This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2020.3003717, IEEE Internet of Things Journal

Resource Allocation and 3D Placement for UAV-Enabled Energy-Efficient IoT Communications

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***Abstract*—As the commercial launch of the fifth-generation (5G) wireless communications gets near, the trend from Internet of Things (IoT) to Internet of Everything (IoE) is emerging. Due to the advantages of the high mobility, high line-of-sight (LoS) probability and low labor cost, unmanned aerial vehicles (UAVs) may play an important role in the future IoT communication networks, e.g., data collection in remote areas. In this paper, we study the three-dimensional (3D) placement and resource allocation of multiple UAV-mounted base stations (BSs) in an uplink IoT network, where the balanced task for the UAV-BSs, the limited channel resource and the signal interference are taken into consideration. In the considered system, the total transmission power of IoT devices is minimized, subject to a signal-to-interference-and-noise ratio (SINR) threshold for each device. First, aiming to balance the task of each UAV, we propose a clustering algorithm based on an improved K-means method to divide IoT devices into several groups, so that the number of devices in each group is roughly the same. Then, based on matching theory, a *Modified-Hungarian-Based Dynamic Many-Many Matching* (HD4M) algorithm is designed for assigning sub-channels to IoT devices, which can efficiently mitigate the interference. Finally, we jointly optimize the transmission power of IoT devices and the altitudes of UAVs via an alternating iterative method. Simulation results show that the total transmission power decreases significantly after applying the proposed algorithms.**

***Index Terms*—Internet of Things, multi-UAV, resource allocation, energy-efficient, Hungarian Method, uplink transmission.**

I. Introduction

The development of Internet of Things (IoT) has a deep influence in many aspects of life. Smart objects, like mobile phones, vehicles, wearable devices, and sensors, are expected to be connected and share information to each other in the future IoT networks. It is perdicted that 75.44 billions devices will be connected to the Internet in 2025 [1], and this process is accelerated by the emergence of the fifth-generation (5G) wireless communications. To truly enable the IoT networks, problems related to data aggregation, security, architecture of network, etc., require deeper investigation [2]. Especially, the problem of collecting data from IoT devices is rather challenging due to their heterogeneous characteristics compared with conventional communication devices [3]. The number of IoT devices is usually large, and they are usually distributed in very large-area regions, e.g., hundreds of fire sensors in the forest. Meanwhile, each IoT device normally has a limited transmission ability, and thus its signal cannot reach a far distance. With these limitations, common ground base stations (BSs) may not cover all the IoT devices and collect their data satisfactorily, while sending unmanned aerial vehicles (UAVs) as temporary air BSs becomes an accessible and cost-effective approach [4], [5].

Introducing UAVs to IoT communication networks has many advantages. First, with the high mobility of UAVs, they can be deployed to particular areas where the ground BSs cannot cover. When ground BSs are damaged in disasters, UAVs can also be used as the temporary replacements of ground BSs to serve IoT devices [6]. Second, the higher hovering altitudes of UAVs provide a higher probability of establishing line-of-sight (LoS) links with ground devices, and thus the quality of communication is enhanced, with energy saved and coverage expanded at the same time [7], [8]. Besides, UAVs have the superiority of flexible three-dimensional (3D) deployment, since they can be rapidly deployed to the optimal positions based on varying distributions of ground IoT devices.

Because of these advantages, UAVs play a key role in energy-constrained IoT networks to extend the working hours of devices and provide ubiquitous massive access [9]. Many companies (such as SeeTree and Luck Stone) have employed UAVs to collect and monitor sensor data on many fields (e.g., farmland and mine monitoring). However, due to the practical size, weight, and power (SWAP) constraints and communication resources, the endurance and reliability may be affected in UAV-aided IoT systems [10]. Recently, many researchers have studied the key techniques and scenarios for UAV-enabled IoT communications [11]–[22].

A. Related Works and Motivation

In [11]–[13], the placement and resource allocation of a single-UAV BS were studied. The authors of [11] used an iterative parameter-assisted block coordinate descent method to maximize the minimal achievable rate of the ground devices, and gave the power and bandwidth allocation scheme of the UAV-BS. The authors of [12] proposed a low-complexity algorithm to solve the placement of the UAV, and obtained the similar performance as exhaustive search (ES) method. In

This work was supported in part by the National Natural Science Foundation of China (NSFC) under grant Nos. 91538204, 61571025, 61827901 and 91738301. The corresponding author is Dr. Zhenyu Xiao with Email: xiaozy@buaa.edu.cn.

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2020.3003717, IEEE Internet of Things Journal

[13], based on efficient differential evolution based method, a low-altitude UAV platform was employed as both a mobile data collector and an aerial anchor node to assist terrestrial BSs in data collection and device positioning. Since the operation time and battery of the UAV are limited and the number of IoT devices is large in a widespread area, it is important to deploy multiple UAVs and design an effective cooperative strategy for providing seamless and long-term services [14].

Due to the strong applicability and high complexity of the multiple-user multiple-UAV network [15], [16], the studies of multi-UAV aided IoT systems are challenging and have gotten a lot of attention. The authors in [17] proposed an efficient iterative algorithm for solving the user scheduling and association, UAV trajectory, and transmission power by applying the block coordinate descent and successive convex optimization techniques. In [18], multiple UAVs served as aerial BSs to collect data from ground IoT devices. By exploiting dynamic clustering and optimal transport theory, the authors minimized the total transmission power of the IoT devices. In [16], a comprehensive overview for UAV-enbled mobile edge computing (MEC) networks was presented in terms of the potential application scenarios, three UAV-enabled MEC architectures, implementation issues and challenges. The authors in [19] designed an energy-efficient MEC network with multiple UAVs via jointly optimizing user association, power control, computation capacity allocation, and location planning. In [20], the authors studied the uplink communication from ground devices to UAV-BSs. With the proposed modularity-based dynamic clustering algorithm relying on a modified Louvain method, the transmission powers of the ground devices were effectively saved. However, for simplicity in analytical analysis, the authors in [17] and [18] assumed that the altitude of UAVs is fixed, and the interference between IoT devices is neglected because of the sufficient spectrum bandwidth in [18]–[20]. In [21], the optimal 3D locations of UAVs were investigated under the interference between the UAV BSs. In addition, the authors of [22] developed an energy-efficient IoT network with multiple UAVs in the interference scenario and interference-free scenario, respectively. The association, uplink power control and trajectory planning problems were studied in these scenarios.

