

- We focus on a practical multi-UAV aided IoT NOMA uplink transmission system, where we aim to maximize the total uplink capacity by jointly optimizing the subchannel assignment, the uplink transmit power of IoT nodes and the flight heights of UAVs, which is a non-convex problem. To tackle this, we design a staged optimization algorithm for searching sub-optimal solutions by decoupling these constraints.

- The classic K-means clustering method is invoked for grouping IoT nodes into subsystems corresponding to the number of UAVs. A low-complexity many-many matching algorithm is designed for realizing efficient subchannel assignment in each subsystem based on the clustering results. Furthermore, relying on the subchannel assignment outcomes, distributed uplink transmit power of IoT nodes and flight heights of UAVs solutions are derived based on successive approximation approach, and an alternative optimization algorithm is proposed to yield a near-optimal solution to the decoupled problem.

- Extensive simulations are conducted for evaluating the performance of the proposed algorithms. Simulation results show that our algorithm has a fast convergence performance as well as a superior capacity performance than OMA schemes.

The rest of this paper is organized as follows. The system model and problem formulation are detailed in Section II. Section III introduces an IoT nodes clustering algorithm based.
on the K-means clustering method and a subchannel assignment algorithm relying on many-many matching theory. In Section IV, distributed IoT nodes’ uplink transmit power and UAVs’ flight height solutions, as well as an AO algorithm are presented. Numerical simulations are conducted in Section V, followed by our conclusions in Section VI.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

In this paper, as shown in Fig. 1, we consider a multi-UAV aided IoT NOMA uplink transmission system, which consists of $M$ UAVs and $N$ IoT nodes. The UAVs are small or mini rotary wing UAVs controlled by ground station (GS) to collect information from IoT nodes. The examples of IoT nodes are various devices used for monitoring the information of buildings, roads, farmlands, etc. We assume that those IoT nodes are static and their locations are known by the GS. The sets of the $M$ UAVs and $N$ IoT nodes are denoted as $\mathcal{M} = \{1,2,\ldots,M\}$ and $\mathcal{N} = \{1,2,\ldots,N\}$, respectively. In this system, each UAV serves a group of IoT nodes while each IoT node can only access one UAV. We assume that all of the $N$ IoT nodes can be covered by the $M$ UAVs. Let $\mathcal{S}_m$ denote the set of IoT nodes served by UAV $m$, and we have $\bigcup_m^{M} \mathcal{S}_m = \mathcal{N}$ and $\mathcal{S}_m \cap \mathcal{S}_{m'} = \emptyset, \forall m, m' \in \mathcal{M}, m \neq m'$. Moreover, for further improving the spectrum efficiency, NOMA is invoked for the uplink transmissions between the IoT nodes and the UAVs, where the bandwidth of each UAV-enabled subsystem is $B$, which are divided into $K$ subchannels. Let $\mathcal{K} = \{1,2,\ldots,K\}$ denote the set of the subchannels. Without loss of generality, we consider a 3D Cartesian coordinate system and the locations of UAV $m \in \mathcal{M}$ and IoT node $n \in \mathcal{N}$ are denoted as $(x_{m}^{\text{uav}}, y_{m}^{\text{uav}}, h_{m})$ and $(x_{n}^{\text{node}}, y_{n}^{\text{node}})$, respectively. Hence, the distance between UAV $m$ and IoT node $n$ is calculated by $d_{m,n} = \sqrt{(x_{m}^{\text{uav}} - x_{n}^{\text{node}})^2 + (y_{m}^{\text{uav}} - y_{n}^{\text{node}})^2 + h_{m}^2}$.

1) Channel Model: Let $g_{m,n,k}$ denote the channel gain on $k$th subchannel from IoT node $n$ to UAV $m$, where $m \in \mathcal{M}$, $n \in \mathcal{N}$ and $k \in \mathcal{K}$. Referring to [13] and [15], we assume that the communications between UAVs and IoT nodes are dominated by line-of-sight (LoS) links, where the channel quality only depends on the communication distance. Thus, $g_{m,n,k}$ follows the free-space path loss model, which can be quantified by:

$$g_{m,n,k} = \frac{\eta}{d_{m,n}^2},$$

(1)

where $\eta$ denotes the unit power gain at the reference distance $d_0 = 1$ m.

2) Interference Model: In NOMA, at the transmitters, each IoT node can transmit data through multiple subchannels and each subchannel can be allocated to multiple IoT nodes, while at the receivers, each UAV adopts SIC to demodulate the targeted message. In our paper, we assume that the decoding order at the UAV is always from the IoT node with a better channel quality to the IoT node with a worse channel quality, otherwise a significant power has to be consumed at the node with worse channel quality for compensating the path loss [30]. Let us take UAV $m$ and its corresponding IoT nodes $\mathcal{S}_m$ as an example to analyze the interference conditions.

Without loss of generality, we assume $n \in \mathcal{S}_m$. For signals received from IoT node $n$, the main interferences are composed of three parts, namely intra-group interferences, inter-group interferences and additive noise. The intra-group interferences come from the other IoT nodes in $\mathcal{S}_m$ whose channel qualities are worse than that of IoT node $n$, while the inter-group interferences come from the other co-tier UAV-enabled subsystems. We first define a power allocation matrix $P_{M \times N \times K}$ and a channel allocation matrix $A_{M \times N \times K}$, where $P_{m,n,k} = p_{m,n,k}$ denotes the uplink transmission power between IoT node $n$ and UAV $m$ on $k$th subchannel and $A_{m,n,k} = a_{m,n,k}$ is the channel indicator. We set $a_{m,n,k} = 1$ if the $k$th subchannel is occupied by the transmission between IoT node $n$ and UAV $m$, otherwise, $a_{m,n,k} = 0$. Then, the intra-group interferences for the uplink transmission between IoT node $n$ and UAV $m$ on $k$th subchannel can be given by:

$$I_{m,n,k} = \sum_{i \in \mathcal{S}_m \setminus n} a_{m,i,k} p_{m,i,k} g_{m,i,k},$$