In a real-world scenario, some practical requirements should be considered. For example, the access from a large number of users to a UAV will lead to network congestion because of the limited capacity. Communication resources of other UAVs may be wasted. Nevertheless, the task of each UAV was unlimited and the sub-channel assignment was not considered in the above works. Common clustering method (e.g., K-means) for the IoT devices in [18], [20] and [22] cannot tackle the network congestion issue and more specific clustering methods need to be further investigated. Besides, considering a generic UAV communication system with co-channel UAVs communicating with their respective ground users [23], the design of a dynamic sub-channel assignment strategy to reduce the co-channel interference is a critical challenge. The authors of [24] introduced the matching theory for addressing pertinent resource management problems in emerging wireless networks and showed that the matching theory could provide a good and stable channel allocation scheme in cognitive radio networks. In [25], the authors designed a many-many matching algorithm for finding the sub-optimal sub-channel assignment strategy to manage intragroup interference and intergroup interference.

B. *Contributions*

Motivated by the above works, in this paper, we study a generic UAV-aided IoT network where multiple UAVs are deployed to collect data from ground IoT devices considering three practical conditions, i.e., the balanced task for the UAV-BSs, the limited channel resource and the signal interference. To the best of our knowledge, this optimization issue has not been studied in the relevant works. The main contributions of this paper are summarized as follows:

1) We model the uplink transmission problem between multiple UAV-BSs and IoT devices to minimize the total transmission power with mentioned practical conditions. Specifically, all the UAVs share the same frequency spectrum, the task of each UAV is approximately equivalent, and the number of sub-channels is limited.
2) To solve the mixed-integer nonconvex problem, we divide it into three parts to find an overall sub-optimal solution. First, we propose a modified algorithm based on K-means to evenly assign all the IoT devices to the UAVs. The probability of an idle sub-channel in the system can be greatly reduced by applying this algorithm, which means that high spectrum efficiency is guaranteed. Then, inspired by the matching theory [24], to mitigate the interference of sharing sub-channels between IoT devices, we design a novel algorithm, i.e., *Modified-Hungarian-Based Dynamic Many-Many Matching* (HD4M) algorithm to determine the sub-channel assignment. Finally, the power control of IoT devices and the altitudes of UAVs are jointly optimized by using an alternating iterative method.
3) We analyze the performance of the proposed solution in terms of the feasibility, convergence and complexity. Extensive simulations show the faster convergence, higher reliability and effectiveness of the proposed algorithms compared with the benchmark scheme. Meanwhile, the proposed solution for 3D positions of UAVs can achieve a performance close to the ES method. Furthermore, the results also reveal a fundamental trade-off between the number of UAVs and the power consumption of IoT devices.

C. *Organization*

The rest of this paper is organized as follows. In Section II we model the scenario and formulate the problem. In Sections III, IV, and V, we introduce the corresponding algorithms to solve the three subproblems, respectively. Then, we analyze the feasibility, convergence, and complexity of the solutions and algorithms in Section VI. Section VII presents the simulation results to demonstrate the performance of the proposed design. Finally, we conclude the paper in Section VIII.

Notation: a, $\mathbf{a}$, $\mathbf{A}$ and $\mathcal{A}$ denote a scalar, a vector, a matrix and a set, respectively. $\|\mathbf{a}\|$ denotes the Frobenius norm of $\mathbf{a}$. $\lfloor a \rfloor$ denotes the largest integer that is not larger than a, and

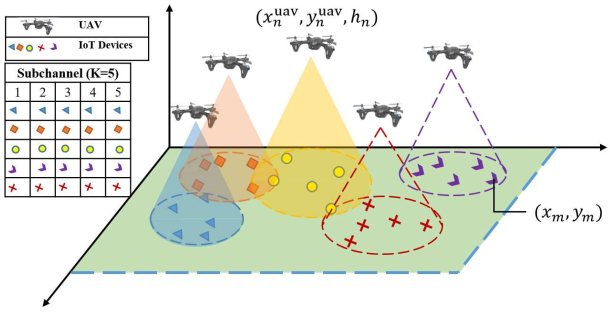

Fig. 1. Illustration of the considered system, where N UAV mounted BSs serve M ground IoT devices in K sub-channels.

$\lceil a \rceil$ denotes the smallest integer that is not less than a. $[\mathbf{A}]_{i,j}$ denotes the entry in the i-th row and j-th column of matrix $\mathbf{A}$.

II. System Model and Problem Formulation

A. System Model

As shown in Fig. 1, we consider a network of IoT devices associated to multiple hovering UAVs through uplink communication. There are M IoT devices and N UAVs in the system, whose index sets are denoted as $\mathcal{M} = \{1, 2, \dots, M\}$ and $\mathcal{N} = \{1, 2, \dots, N\}$, respectively. The locations of device $m \in \mathcal{M}$ and UAV $n \in \mathcal{N}$ are given by $\boldsymbol{x}_m = (x_m, y_m)$ and $\boldsymbol{v}_n = (x_n^{uav}, y_n^{uav}, h_n)$, respectively. Note that the locations of the M devices are static and prior known by a control center.

Without loss of generality, we assume that each UAV serves more than one IoT device and all UAVs share the same frequency spectrum. Due to the limitation of UAVs' service capability, we assume that all devices are evenly scheduled to UAVs, i.e., the number of devices that a UAV can serve is $\frac{M}{N}$. If M is not multiple of N, the number of devices that associate to a UAV would be $\left\lfloor \frac{M}{N} \right\rfloor$ or $\left\lceil \frac{M}{N} \right\rceil$. We assume that there are K orthogonal sub-channels for each UAV, whose index sets are denoted as $\mathcal{K} = \{1, 2, \dots, K\}$, and we need to allocate one sub-channel to serve one IoT device. Let $K = \left\lceil \frac{M}{N} \right\rceil$, which means that we want to use the minimal number of sub-channels to serve all the IoT devices [1]. This leads to the situation that any two groups of devices served by different UAVs will interfere with each other, while interference does not exist between devices in the same group. To be exact, if device m_1 is served by UAV n_1 in sub-channel $k \in \mathcal{K}$, which is also allocated to device m_2 that associates to UAV n_2, the two devices will interfere with each other.