(2)

where $\mathcal{S}_m \setminus \{i \mid i \in \mathcal{S}_m \setminus g_{m,i,k} \}$ denotes the set of IoT nodes in $\mathcal{S}_m$ whose channel qualities are worse than that of IoT node $n$. Moreover, the inter-group interferences can be given by:

$$\hat{I}_{m,n,k} = \sum_{j=1}^{N} \sum_{i \neq m} a_{i,j,k} p_{i,j,k} g_{m,j,k}.$$  

(3)

Thus, the signal to interference and noise ratio (SINR) of the received signal from IoT node $n$ on $k$th subchannel and the corresponding uplink capacity can be denoted as:

$$\gamma_{m,n,k} = \frac{p_{m,n,k} g_{m,n,k}}{I_{m,n,k} + \hat{I}_{m,n,k} + \sigma^2},$$

(4)
and
\[ R_{m,n,k} = \frac{B}{K} a_{m,n,k} \log_2 (1 + \gamma_{m,n,k}) \],

respectively, where \( \sigma^2 \) is the variance of the additive white Gaussian noise (AWGN).

\section*{B. Problem Formulation}

In this section, we will formulate the resource allocation problem for the multi-UAV aided IoT NOMA uplink transmission system. Our goal is to maximize the total uplink transmission capacity, which is expressed as:
\[ R^{\text{total}} = \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{B}{K} a_{m,n,k} \log_2 (1 + \gamma_{m,n,k}) \].

The considered constraints are listed as follows:

1) The IoT nodes’ power constraint: For maintaining the fairness of the IoT nodes and considering the practical limit of the battery size, each IoT node in this system has a minimum uplink transmit power constraint of \( p_{\text{min}} \) and a maximum constraint of \( p_{\text{max}} \). Therefore, for \( \forall n \in \mathcal{N} \), we have:
\[ p_{\text{min}} \leq \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} a_{m,n,k} p_{m,n,k} \leq p_{\text{max}} \].

Moreover, the non-negativity constraint of power yields:
\[ p_{m,n,k} \geq 0, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \].

2) The UAVs’ flight height constraint: For the safety of the UAVs, each UAV in our paper is assumed to have a minimum flight height constraint of \( h_{\text{min}} \), otherwise, these UAVs may run into trees or buildings. Furthermore, they are also assumed to have a maximum flight height constraint of \( h_{\text{max}} \) as an excessive height will lead to fast battery consumption and a more difficult flying control. Hence, for \( \forall m \in \mathcal{M} \), we have:
\[ h_{\text{min}} \leq h_m \leq h_{\text{max}} \].

In practice, the UAVs should also satisfy the collision avoidance constraint, i.e.,
\[ \sum_{i,j \in \mathcal{M}, i \neq j} (h_i - h_j)^2 \geq \chi^2 \],

where \( \chi^2 \) is the minimum variance of the altitudes of the UAVs.

3) The channel allocation constraint: Note that the UAVs adopt SIC technique to demodulate the collected message and this may result in considerable complexity at the receiver because as the number of IoT nodes over the same subchannel grows, the implementation complexity of SIC increases. For decreasing the decoding complexity, we assume that each subchannel can be allocated to at most \( D_1 \) IoT nodes. Given a proper value of \( D_1 \), the decoding complexity can be reduced to a tolerable level. Furthermore, considering the scarce spectrum resource, we also assume that each IoT node can occupy at most \( D_2 \) subchannels. By choosing a proper value of \( D_2 \), all the IoT nodes can be scheduled and the user fairness is guaranteed. We assume that \( ND_2 < KD_1 \). Therefore, we have:
\[ a_{m,n,k} \leq D_1, \forall m \in \mathcal{M}, \forall k \in \mathcal{K} \],
\[ \sum_{k=1}^{K} a_{m,n,k} \leq D_2, \forall m \in \mathcal{M}, \forall n \in \mathcal{N} \].

Moreover, the channel allocation indicator satisfies:
\[ a_{m,n,k} \in \{0, 1\}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \).

Hence, the resource allocation problem for the multi-UAV aided IoT NOMA uplink transmission system can be formulated as:
\[ \max_{P,A,v_m} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{B}{K} a_{m,n,k} \log_2 (1 + \gamma_{m,n,k}) \]
\[ \text{s.t.} \ \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} a_{m,n,k} p_{m,n,k} \leq p_{\text{max}}, \forall n \in \mathcal{N} \],
\[ \rho_{m,n,k} \geq 0, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \],
\[ h_{\text{min}} \leq h_m \leq h_{\text{max}} \],
\[ \sum_{i,j \in \mathcal{M}, i \neq j} (h_i - h_j)^2 \geq \chi^2 \],
\[ \sum_{n=1}^{N} a_{m,n,k} \leq D_1, \forall m \in \mathcal{M}, \forall k \in \mathcal{K} \],
\[ \sum_{k=1}^{K} a_{m,n,k} \leq D_2, \forall m \in \mathcal{M}, \forall n \in \mathcal{N} \],
\[ a_{m,n,k} \in \{0, 1\}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K} \)
flight heights to maximize the uplink transmission capacity. Finally, we give a sub-optimal solution based on the results obtained from the preceding steps. Note that unlike most of the existing works [13], [14], [17], we focus on optimizing UAVs’ flight heights instead of the horizontal locations. That is because optimizing the flight height is much simpler to analyze in comparison to optimizing the 2D coordinates of horizontal locations. Moreover, given the fixed UAV-device association, frequently changing the horizontal locations of UAVs may lead to severe inter-interferences between adjacent uplink transmission subsystems and increase the risk of flight collision. Additionally, considering the limited battery size, changing the flight heights is more energy-saving comparing with adaptively moving around for supporting the bursty traffic of the IoT nodes.