First, we introduce the channel response from IoT devices to UAVs. In the considered system, both LoS and non-line-of-sight (NLoS) links are possible. While it has been discussed in Section I that the probability of LoS link increases as the height of the UAV-mounted BSs increases, the ground devices could still face NLoS links with UAVs because of the uncertain obstacles like buildings, trees or mountains. According to [26], the LoS probability from device m to UAV n, which could be affected by the environment, locations of ground devices and UAVs, is denoted as

$$P_{m,n}^{LoS} = \frac{1}{1 + \rho \exp\left[-\vartheta \left(\theta_{m,n} - \rho\right)\right]}, \tag{1}$$

where ρ and ϑ are the constants related to the environmental condition and the carrier frequency, respectively [27]. $\theta_{m,n}$ is the elevation angle from device m to UAV n, which is given by $\theta_{m,n} = \frac{180}{\pi} \tan^{-1}\left(\frac{h_n}{r_{m,n}}\right)$ with the altitude of UAV n denoted by h_n and the horizontal distance from device m to UAV n denoted as $r_{m,n} = \sqrt{(x_m - x_n^{uav})^2 + (y_m - y_n^{uav})^2}$. Correspondingly, the NLoS probability is $P_{m,n}^{NLoS} = 1 - P_{m,n}^{LoS}$.

The path loss of the LoS and NLoS links can be expressed as [28]

$$L_{m,n}^{LoS} = \left(\frac{4\pi f_c d_{m,n}}{c}\right)^{\alpha} \eta_{LoS}, \tag{2}$$

$$L_{m,n}^{NLoS} = \left(\frac{4\pi f_c d_{m,n}}{c}\right)^{\alpha} \eta_{NLoS}, \tag{3}$$

where $d_{m,n} = \sqrt{(x_m - x_n^{uav})^2 + (y_m - y_n^{uav})^2 + h_n^2}$ is the 3D distance between device m and UAV n, α is path loss exponent, η_{LoS} and η_{NLoS} are excessive path loss coefficients, f_c is carrier frequency, and c is the speed of light. Taking the randomness of the LoS and NLoS links into consideration, we use the average path loss to describe the loss of transmission power. Based on (1)-(3), we have the average path loss from device m to UAV n given by

$$\begin{aligned}
\overline{L}_{m,n} &= P_{m,n}^{LoS} L_{m,n}^{LoS} + P_{m,n}^{NLoS} L_{m,n}^{NLoS} \\
&= P_{m,n}^{LoS} \left(\frac{4\pi f_c d_{m,n}}{c}\right)^{\alpha} \eta_{LoS} + P_{m,n}^{NLos} \left(\frac{4\pi f_c d_{m,n}}{c}\right)^{\alpha} \eta_{NLoS} \\
&= \left[P_{m,n}^{LoS} \eta_{LoS} + P_{m,n}^{NLoS} \eta_{NLoS}\right] \left(\frac{4\pi f_c d_{m,n}}{c}\right)^{\alpha}.
\end{aligned} \tag{4}$$

Therefore, the average channel gain between device m and UAV n is $\overline{g}_{m,n} = \frac{1}{\overline{L}_{m,n}}$.

Then, we model the interference caused by the devices sharing the same sub-channels. Here we define a set $\{c_{m,n,k}\}$ to indicate the association from an IoT device to a UAV. If device m is served by UAV n in sub-channel k, we set $c_{m,n,k} = 1$. Otherwise $c_{m,n,k} = 0$. For different devices that associate with the same UAV, they are allocated with different sub-channels. If device m_1 served by UAV n_1 shares sub-channel k with device m_2 served by n_2, i.e., $c_{m_1,n_1,k} = c_{m_2,n_2,k} = 1$, it indicates that the interference exists between the two devices. Denoting a set of transmission powers as $\{p_m,\ m \in \mathcal{M}\}$, the interference experienced by device m that associates to UAV n in sub-channel k can be denoted as

$$I_{m,n,k} = \sum_{\substack{i=1 \\ i \neq m}}^{M} \sum_{j=1}^{N} c_{i,j,k} p_i \overline{g}_{i,n}, \tag{5}$$

where p_i is the transmission power of device i. Then the SINR

[1] In practice, K can be larger than $\lceil M/N \rceil$. When K is larger, the probability of interference is lower and the design becomes easier, but the spectrum efficiency is lower. Thus, $K = \lceil M/N \rceil$ is in fact the harshest condition here, and the proposed solution in this paper can be easily extended to the easier cases when $K > \lceil M/N \rceil$.

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of device m can be expressed as

$$\gamma_{m,n,k} = \frac{p_m \overline{g}_{m,n}}{I_{m,n,k} + \sigma^2}, \tag{6}$$

with σ^2 as the variance of additive white Gaussian noise (AWGN). In some multi-cell multi-user systems that maximize the transmission capacity, the SINR requirement may not be considered [25], [29]. However, to maintain the connectivity of the IoT uplink network, each device should meet a certain SINR requirement so that the receivers can demodulate the signal [30], [31]. When the SINR requirement is satisfied, the achievable rate of each device is also guaranteed, in which the achievable rate of device m is

$$R_m = \log_2 \left(1 + \sum_{n=1}^{N} \sum_{k=1}^{K} c_{m,n,k} \gamma_{m,n,k} \right). \tag{7}$$

B. Problem Formulation

The target of our optimization problem is to minimize the total transmission power of all the ground IoT devices. The optimization problem is formulated as follows.