III. IoT NODES CLUSTERING AND SUBCHANNEL ASSIGNMENT

In this section, we propose a simple but effective sub-optimal algorithm to assign subchannels to IoT nodes with given UAVs’ locations and IoT nodes’ power allocation method. Before that, we first determine the indexes of the IoT nodes served by each UAV. Since the locations of the IoT nodes are known by the GS, a natural and practical approach will be that each UAV serves a group of IoT nodes which are located in proximity of each other. This approach can significantly shorten the communication distance between the IoT nodes and the corresponding UAV as well as mitigate the possibility of having strong interference between two closely located uplink transmission subsystems. Since the locations and distances are the main considerations when grouping the IoT nodes into different clusters, we adopt the classic K-mean clustering method [31], which can effectively group the IoT nodes into M clusters while merely brings low implementation complexity. The M clusters correspond to \{S_1, S_2, ..., S_M\}. Moreover, we fix the horizontal location of UAV m at the mean location of IoT nodes in S_m, which can be denoted as:

\[
(x_{m}^{\text{uav}}, y_{m}^{\text{uav}}) = \frac{1}{|S_m|} \sum_{n \in S_m} (x_n^{\text{node}}, y_n^{\text{node}}),
\]

where |S_m| represents the cardinality of S_m. As mentioned before, the benefits are that it can significantly decrease both the inter-interferences between the adjacent uplink transmission subsystems and the risk of flight collision.

Next we will assign the K subchannels for each UAV-enabled uplink transmission subsystem. After clustering IoT nodes into M clusters, we have:

\[
a_{m,n,k} = 0, \forall n \notin S_m.
\]

Therefore, we only need to focus on the subchannel assignment in each subgroup. In the following, we will take UAV m and its corresponding IoT nodes S_m as an example to show our channel assignment strategy.

Since the horizontal location of UAV m is fixed by Eq. (15), we assume that the flight height of UAV m is fixed at h_0. Moreover, each IoT node is assumed to adopt the equal power allocation method, in which the maximum power p_{max} is equally allocated to the assigned subchannels. Under these assumptions, we model the subchannel assignment process as a many-many matching process between the IoT nodes and the subchannels. We assume that the kth subchannel prefers to be allocated to IoT node n1 over n2 if \(g_{m,n_1,k} > g_{m,n_2,k}\). Then we can obtain preference lists of all subchannels, which is given by:

\[
\mathcal{P} = \{\mathcal{P}_1, \mathcal{P}_2, ..., \mathcal{P}_K\},
\]

where \(\mathcal{P}_k\) denotes the preference list of the kth subchannel, which is in the decreasing order of channel gains of IoT nodes in \(S_m\). Then we design a many-many matching algorithm for finding the sub-optimal subchannel assignment strategy, which is described in Algorithm 1. To elaborate, each subchannel is first allocated to its most preferred IoT node, if the number of this node’s assigned subchannels is less than \(D_2\), then this assignment is accepted. Otherwise, comparing this subchannel with the assigned subchannel which has the lowest uplink transmission capacity, and it will replace the assigned subchannel if it has higher uplink transmission capacity. This match process will terminate if all of the IoT nodes are assigned with \(D_2\) subchannels. The complexity of Algorithm 1 mainly comes from the sorting phase and the matching phase. In the sorting phase, each subchannel obtains its preference list of \(|S_m|\) users, in which the complexity is \(O(K|S_m|^2)\), while in the matching phase, each subchannel will be assigned at most \(K|S_m|\) times, resulting in the total complexity of \(O(K|S_m|^2)\). Comparing with the optimal exhaustive search, which has a complexity order of \(O(K^2|S_m|)\), the proposed algorithm is more suitable for practical applications.

IV. POWER ALLOCATION AND FLIGHT HEIGHT DESIGN

In this section, we provide solutions to the joint optimization problem in terms of the IoT nodes’ power allocation and UAVs’ flight heights. Given the horizontal locations of UAVs obtained from Eq. (15) and the channel allocation matrix obtained from Algorithm 1, problem (14) can be reduced to:

\[
\max_{p, h} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} B \sum_{i \in M} a_{m,n,k} \log_2 (1 + g_{m,n,k}) \quad (18a)
\]

s.t. \(p_{\min} \leq \sum_{m=1}^{M} \sum_{k=1}^{K} a_{m,n,k} p_{m,n,k} \leq p_{\max}, \forall n \in \mathcal{N}\), \(h_{\min} \leq h_{m} \leq h_{\max}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}\), \(\sum_{i,j \in \mathcal{M}, i \neq j} (h_i - h_j)^2 \geq \gamma^2\) \(\quad (18d)\)

where \(H = [h_1, h_2, ..., h_M]^T\). However, problem (18) is still non-convex. Considering the structure of problem (18), in the following, we use an alternative optimization (AO) method to solve it. To elaborate, we first fix the UAVs’ flight heights and design IoT nodes’ power allocation matrix \(P\). Then, relying on the power allocation matrix \(P\) obtained, we optimize the UAVs’ flight heights. Also an AO algorithm is proposed to further increase the total uplink transmission capacity.
A. Power Allocation Design of IoT Nodes

Given the fixed UAVs’ flight heights of $h_0$, problem (18) can be reformulated as a power allocation problem:

$$
\max_P \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} B \alpha_{m,n,k} \log_2 \left(1 + \gamma_{m,n,k}\right) \quad (19)
$$

s.t. $\sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} a_{m,n,k} p_{m,n,k} \geq p_{\text{min}}, \forall n \in \mathcal{N}$, \hspace{1cm} (19a)