$$\min_{\substack{\{c_{m,n,k}\},\\ \{p_m\},\{v_n\}}} \sum_{m=1}^{M} p_m \tag{8}$$

$$s.t. \quad \sum_{n=1}^{N} \sum_{k=1}^{K} c_{m,n,k} \gamma_{m,n,k} \geq \gamma_0, \forall m \in \mathcal{M}, \tag{8a}$$

$$\left\lfloor \frac{M}{N} \right\rfloor \leq \sum_{m=1}^{M} \sum_{k=1}^{K} c_{m,n,k} \leq \left\lceil \frac{M}{N} \right\rceil, \forall n \in \mathcal{N}, \tag{8b}$$

$$\sum_{n=1}^{N} \sum_{k=1}^{K} c_{m,n,k} = 1, \forall m \in \mathcal{M}, \tag{8c}$$

$$\sum_{m=1}^{M} \sum_{n=1}^{N} c_{m,n,k} \leq N, \forall k \in \mathcal{K}, \tag{8d}$$

$$c_{m,n,k} \in \{0,1\}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}, \tag{8e}$$

$$0 \leq \sum_{n=1}^{N} \sum_{k=1}^{K} c_{m,n,k} p_m \leq P_{\max}, \forall m \in \mathcal{M}, \tag{8f}$$

$$h_{\min} \leq h_n \leq h_{\max}, \forall n \in \mathcal{N}. \tag{8g}$$

Constraint (8a) indicates that the SINR of each device is no smaller than the threshold γ_0[2] . Constraint (8b) requires that all the UAVs serve approximately the equal number of devices. Constraint (8c) indicates that each device is only associated with one UAV through only one sub-channel. It also guarantees that all devices will be served. Constraint (8d) ensures that each sub-channel is shared by N devices at most. Constraint (8e) indicates that c is binary. Constraint (8f) indicates the maximal transmission power of each devices, which is denoted as $P_{\max}$. Constraint (8g) indicates that the altitude of UAVs is between $h_{\min}$ and $h_{\max}$.

[2]In general, the data requirements for homogeneous IoT devices, such as sensors or web cameras, are approximately uniform. Similar to [22], [30] and [31], we set a uniform SINR threshold for IoT devices. The proposed method can be used in different SINR constraint scenarios, while the solution may not be optimal. More general case with different SINR thresholds will be considered in our future work.

Problem (8) is a mixed-integer programming (MIP) problem, which is nonconvex. Therefore, the global optimal solution is challenging to find. Next, a three-step algorithm is proposed to find a sub-optimal solution of problem (8). In the first step, we propose a clustering algorithm based on the K-means strategy to determine the association between devices and UAVs, with 2D locations of UAVs derived at the same time[3]. Then we allocate sub-channels to devices using the proposed HD4M algorithm. Finally, the transmission power of each IoT device and the altitudes of UAVs are jointly optimized.

III. IoT Devices Clustering

In this section, we propose a clustering algorithm based on the K-means strategy to evenly divide all the IoT devices into N clusters/groups. As discussed in Section I, based on the distance between devices and cluster centers, the original K-means algorithm is an effective clustering strategy [33]. With each UAV serving a cluster of devices, the K-means approach may significantly mitigate the strong interference between two closely located devices [22]. However, using the original K-means algorithm may lead to an uneven clustering of IoT devices, which means the numbers of devices in some clusters may exceed the service capability of the UAV. As a result, there will be serious interference between the IoT devices in those clusters. Meanwhile, idle sub-channels may appear in the cluster with a small number of devices, and thus frequency spectrum resource is wasted. To overcome the drawback of the original K-means strategy, we propose a modified K-means clustering algorithm, ensuring that each UAV approximately serves the same number of IoT devices. With the proposed algorithm, the spectrum resource can be almost fully used.

Without loss of generality, we let the horizontal location of each UAV, $\boldsymbol{v}_n^{2D} = (x_n^{uav}, y_n^{uav})$, be fixed at the center of each cluster [28], where n denotes both "UAV" and "cluster center". This placement can decrease the average path loss, and save the transmission powers of IoT devices [25]. Then we define $a_{m,n} = \sum_{k=1}^{K} c_{m,n,k}$ as the association between device m and UAV n. For each device, it can only associate one UAV, so we have $a_{m,n} \in \{0,1\}$ here. With $\boldsymbol{v}_n^{2D} = (x_n^{uav}, y_n^{uav})$ and $r_{m,n}^2 = \left\| \boldsymbol{x}_m - \boldsymbol{v}_n^{2D} \right\|^2$, the subproblem of evenly clustering M IoT devices is expressed as

$$\min_{\{a_{m,n}\}} \sum_{m=1}^{M} \sum_{n=1}^{N} a_{m,n} r_{m,n}^2 \tag{9}$$

$$s.t. \quad \left\lfloor \frac{M}{N} \right\rfloor \leq \sum_{m=1}^{M} a_{m,n} \leq \left\lceil \frac{M}{N} \right\rceil, \forall n \in \mathcal{N}, \tag{9a}$$

$$\sum_{n=1}^{N} a_{m,n} = 1, \forall m \in \mathcal{M}, \tag{9b}$$

[3]In multiple-user multiple-UAV scenarios, the problem of UAVs 3D deployment is difficult and challenging [16], [23]. The grid search method as an ES method can be used to find the optimal positions of UAVs [32]. However, the ES method results in a high computational complexity. For simplicity, we fix the horizontal positions of UAVs and optimize the altitudes of UAVs. The performance of the proposed scheme compared to 3D optimiazation deployment will be evaluated via the simulations in Section VII.

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$$a_{m,n} \in \{0,1\}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}. \tag{9c}$$

Note that the clustering problem has been proven NP-hard [34], which means subproblem (9) is also NP-hard. We propose a three-step solution for subproblem (9).

Firstly, we use K-means++ to initialize the centers of all the clusters, so that they are separated far enough from each other [35].

Secondly, we associate the M devices to the nearest UAVs in sequence. We define $n_{up} = \left\lceil \frac{M}{N} \right\rceil$, $n_{down} = \left\lfloor \frac{M}{N} \right\rfloor$ and $R = \mod(M, N)$. Restricted by constraint (9a), there will be R UAVs serving n_{up} devices and $(N - R)$ UAVs serving n_{down} devices. In the association process, when a device is to associate to its nearest UAV that has already served n_{up} devices, the device will change to associate to the nearest UAV among remaining UAVs. In the end, we know that there may exist devices whose associated UAVs are not the nearest ones, and these devices may suffer from performance loss. Therefore, we define a device associated to a UAV that is not nearest to it as an *uncommon device*. Correspondingly, devices that are associated to their nearest UAVs are *common devices*. On the other hand, the association result of the second step depends on the execution sequence of the devices. Thus, there still exist a small space to improve the clustering operation.

Lastly, we further improve the performance of the uncommon devices with an iterative process. In each iteration, we first update the center of each cluster as the mean location of the devices, and meanwhile update the uncommon devices. Then, two operations, namely, *giving operation* and *swap operation*, are conducted to adjust the association. For an uncommon device i, assume that UAV n_1 and UAV n_2 denote its associated UAV and nearest UAV, respectively.

If the number of devices served by UAV n_1 is larger than that of devices served by UAV n_2, we execute the giving operation, i.e., we let device i associate to UAV n_2. The operation improves the clustering performance and the constraint (9a) is still satisfied.

If the number of devices served by UAV n_1 is no larger than that of devices served by UAV n_2, we execute the swap operation. Note that for each device j that associates to UAV n_2, the swap for association between UAVs n_1, n_2 and devices i, j, may decrease the value of the objective function in (9). We define the set $\{r_j\}$ where $j \in \{m | a_{m,n_2} = 1\}$ to describe the reduction of the objective function, in which

$$r_j = \left(r_{i,n_1}^2 + r_{j,n_2}^2\right) - \left(r_{i,n_2}^2 + r_{j,n_1}^2\right). \tag{10}$$

Then, we find the optimal swap device j^* to minimize the objective function, which is given by

$$j^* = \arg\max_{j} \{r_j\}. \tag{11}$$

It is worth noting that only when $r_{j^*} > 0$, the association for devices i and j^* are swapped. The iteration is repeated until the objective function in (9) converges.

We summarize the above process in Algorithm 1. Sequential device clustering is conducted in Steps 3-9. Let R_0, where $R_0 \le R$, denote the actual number of clusters that have $\left\lceil \frac{M}{N} \right\rceil$ devices when running Algorithm 1. If $R_0 > R$, there must exist that a remaining UAVs serves less than $\left\lfloor \frac{M}{N} \right\rfloor$ devices. The iteration is conducted in Steps 10-26. The giving and swap operations are conducted in Step 17 and Steps 19-23, respectively.

Algorithm 1: IoT Device Clustering Algorithm

Input: $\{\boldsymbol{x}_m\}$, N.
Output: $\{a_{m,n}\}, \{\boldsymbol{v}_n^{2D}\}$.
1: Initialize $R_0 = 0$ and $\hat{N}_n = 0$ as the number of devices that UAV n serves. Set $a_{m,n}$ to zero. Calculate $r_{m,n}$. Initialize $\mathcal{L} = \varnothing$ as the set of uncommon devices. Initialize n_{up}, n_{down} and R.
2: Initialize locations of cluster centers $\{\boldsymbol{v}_n^{2D}\}$ using K-means++.
3: **for** $m = 1$ to M **do**
4:   **if** $R_0 < R$ **then**
5:     Find the nearest cluster center n with $\hat{N}_n < n_{up}$, and set $a_{m,n} = 1$. Update R_0.
6:   **else**
7:     Find the nearest cluster center n with $\hat{N}_n < n_{down}$, and set $a_{m,n} = 1$. Update R_0.
8:   **end if**
9: **end for**
10: **repeat**
11:   Compute the value of objective function in (9).
12:   Update the cluster center set $\{\boldsymbol{v}_n^{2D}\}$.
13:   Update the uncommon device set $\mathcal{L}$.
14:   **for** $i \in \mathcal{L}$ **do**
15:     Find UAV n_1 associated to device i and UAV n_2 nearest to device i. Set $\{r_j\} = \varnothing$.
16:     **if** $\hat{N}_{n_1} > \hat{N}_{n_2}$ **then**
17:       Set $a_{i,n_2} = 1$ and $a_{i,n_1} = 0$.
18:     **else**
19:       Compute (10) to get $\{r_j\}$.
20:       Compute (11) to get j^*.
21:       **if** $r_{j^*} > 0$ **then**
22:         Set $a_{i,n_2} = 1$, $a_{j^*,n_1} = 1$, $a_{i,n_1} = 0$ and $a_{j^*,n_2} = 0$.
23:       **end if**
24:     **end if**
25:   **end for**
26: **until** the objective function in (9) converges.
27: **return** $\{a_{m,n}\}$, $\{\boldsymbol{v}_n^{2D}\}$.

IV. Sub-channel Assignment

After clustering, the association between devices and UAVs and horizontal location $\boldsymbol{v}_n^{2D}$ of each UAV are derived. However, with $\{c_{m,n,k}\}, \{p_m\}$ and $\{h_n\}$ uncertain and the complicated coupling relationship between them, the original problem (8) is still nonconvex. To address this problem, we design the sub-channel assignment strategy to get $\{c_{m,n,k}\}$ in this section, aiming at minimizing the interference among different clusters.

In a scenario where multiple UAVs serve a large number of ground devices, if two close devices are using the same

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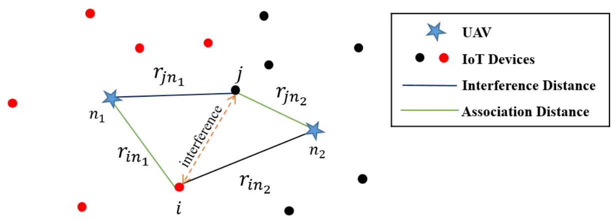

Fig. 2. Illustration of Interference Link and Association Link.

sub-channel to transmit their data, the uplink signals to UAVs will experience strong interference. The dilemma here is that increasing the transmission power of one device to overcome the interference will produce stronger interference to the other devices, and then the other devices will need even higher transmission power and produce stronger interference in return. In the worst situation that the interference is so strong that the transmission power required is beyond the limit of ground devices, the UAV may fail to demodulate the received messages. The matching theory is a good solution for channel allocation [24]. We can model the sub-channel assignment process as a many-many matching process between IoT devices and sub-channels [25]. To address this problem, we design an HD4M algorithm to find a sub-optimal solution.