$\sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} a_{m,n,k} p_{m,n,k} \leq p_{\text{max}}, \forall n \in \mathcal{N}$, \hspace{1cm} (19b)

$p_{m,n,k} \geq q, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}$. \hspace{1cm} (19c)

However, although the constraints of problem (19) are convex, the objective is still non-convex in terms of $P$. To overcome this problem, we adopt successive convex approximation (SCA) [32] approach to find a near-optimal solution. The objective of problem (19) is non-convex because of the non-convex term $\log_2 (1 + \gamma_{m,n,k})$, thus we first approximate this non-convex term by logarithmic approximation [33] as follows:

$$\log_2 (1 + \gamma_{m,n,k}) \geq \frac{\alpha_{m,n,k} \ln \left(\gamma_{m,n,k}\right) + \beta_{m,n,k}}{\ln 2}$$

(20)

which is tight at $\gamma_{m,n,k} = \gamma_{m,n,k}$ when the approximation constants are chosen as:

$$\alpha_{m,n,k} = \frac{\gamma_{m,n,k}}{1 + \gamma_{m,n,k}}$$

(21)

$$\beta_{m,n,k} = \ln (1 + \gamma_{m,n,k}) - \frac{\gamma_{m,n,k}}{1 + \gamma_{m,n,k}} \ln (\gamma_{m,n,k})$$

(22)

Moreover, let $P_{m,k} = e^{\tilde{p}_{m,n,k}}$, then the objective of problem (19) can be approximated by a concave lower bound, which is given by:

$$R_{\text{total}}^{\text{L}} \geq \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{B}{K} \alpha_{m,n,k} \ln \left[\gamma_{m,n,k} \left(\tilde{p}_{m,n,k}\right)\right] + \beta_{m,n,k}$$

(23)

where

$$\gamma_{m,n,k} \left(\tilde{p}_{m,n,k}\right) = \frac{g_{m,n,k} e^{\tilde{p}_{m,n,k}}}{\sum_{i \in \mathcal{S}_n} a_{i,k,1} g_i e^{\tilde{p}_{i,j,k}} + \sum_{i=1}^{M} \sum_{j=1}^{N} a_{i,j,k} g_{i,j,k} e^{\tilde{p}_{i,j,k}} + \sigma^2}$$

(24)

And now, problem (19) can be approximated by a convex problem, which is denoted as:

$$\max_P \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} B \alpha_{m,n,k} \ln \left[\gamma_{m,n,k} \left(\tilde{p}_{m,n,k}\right)\right] + \beta_{m,n,k}$$

(25)

s.t. $-\sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} a_{m,n,k} e^{\tilde{p}_{m,n,k}} + p_{\min} \leq 0, \forall n \in \mathcal{N}$, \hspace{1cm} (25a)

$\sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} a_{m,n,k} e^{\tilde{p}_{m,n,k}} - p_{\max} \leq 0, \forall n \in \mathcal{N}$ \hspace{1cm} (25b)

Note that the solution to problem (25) is only the lower bound of the optimal solution to problem (19). To further approach the optimal solution, we can update the parameters in Eq. (21).
and Eq. (22) in the following iterations until the results are converged.

Problem (25) is a standard convex optimization problem, which can be efficiently solved by the standard convex optimization solvers. To further reduce the computational complexity, we adopt Lagrangian dual method to solve this problem. Let \( L(e^{\tilde{p}_{m,n,k}}, \lambda, \omega) \) be the Lagrangian function, which can be written as:

\[
L(e^{\tilde{p}_{m,n,k}}, \lambda, \omega) = - \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{B a_{m,n,k}}{\ln 2} \alpha_{m,n,k} \ln [\gamma_{m,k} (\tilde{p}_{m,n,k})] + \beta_{m,n,k} + \sum_{n=1}^{N} \lambda_n \left( - \sum_{m=1}^{M} \sum_{k=1}^{K} a_{m,n,k} e^{\tilde{p}_{m,n,k}} + p_{\min} \right) + \sum_{n=1}^{N} \omega_n \left( \sum_{m=1}^{M} \sum_{k=1}^{K} a_{m,n,k} e^{\tilde{p}_{m,n,k}} - p_{\max} \right),
\]

where \( \lambda = [\lambda_1, \lambda_2, ..., \lambda_M]^T \) and \( \omega = [\omega_1, \omega_2, ..., \omega_M]^T \) are the Lagrangian multipliers associated with the constraints. And the Lagrangian dual function is calculated by:

\[
L(\lambda, \omega) = \sup_{e^{\tilde{p}_{m,n,k}}} L(e^{\tilde{p}_{m,n,k}}, \lambda, \omega).
\]

Since problem (25) is a convex optimization problem, the optimal solutions of the original problem and the dual problem should satisfy the Karush-Kuhn-Tucker conditions \cite{34}, thus by solving \( \partial L(e^{\tilde{p}_{m,n,k}}, \lambda, \omega) = 0 \), we can obtain the optimal solution in the form of Lagrangian multipliers. Note that \( \tilde{p}_{m,n,k} \) can show up as the wanted signal, the intra-interference and the inter-interference, hence \( \tilde{p}_{m,n,k} \) exists in four parts of Eq. (26), which can be given by:

\[
\Phi_1 (\tilde{p}_{m,n,k}) = - \frac{B a_{m,n,k}}{\ln 2} \alpha_{m,n,k} \ln [\gamma_{m,k} (\tilde{p}_{m,n,k})] + \beta_{m,n,k},
\]

\[
\Phi_2 (\tilde{p}_{m,n,k}) = - \sum_{i \in \mathcal{S}_{m,n}} \frac{B a_{m,i,n,k}}{\ln 2} \alpha_{m,i,n,k} \ln [\gamma_{m,k} (\tilde{p}_{m,i,k})] + \beta_{m,i,k},
\]