Define $\mathcal{P}_k$, where $k \in \mathcal{K}$, as a set of the devices that share sub-channel k. Initialize $\mathcal{P}_k = \varnothing$. Sub-channels are assigned to clusters in sequence, denoted as $\{\pi_n\}$, where $\pi_n \in \mathcal{N}$. Since the interference is severe for adjacent clusters, the first two clusters, whose centers are nearest, are selected as π_1 and π_2. The cluster π_n, $3 \leq n \leq N$, is selected which is nearest to the previous clusters, i.e., $\pi_n = \arg\min_{\pi_n} \left\{ \sum_{i=1}^{n-1} \left\| \boldsymbol{v}_{\pi_n}^{2D} - \boldsymbol{v}_{\pi_i}^{2D} \right\| \right\}$. First, devices in cluster π_1 are initially assigned with sub-channels in random, which has no influence on the optimality, and $\{\mathcal{P}_k\}$ is updated. Then, sub-channels are assigned from cluster π_2 to π_N. We denote the cluster in which devices need to be assigned with the sub-channels as the target cluster. For each target cluster, the assignment can be modeled as a bipartite matching problem. This kind of problem can be solved by using the Hungarian method [36].

Assuming that devices i and j that communicates to UAVs n_1 and n_2 utilize the same sub-channel, we define r_{i,n_2} and r_{j,n_1} as *interference distance*, while r_{i,n_1} and r_{j,n_2} as *association distance*, as shown in Fig. 2. Here a larger r_{i,n_1} means device i is farther from its associated UAV n_1, which requires a higher transmission power of device i. Meanwhile, a smaller r_{i,n_2} means device i is closer to its interfered UAV n_2, and thus device j needs a higher transmission power to counter the interference. Thus, we define a fitness set $\{w_{i,j}\}$ to describe the interference between any two devices, in which

$$w_{i,j} = \frac{\left(r_{i,n_1}^2 + r_{j,n_2}^2\right)}{\left(r_{i,n_2}^2 + r_{j,n_1}^2\right)}. \tag{12}$$

We can see from (12) that both smaller association distance and larger interference distance lead to a smaller value of $w_{i,j}$, indicating less interference between device i and j. The qualification matrix between sub-channels and devices in each target cluster are determined as follows,

$$[\boldsymbol{\Lambda}]_{i,k} = \lambda_{i,k} = \sum_{j \in \mathcal{P}_k} w_{i,j}, \tag{13}$$

where $\lambda_{i,k}$ indicates the total interference between device i and other devices in sub-channel k. When there are no devices assigned to a sub-channel, i.e. if $\mathcal{P}_k = \varnothing$, we have $\lambda_{i,k} = 0$.

With qualification matrix $\boldsymbol{\Lambda}$ obtained, after applying the Hungarian method [36], we get matching matrix $\mathbf{S}$ whose binary elements are denoted as $s_{i,k}$. With $s_{i,k} = 1$, device i transmits data through sub-channel k, i.e., $\mathcal{P}_k = \mathcal{P}_k \cup i$. The process continues until devices in all target clusters are assigned with sub-channels.

We summarize the above process in Algorithm 2. The set of devices in the target cluster π_n is denoted as $\mathcal{I}_n$.

Algorithm 2: HD4M Algorithm

Input: $\{\boldsymbol{x}_m\}$, $\{a_{m,n}\}$, $\{\boldsymbol{v}_n^{2D}\}$.
Output: $\{c_{m,n,k}\}$, $\{\mathcal{P}_k\}$.
Initialize $\{c_{m,n,k}\}$ to zeros.
Initialize $\{\mathcal{P}_k\}$ to $\varnothing$.
Initialize the target clustering preference list $\{\pi_n\}$.
Initialize the sub-channel assignment in target cluster π_1 and update $\{\mathcal{P}_k\}$.
for $n = 2$ to N **do**
  Obtain the set $\mathcal{I}_n$ as devices in the target cluster π_n.
  Calculate $\{\lambda_{i,k}\}$ according to (13).
  Using the Hungarian method to get matching matrix $\mathbf{S}$.
  Set $c_{i,\pi_n,k} = 1$ when $s_{i,k} = 1$.
  Update $\{\mathcal{P}_k\}$.
end for
return $\{c_{m,n,k}\}$, $\{\mathcal{P}_k\}$.

V. Jiont Power Control and Altitude Optimization

In this section, we optimize the altitudes of UAVs and the transmission power of each IoT device. From Sections III and IV, we have already derived $\{c_{m,n,k}\}$ and 2D locations of UAVs $\{\boldsymbol{v}_n^{2D}\}$. Now the original problem (8) can be simplified.

According to $\{c_{m,n,k}\}$, expression (5) can be transformed to

$$I_m = \sum_{\substack{i \in \mathcal{P}_{k^{(m)}}, \\ i \neq m}} p_i \overline{g}_{i,n^{(m)}} \left(h_{n^{(m)}}\right), \ \forall m \in \mathcal{M}, \tag{14}$$

where $n^{(m)}$ denotes the associated UAV of device m, and $k^{(m)}$ denotes the sub-channel assigned to device m. Meanwhile, we define

$$\gamma_m \triangleq \sum_{n=1}^{N} \sum_{k=1}^{K} c_{m,n,k} \gamma_{m,n,k}, \ \forall m \in \mathcal{M}. \tag{15}$$

Therefore, the SINR constraint takes form of $\gamma_m \geq \gamma_0, \forall m \in \mathcal{M}$. Then substituting (14) into (6), we can transform (15) to

$$\gamma_m = \frac{p_m \overline{g}_{m,n^{(m)}} \left(h_{n^{(m)}}\right)}{\sum\limits_{\substack{i \in \mathcal{P}_{k^{(m)}}, \\ i \neq m}} p_i \overline{g}_{i,n^{(m)}} \left(h_{n^{(m)}}\right) + \sigma^2}, \ \forall m \in \mathcal{M}, \tag{16}$$

and the simplified problem (8) is now expressed as

$$\min_{\{p_m\},\{h_n\}} \sum_{m=1}^{M} p_m \tag{17}$$

$$s.t. \quad \frac{p_m \overline{g}_{m,n^{(m)}}\left(h_{n^{(m)}}\right)}{\sum\limits_{\substack{i\in\mathcal{P}_{k^{(m)}},\\ i\neq m}} p_i \overline{g}_{i,n^{(m)}}\left(h_{n^{(m)}}\right)+\sigma^2} \geq \gamma_0,\ \forall m\in\mathcal{M}, \tag{17a}$$

$$0\leq p_m \leq P_{\max},\quad \forall m\in\mathcal{M}, \tag{17b}$$

$$h_{\min}\leq h_n \leq h_{\max},\quad \forall n\in\mathcal{N}. \tag{17c}$$

The average path gain in (17a) is related to the altitudes of UAVs. Note that the average path gain is a nonconvex function of h_n according to (2)-(4). Therefore, the constraint (17a) is also nonconvex. Besides, the transmission powers of IoT devices and UAVs altitudes are not independent, which makes the problem more complicated. To find the solution of problem (17), we propose an alternating iterative optimization method here. We first fix the altitudes of UAVs and optimize the transmission powers of IoT devices. Then, we begin the iterative process and in each iteration, we optimize the altitude of each UAV in turn to minimize total transmission power of IoT devices.