\[
\Phi_3 (\tilde{p}_{m,n,k}) = - \sum_{i=1, j=1}^{M} \frac{B a_{i,j,k}}{\ln 2} \alpha_{i,j,k} \ln [\gamma_{i,j,k} (\tilde{p}_{i,j,k})] + \beta_{i,j,k},
\]

\[
\Phi_4 (\tilde{p}_{m,n,k}) = - \lambda_n a_{m,n,k} e^{\tilde{p}_{m,n,k}} + \omega_n a_{m,n,k} e^{\tilde{p}_{m,n,k}},
\]

where \( \mathcal{S}_{m,n} = \{ i | g_{m,i,n,k} > g_{m,n,k} \} \). Therefore, by solving

\[
\frac{\partial L(e^{\tilde{p}_{m,n,k}}, \lambda, \omega)}{\partial p_{m,n,k}} = \frac{\partial \Phi_1}{\partial \tilde{p}_{m,n,k}} + \frac{\partial \Phi_2}{\partial \tilde{p}_{m,n,k}} + \frac{\partial \Phi_3}{\partial \tilde{p}_{m,n,k}} + \frac{\partial \Phi_4}{\partial \tilde{p}_{m,n,k}} = 0,
\]

we can achieve the optimal solution as shown in Eq. (33), where

\[
[x]^+ = \max\{x, 0\},
\]

and we let

\[
I_{m,n,k} [t] = \sum_{i \in \mathcal{S}_{m,n}} a_{m,i,k} g_{m,i,k} e^{\tilde{p}_{m,i,k}[t]},
\]

\[
\tilde{I}_{m,n,k} [t] = \sum_{i=1, j=1}^{M} \sum_{i \neq m} a_{i,j,k} g_{m,j,k} e^{\tilde{p}_{i,j,k}[t]},
\]

which are calculated using the results obtained in the t-th iteration. Moreover, since \( L(\lambda, \omega) \) is not differentiable, we can use the subgradient method to obtain the optimal Lagrangian multipliers in Eq. (33), where the Lagrangian multipliers are updated as follows:

\[
\lambda_n [t + 1] = \left[ \lambda_n [t] - \delta_n [t+1] \left( \sum_{m=1}^{M} \sum_{k=1}^{K} a_{m,n,k} p_{m,n,k} - p_{\min} \right) \right]^+, 
\]

\[
\omega_n [t + 1] = \left[ \omega_n [t] - \delta_n [t+1] \left( p_{\max} - \sum_{m=1}^{M} \sum_{k=1}^{K} a_{m,n,k} p_{m,n,k} \right) \right]^+, 
\]

where \( t \) and \( \delta_n [t+1] \) denote the iteration step and the step size, respectively.

Till now, we can use a SCA based iterative algorithm to find a near-optimal solution to problem (19). The algorithm is summarized in Algorithm 2. To elaborate, in the outer loop of Algorithm 2, problem (19) is approximated as a convex optimization problem, and the outputs obtained from the previous loop are used as inputs in the coming loop. Moreover, in the inner loop of Algorithm 2, the approximated convex optimization problem is solved with the Lagrangian dual method. Since the problem in the inner loop is solved optimally, Algorithm 2 is guaranteed to converge. In each round of Algorithm 2, a total number of \( MNK \) parameters need to be updated, thus Algorithm 2 has a worst-case complexity order of \( O(MNK L_1 L_2) \), where \( L_1 \) and \( L_2 \) are the maximum number of the iterations for the inner loop and outer loop, respectively. However, considering the relatively small \( L_1 \) and \( L_2 \), Algorithm 2 actually shows fast computational performance.

**B. Flight Heights Design of UAVs**

As mentioned before, in Section IV-A, we optimize the uplink power of IoT nodes with fixed heights. In this section, with the power allocation results obtained, we will optimize the flight heights of UAVs. Given the power allocation matrix \( P \), the flight height optimization problem can be formulated as:

\[
\max_{H} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{B a_{m,n,k}}{\ln 2} \log_2 (1 + \gamma_{m,n,k})
\]

s.t.

\[
\sum_{i,j \in \mathcal{M}, i \neq j} (h_i - h_j)^2 \geq \chi^2.
\]
Problem (39) is a non-convex optimization problem in terms of $H$ because of the non-convex term $\log_2(1 + \gamma_{m,n,k})$ and constraint Eq. (39b). In the following, we still adopt the SCA approach to overcome this problem. Note that the horizontal locations of the UAVs are fixed by Eq. (15), thus the horizontal distance between UAV $m$ and IoT node $n$ can be given by:

$$l_{m,n} = \sqrt{(x_{m,n}^{\text{nav}} - x_n^{\text{node}})^2 + (y_{m,n}^{\text{nav}} - y_n^{\text{node}})^2}.$$  \hspace{1cm} (40)

Substitute Eq. (40) into Eq. (1), $g_{m,n,k}$ can be rewritten as:

$$g_{m,n,k} = \frac{\eta}{h_m^2 + l_{m,n}^2}.$$  \hspace{1cm} (41)

Therefore, the non-convex term $\log_2(1 + \gamma_{m,n,k})$ can be written as:

$$\log_2(1 + \gamma_{m,n,k})$$

$$= \log_2 \left( 1 + \frac{p_{m,n,k} \eta}{h_m^2 + l_{m,n}^2} + \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{\alpha_{i,j,k} P_{i,j,k} \eta}{h_m^2 + l_{m,n}^2} + \sigma^2 \right)$$

$$= \log_2 \left( \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{\alpha_{i,j,k} P_{i,j,k} \eta}{h_m^2 + l_{m,n}^2} + \sigma^2 \right).$$  \hspace{1cm} (42)

where

$$\tilde{R}_{m,n,k} = \log_2 \left( \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{\alpha_{i,j,k} \eta}{h_m^2 + l_{m,n}^2} + \sigma^2 \right),$$  \hspace{1cm} (43)

$$\tilde{R}_{m,n,k} = \log_2 \left( \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{\alpha_{i,j,k} \eta}{h_m^2 + l_{m,n}^2} + \sigma^2 \right).$$  \hspace{1cm} (44)

\begin{algorithm}
1: Initialize $s = 1$, $\alpha_{m,n,k,1} = 1$, $\beta_{m,n,k,1} = 0$ and $p_{m,n,k,1} = 0$.
2: repeat
3: Initialize $\lambda_n[1] > 0$ and $\delta_n = 1$. Set $t = 1$.
4: for $m = 1$ to $M$ do
5: for $k = 1$ to $K$ do
6: Update $I_{m,n,k}[t]$ according to Eq. (35). Set $t = t + 1$.
7: end for
8: Update $\lambda_n[t + 1]$ according to Eq. (37). Set $t = t + 1$.
9: end for
10: Update $\omega_n[t + 1]$ according to Eq. (38). Set $t = t + 1$.
11: end for
12: for $n = 1$ to $N$ do
13: Update $\alpha_{m,n,k}[s + 1]$ and $\beta_{m,n,k}[s]$ according to Eq. (21) and Eq. (22). Set $s = s + 1$.
14: end for
15: Update $p_{m,n,k}$ converges.
16: until $p_{m,n,k}$ converges.

\end{algorithm}
and
\[
\hat{R}_{m,n,k} = - \log_2 \left( \sum_{i \in S_{m,n}} a_{m,i} p_{m,i,k} + \sum_{i \neq m} \sum_{j=1}^{N} a_{i,j,k} p_{i,j,k} + \sigma^2 \right).
\]

Note that \(\hat{R}_{m,n,k}\) and \(\tilde{R}_{m,n,k}\) are still non-convex in terms of \(H\). Let us introduce a set of slack variables \(\tau = [\tau_1, \tau_2, \ldots, \tau_M]\), where \(\tau_m = h_m^2\). Replace the \(h_m^2\) in \(\tilde{R}_{m,n,k}\) with \(\tau_m\), then \(\tilde{R}_{m,n,k}\) can be rewritten as:
\[
\tilde{R}_{m,n,k} = - \log_2 \left( \sum_{i \in S_{m,n}} a_{m,i} p_{m,i,k} + \sum_{i \neq m} \sum_{j=1}^{N} a_{i,j,k} p_{i,j,k} + \sigma^2 \right),
\]
and problem (39) can be reformulated as:
\[
\max_{H, \tau} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} B \sum_{i \in S_{m,n}} a_{m,i} k p_{m,i,k} \tilde{R}_{m,n,k} + \tilde{R}_{m,n,k}
\]
\[\text{s.t.} \quad h_{\min} \leq h_m, \forall m \in M, \quad (46a)
\]
\[h_m \leq h_{\max}, \forall m \in M, \quad (46b)
\]
\[\chi^2 \leq \sum_{i,j \in M, i \neq j} (h_i - h_j)^2, \quad (46c)
\]
\[\tau_m \leq h_m^2, \forall m \in M. \quad (46d)
\]

It can be verified that the constraints in Eq. (46d) can be met with the equality, otherwise we can always increase \(\tau_m\) without decreasing \(\tilde{R}_{m,n,k}\), thus problem (46) actually shares the same optimal solution with problem (39). It is easy to find out that \(\tilde{R}_{m,n,k}\) is now concave with respect to \(\tau\). However, \(\hat{R}_{m,n,k}\) is still non-concave. Moreover, the constraints in Eq. (46d) are not convex because the resulting set is not a convex set. To overcome this problem, we use the first-order Taylor expansion to approximate them. Specifically, since \(\hat{R}_{m,n,k}\) is convex with respect to \(h_m^2\), we can approximate it with the lower bound \(\hat{R}_{m,n,k}^{lb}\) shown in Eq. (46), where \(H[r]\) is the given local point, which equals the result obtained in the \(r\)th iteration in SCA approach. Moreover, the constraint in Eq. (46c) can be written as:
\[
\chi^2 \leq \sum_{i,j \in M, i \neq j} (h_i - h_j)^2 = H^T Q H, \quad (47)
\]
where \(Q = \text{diag}(M) - 1\), in which \(\text{diag}(M)\) denotes a diagonal matrix with all diagonal elements equaling 1 and \(1\) is an \(M \times M\) matrix with all the elements equaling 1. Therefore, by applying the first-order Taylor expansion at the given point \(H[r]\), the constraint can be lower bounded by:
\[
\chi^2 \leq H^T[r] Q H[r] + 2H^T[r] Q (H - H[r]), \quad (48)
\]
Similarly, the constraints in Eq. (46d) can also be lower bounded by:
\[
\tau_m \leq h_m^2[r] + 2h_m[r] (h_m - h_m[r]). \quad (48)
\]

Therefore, problem 39 can be approximated by the following problem:
\[
\max_{H, \tau} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} B \sum_{i \in S_{m,n}} a_{m,i} k p_{m,i,k} \left( \hat{R}_{m,n,k}^{lb} + \hat{R}_{m,n,k}[r] \right)
\]
\[\text{s.t.} \quad h_{\min} \leq h_m, \forall m \in M, \quad (49a)
\]
\[h_m \leq h_{\max}, \forall m \in M, \quad (49b)
\]
\[\chi^2 \leq H^T[r] Q H[r] + 2H^T[r] Q (H - H[r]), \quad (49c)
\]
\[\tau_m \leq h_m^2[r] + 2h_m[r] (h_m - h_m[r]), \forall m \in M. \quad (49d)
\]

Obviously, \(\hat{R}_{m,n,k}^{lb}\) and \(\tilde{R}_{m,n,k}\) are now joint concave with respect to \(H\) and \(\tau\), and the constraints are all linear constraints. Therefore, problem (49) is now a convex problem. However, comparing with problem (25), it is too complicated to be solved with the Lagrangian dual method for the existence of \(\tau\). And solving \(\frac{dL}{d\tau} = 0\) will not result in intuitional solutions like Eq. (33). Fortunately, considering the relatively small dimensions of \(H\) and \(\tau\), problem (49) can be efficiently solved by standard convex optimization solvers such as CVX [35].