A. Optimal Transmission Powers of IoT Devices

With fixed altitudes of UAVs, we restate problem (17) as follows.

$$\min_{\{p_m\}} \sum_{m=1}^{M} p_m \tag{18}$$

$$s.t. \quad \frac{p_m \overline{g}_{m,n^{(m)}}}{\sum\limits_{\substack{i\in\mathcal{P}_{k^{(m)}},\\ i\neq m}} p_i \overline{g}_{i,n^{(m)}}+\sigma^2} \geq \gamma_0,\ \forall m\in\mathcal{M}, \tag{18a}$$

$$0\leq p_m \leq P_{\max}, \forall m\in\mathcal{M}. \tag{18b}$$

Theorem 1. *The optimal solution of problem (18) is obtained if and only if the following condition is satisfied.*

$$\frac{p_m \overline{g}_{m,n^{(m)}}}{\sum\limits_{\substack{i\in\mathcal{P}_{k^{(m)}},\\ i\neq m}} p_i \overline{g}_{i,n^{(m)}}+\sigma^2} = \gamma_0,\ \forall m\in\mathcal{M}. \tag{19}$$

Proof: Assume that the optimal solution of problem (18) is $\{p_m^\dagger\}$. Then assume that

$$\exists m_0\in\mathcal{M},\ \gamma_{m_0}=\frac{p_{m_0}^\dagger \overline{g}_{m_0,n^{(m_0)}}}{I_{m_0}+\sigma^2}>\gamma_0. \tag{20}$$

For the rest $(M-1)$ devices, we have

$$\gamma_m=\frac{p_m^\dagger \overline{g}_{m,n^{(m)}}}{I_m+\sigma^2}\geq\gamma_0,\quad \forall m\in\mathcal{M}, m\neq m_0. \tag{21}$$

Let $\delta>0$ and $p_{m_0}^*=p_{m_0}^\dagger-\delta$. According to (20), γ_{m_0} decreases as $p_{m_0}^\dagger$ decreases. Therefore, $\exists\delta>0$ that makes

$$\hat{\gamma}_{m_0}=\frac{p_{m_0}^* \overline{g}_{m_0,n^{(m_0)}}}{I_{m_0}+\sigma^2}\geq\gamma_0. \tag{22}$$

With the transmission power of device m_0 decreasing from $p_{m_0}^\dagger$ to $p_{m_0}^*$, the interference also decreases between m_0 and devices sharing sub-channel with m_0. To be exact,

$$I_m^*=p_{m_0}^*\overline{g}_{i,n^{(m_0)}}\left(h_{n^{(m_0)}}\right)+\sum_{\substack{i\in\mathcal{K}_{k^{(m)}},\\ i\neq m_0, i\neq m}} p_i^\dagger \overline{g}_{i,n^{(m)}}\left(h_{n^{(m)}}\right)$$
$$<I_m,\ \forall m\in\mathcal{P}_{k^{(m_0)}}, m\neq m_0. \tag{23}$$

Therefore,

$$\gamma_m^*=\frac{p_m^\dagger \overline{g}_{m,n^{(m)}}}{I_m^*+\sigma^2}>\gamma_0,\ \forall m\in\mathcal{P}_{k^{(m_0)}}, m\neq m_0. \tag{24}$$

Expression (22) and (24) indicate that constraint (18a) is still satisfied. Therefore, the real optimal transmission power of device m_0 must be smaller than $p_{m_0}^\dagger$, which contradicts to its optimality assumption. Consequently, assumption (20) does not hold, which means there must be $\gamma_{m_0}=\gamma_0$ for the optimal p_{m_0}. ■

Then, constraint (18a) can be rewritten as

$$\gamma_0\sum_{\substack{i\in\mathcal{P}_{k^{(m)}},\\ i\neq m}} p_i\overline{g}_{i,n^{(m)}}+\sigma^2\gamma_0-p_m\overline{g}_{m,n^{(m)}}=0,\ \forall m\in\mathcal{M}. \tag{25}$$

Now the problem turns into a linear programming problem. It can be solved by a linear programming tool, e.g. CVX [37]. With Theorem 1, each IoT device has an achievable rate of $\log_2(1+\gamma_0)$ bps/Hz.

B. Optimization of the UAVs' Altitudes

Denote the minimal total transmission power of devices derived at a fixed UAV altitude as $\{p_m^*\}$, and the problem (17) can be expressed as

$$\min_{\{h_n\}} \sum_{m=1}^{M} p_m^* \tag{26}$$

$$s.t. \quad \frac{p_m^* \overline{g}_{m,n^{(m)}}\left(h_{n^{(m)}}\right)}{\sum\limits_{\substack{i\in P_{k^{(m)}},\\ i\neq m}} p_i^* \overline{g}_{i,n^{(m)}}\left(h_{n^{(m)}}\right)+\sigma^2} \geq \gamma_0,\ \forall m\in\mathcal{M}, \tag{26a}$$

$$h_{\min}\leq h_n \leq h_{\max},\ \forall n\in\mathcal{N}. \tag{26b}$$

Due to the existence of $P_{m,n}^{LoS}$, $P_{m,n}^{\mathrm{NLoS}}$ and $d_{m,n}$ in the expression of $\overline{g}_{m,n}$, problem (26) is still nonconvex. To reduce the dimension of the variables and obtain a sub-optimal solution of problem (26), we first investigate the optimal altitude of each UAV one by one in sequence. After deriving the altitudes of all UAVs, $\{p_m^*\}$ is updated. Then the altitudes are calculated again and the process is iterated until $\{p_m^*\}$ converges. The optimization problem for the altitude of UAV n is given by

$$\min_{h_n} \sum_{m=1}^{M} p_m^* \tag{27}$$

$$s.t. \quad \frac{p_m^* \overline{g}_{m,n^{(m)}}\left(h_{n^{(m)}}\right)}{\sum\limits_{\substack{i\in P_{k^{(m)}},\\ i\neq m}} p_i^* \overline{g}_{i,n^{(m)}}\left(h_{n^{(m)}}\right)+\sigma^2} \geq \gamma_0,\ \forall m\in\mathcal{M}, \tag{27a}$$

$$h_{\min}\leq h_n \leq h_{\max}. \tag{27b}$$

This problem is a one-dimensional optimization problem which is still nonconvex by now because of the existence of $\overline{g}$ in (27a). We use one-dimensional optimization searching method, e.g. golden-section search, to solve problem (27).