Till now, we can use a SCA based iterative algorithm to find a near-optimal solution to problem (39). The algorithm is summarized in Algorithm 3. To elaborate a little further, in the \(r\)th iteration, we solve problem (49) with given local point \(H[r]\), whilst in the \((r+1)\)th iteration, the optimal result obtained in the \(r\)th iteration is used as a local point to further approach the optimal solution. According to [36], Algorithm 3 is guaranteed to converge and it has a worst-case complexity order of \(O(M^{3.5}L_3)\), where \(L_3\) is the maximum number of the iteration rounds.

**Algorithm 3 SCA Based Flight Heights Optimization Algorithm for Problem (39)**

1. Initialize an initial feasible solution \(H^1[1]\), set \(r = 1\).
2. \textbf{repeat}
3. Obtain \(H^r\) by solving
4. Update \(H[r+1] = H^r\).
5. Update \(r = r + 1\).
6. \textbf{until} \(H\) converges.

**C. Joint Power Allocation and Flight Height Optimization**

In Section IV-A and Section IV-B, we have decomposed problem (18) into two subproblems in order to achieve the near-optimal power allocation matrix of IoT nodes and the flight heights of UAVs. However, the results obtained from the two subproblems are only the feasible solutions to problem (18), since we only optimize one set of variables in each subproblem. In this section, we design an AO algorithm to further approach the optimal solution to problem (18), where
we alternatively optimize one of the two set of variables, while keeping the other set of variables fixed. The algorithm is summarized in Algorithm 4. It should be noticed that the AO algorithm requires that the subproblem must be solved optimally to guarantee convergence, which unfortunately can not be met by Algorithm 4 since we only obtain the near-optimal solution for each subproblem. However, it is easy to prove that Algorithm 4 is converged. Let \( \Theta(\mathbf{P}[z], \mathbf{H}[z]) \) denote the objective of problem (18) in \( z \)th iteration, we will have:

\[
\begin{align*}
\Theta(\mathbf{P}[z], \mathbf{H}[z]) & \leq \Theta(\mathbf{P}[z+1], \mathbf{H}[z]) \\
& \leq \Theta(\mathbf{P}[z+1], \mathbf{H}[z+1]),
\end{align*}
\]

where (a) and (b) hold because the problems we solved in Algorithm 2 and Algorithm 3 are only lower bounds to problem (19) and problem (39), for we approximate these two problem with the logarithmic approximation and the first-order Taylor expansion, respectively. Eq. (50) indicates that the objective of problem(18) is non-decreasing after each iteration. Since the the objective of problem(18) is upper bounded by a finite value, Algorithm 4 is guaranteed to coverage. Since Algorithm 2 and Algorithm 3 have the complexity orders of \( O(MNKL_1L_2) \) and \( O(MNKL_1L_2) \), respectively, Algorithm 4 has a worst-case complexity order of \( O((MNKL_1L_2 + M^{3.5}L_3) L_4) \), where \( L_4 \) is the maximum number of the iterations.

\begin{algorithm}
\begin{algorithmic}
\State Initialize an initial flight height \( \mathbf{H}[1] = \{h_0\} \), set \( z = 1 \).
\Repeat
\State For given \( \mathbf{H}[z] \), solve problem (19) with Algorithm 2, denote the solution as \( \mathbf{P}[z+1] \).
\State For given \( \mathbf{P}[z+1] \), solve problem (39) with Algorithm 3, denote the solution as \( \mathbf{H}[z+1] \).
\State Update \( z = z + 1 \).
\Until \( \mathbf{H} \) and \( \mathbf{P} \) converge.
\end{algorithmic}
\end{algorithm}

V. SIMULATION RESULTS

In this section, numerical results are presented for evaluating the performance of the proposed algorithms. In the simulation, we assume that all the IoT nodes are randomly distributed in a squared area of size 2000 m x 2000 m. The maximum and minimum uplink transmit power of each IoT node are set to be \( p_{\text{max}} = 500 \) mW and \( p_{\text{min}} = 100 \) mW, respectively. The flying heights of the UAVs are assumed to span from \( h_{\text{min}} = 100 \) m to \( h_{\text{max}} = 500 \) m, and the minimum variance of the altitudes is \( \chi^2 = 100 \). Furthermore, we assume that the total bandwidth of each UAV-enabled subsystem is \( B = 120 \) kHz, which is divided into \( K = 16 \) subchannels. The AWGN power spectrum density is \( -174 \) dBm/Hz. Each subchannel can be assigned to at most \( D_1 = 3 \) IoT nodes and each IoT node can access \( D_2 = 2 \) subchannels. The reference-distance unit power gain is set to be \( \eta = 1.4 \times 10^{-4} \) [15], [37].

We first evaluate the convergence performances of the proposed algorithms. The results are shown in Fig. 3, where we assume that there are \( M = 3 \) UAVs serving \( N = 30 \) IoT nodes. It can shown in Fig. 3 that all the iterative algorithms described in Algorithm 2, Algorithm 3 and Algorithm 4 have fast convergence speed. Specifically, relying on the SCA approach, the algorithms proposed in Algorithm 2 and Algorithm 3 converge within 12 and 6 steps, respectively. Moreover, relying on the near-optimal solutions obtained by Algorithm 2 and Algorithm 3 in each iteration, the AO algorithm described in Algorithm 4 is capable of achieving convergence in as few as 4 steps, which validates our proof in Section IV-C.

Fig. 4 shows one snapshot of the system realization relying on the proposed approaches. In this figure, there are \( N = 30 \) IoT nodes randomly distributed in a 2000 m x 2000 m squared area. It is shown that these IoT nodes are clustered into three groups (identified by colors) using the K-means clustering method. Furthermore, by fixing the horizontal location of the UAVs using Eq. (15), these IoT nodes are evenly distributed in the surrounding area of the corresponding UAV, which can in fact minimize the total horizontal transmission distance. Moreover, Fig. 4 reveals that, for the sake of maximizing the total uplink capacity, the system trends to maximize the uplink transmit power of the near IoT nodes while minimize the uplink transmit power of the remote IoT nodes. This is due to the fact that the nearer IoT nodes have higher channel gains and maximizing the uplink transmit power of these IoT nodes can simply increase the total capacity. By contrast, minimizing the uplink transmit power of remote IoT nodes can decrease the intra-group interferences as well as the inter-group interferences since the remote IoT nodes are usually nearer to the IoT nodes in other subsystems.

Fig. 5 and Fig. 6 depict the total system capacity versus the maximum transmit power of IoT nodes and the number of IoT nodes, respectively. In Fig. 5, we set \( N = 30 \) and \( p_{\text{min}} = 0.2 \times p_{\text{max}} \). It is observed that the system capacity increases with the maximum transmit power of IoT nodes, which appeals to our general knowledge. Moreover, the growth of the system capacity becomes slower as the maximum power increases, which is due to the increment of the interferences. It is shown in Fig. 6 that the system capacity increases with the number of IoT nodes. Similarly, as the number of IoT nodes increases, the rate of growth becomes slower, which fits
Fig. 3. The convergence performances of the proposed algorithms with $(M, N) = (3, 30)$, where (a), (b) and (c) represent the convergence performance of Algorithm 2, Algorithm 3 and Algorithm 4, respectively.

Fig. 5. The total system capacity versus the maximum uplink transmit power of IoT nodes parameterized by different number of UAVs with $N = 30$.

Fig. 6. The total system capacity versus the number of IoT nodes parameterized by different number of UAVs.

Fig. 7. The total system capacity versus the number of IoT nodes with $M = 3$.

Fig. 8. The number of accessed IoT nodes versus the number of IoT nodes.

The Shannon’s formula. Fig. 6 also demonstrates that a larger number of UAVs leads to a higher system capacity, and the gap becomes larger as the number of IoT nodes increases. The reason is that the total transmission distance decreases as the number of UAVs increases since each UAV serves less IoT nodes. Moreover, an increment of UAV-enabled subsystems also results in a decrement of both the intra-group interferences and inter-group interferences since subchannels are assigned to less IoT nodes.

In Fig. 7, we compare our scheme with other schemes in terms of system capacity with $M = 3$. Specifically, the “NOMA scheme” is the method described in Algorithm 1-4 and the “NOMA scheme with fixed aerial BS” is a modified method relying on Algorithm 1-2, where the flying heights of the UAVs are fixed to $[100, 150, 200]$ m for satisfying the collision avoidance constraint. By contrast, in the “OMA scheme” and the “OMA scheme with fixed BS”, each subchannel can only be assigned to one IoT node and each IoT node can access one subchannel. We adopt a simple subchannel assignment approach, in which the subchannels are assigned to the IoT nodes in the decreasing order of channel gains. It
can be observed that the proposed scheme outperforms other schemes and both the two NOMA schemes have higher system capacity than the OMA schemes. To explain, we show the the number of accessed IoT nodes versus the number of IoT nodes of different schemes in Fig. 8. It shows that, when the number of IoT nodes is small, all the IoT nodes can access at least one subchannel, while the NOMA schemes outperform OMA schemes for their higher spectrum efficiency. By contrast, when the number of IoT nodes grows larger than the number of subchannels, more IoT nodes can access the UAVs in the NOMA schemes than in OMA schemes since each subchannel can only be assigned to one IoT node in OMA schemes. Therefore, the NOMA schemes still outperform the OMA schemes although they have higher interferences.

Finally, Fig. 9 compares the average rate of accessed IoT nodes versus the number of IoT nodes of different schemes. It is shown that in general, the average rate of accessed IoT nodes decreases with the number of IoT nodes. The reason is that the increment of IoT nodes results in higher interferences. Additionally, Fig. 9 demonstrates that when the number of IoT nodes is smaller than a threshold, i.e., the total number of subchannels, the NOMA schemes still outperform the OMA schemes. Moreover, when the number of IoT nodes exceeds the threshold, comparing with the OMA schemes, the NOMA schemes achieve same performance in terms of average rate, but more IoT nodes can be served, which validates the superiority of the NOMA schemes.

![Graph showing average rate of accessed IoT nodes versus number of IoT nodes with different schemes]

Fig. 9. The average rate of accessed IoT nodes versus the number of IoT nodes with $M = 3$.

VI. CONCLUSIONS

In this paper, we studied a resource allocation problem in the context of a multi-UAV aided IoT NOMA uplink transmission system. Specifically, we jointly optimized the channel assignment, the uplink transmit power of IoT nodes and the flying heights of UAVs for maximizing the system capacity. We proposed an efficient subchannel assignment algorithm relying on the K-means clustering method and matching theory. And an AO algorithm for finding near-optimal uplink transmit power of IoT nodes and flying heights of UAVs was proposed relying on the SCA approach. Numerical results showed that the proposed algorithms have fast convergence speed and the system has higher capacity than the OMA schemes. These results confirm that combine UAV communication and NOMA techniques is beneficial for constructing high-performance IoT systems.

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