As discussed above, We summarize Algorithm 3 to obtain a sub-optimal solution of problem (17).

Algorithm 3: Altitude and Power Control Algorithm

Input: Up and down altitude limits $h_{\max}$ and $h_{\min}$.
Output: $\{h_n\}, \{p_m\}$.
1: Initialize the altitudes of UAVs as $\{\hat{h}_n\}$, set the iteration counter $L_3 = 0$.
2: Solve problem (18) with the CVX to derive $\{p_m^*\}$.
3: **repeat**
4: **for** $n = 1$ to N **do**
5: Solve problem (27) by using golden section search method to get h_n, and update $\{p_m^*\}$.
6: **end for**
7: Update $\{h_n\}$.
8: $L_3 = L_3 + 1$.
9: **until** $\{p_m^*\}$ converges.
10: $\{p_m\} = \{p_m^*\}$.
11: **return** $\{h_n\}, \{p_m\}$.

VI. Overall solution

In this section, we provide analyses about the feasibility of the solution as well as the convergence and complexity of the algorithms.

A. Solution Reality and Feasibility

For UAV-enabled IoT systems, the fixed positions of IoT devices (e.g., farm sensors) can be a priori known for the control center. With the known position information of devices and using the proposed algorithms, UAVs can be deployed to the appropriate locations in advance and collect data. Even though the positions of devices change, we can timely adjust the UAVs deployment through the proposed low-complexity algorithms. Therefore, the solution which resolves the device clustering, sub-channel assignment, power control and UAV placement, is reasonable and has a real-world significance.

In fact, the uneven device distribution, channel assignment strategy and/or other strict constraints that seriously affect the SINR will lead to the severe interference for IoT devices. It is likely that there is no feasible solution if constraints are stringent. The proposed algorithms are designed for finding a feasible solution of the original problem to the greatest extent. For subproblems of the device clustering and sub-channel assignment, there always exist feasible solutions by employing Algorithm 1 and Algorithm 2, respectively. However, the altitude design and power control subproblem solved by Algorithm 3 may not always be feasible. In such a case, we refer to the proposed solution of the original problem being infeasible. One possible way to handle this issue is to increase the number of UAV-BSs, such that the requirements of all the devices are satisfied. The feasibility of the proposed solution will be evaluated via the simulations in Section VII.

B. Convergence Analysis

In Algorithm 1, both the giving operation and swap operation are activated only when the value of objective function decreases. In some rounds of iterations, the association of devices does not change, and thus the cluster centers will not change, ensuring the convergence of the algorithm. In Algorithm 3, the total transmission power of the IoT devices is always decreasing in the iterative process of optimizing the altitude of each UAV, which guarantees convergence of the algorithm. In Section VII, we will show the specific convergence behaviour of the proposed algorithms.

C. Computational Complexity

In the following, we will discuss the complexity of the algorithms.

The computational complexity of Algorithm 1 mainly depends on Steps 10-26, with maximum computational complexity is denoted as $\mathcal{O}(MK)$, i.e., $\mathcal{O}\left(M\left\lceil\frac{M}{N}\right\rceil\right)$. Therefore, the computational complexity of Algorithm 1 is $\mathcal{O}\left(M\left\lceil\frac{M}{N}\right\rceil L_1\right)$, where L_1 denotes the number of iterations in Algorithm 1.

The computational complexity of Algorithm 2 mainly depends on Step 7 or the Hungarian matching algorithm. Since the number of devices sharing a sub-channel is no larger than N according to (8d), the maximum computational complexity of Step 7 is $\mathcal{O}(K^2N)$, i.e., $\mathcal{O}\left(\left\lceil\frac{M}{N}\right\rceil^2 N\right)$. The computational complexity of Hungarian algorithm depends on the dimension of matrix $\mathbf{\Lambda}$, which is given by $\mathcal{O}\left(\left\lceil\frac{M}{N}\right\rceil^3\right)$ [38]. Hence the computational complexity of Algorithm 2 is $\max\left\{\mathcal{O}\left(\left\lceil\frac{M}{N}\right\rceil^2 N^2\right), \mathcal{O}\left(\left\lceil\frac{M}{N}\right\rceil^3 N\right)\right\}$.

Since the golden-section search and the linear programming problem in Algorithm 3 have the computational complexities of $\mathcal{O}\left(\log_2\left(\frac{h_{\max}-h_{\min}}{\epsilon}\right)\right)$ and $\mathcal{O}(M^{3.5})$, respectively, the computational complexity of Step 5 is $\mathcal{O}(M^{3.5}\log_2(\frac{h_{\max}-h_{\min}}{\epsilon}))$, where ϵ is the search accuracy [39], [40]. Steps 4-6 have the complexity of $\mathcal{O}\left(NM^{3.5}\log_2(\frac{h_{\max}-h_{\min}}{\epsilon})\right)$. Therefore, the computational complexity of Algorithm 3 is $\mathcal{O}\left(NM^{3.5}L_3\log_2\left(\frac{h_{\max}-h_{\min}}{\epsilon}\right)\right)$.

Due to $N \le M$, we can easily derive that $\max\left\{\left\lceil\frac{M}{N}\right\rceil^2 N^2, \left\lceil\frac{M}{N}\right\rceil^3 N\right\} < NM^{3.5}L_3\log_2\left(\frac{h_{\max}-h_{\min}}{\epsilon}\right)$. Thus, the total computational complexity of the proposed solution is $\mathcal{O}\left(M\left\lceil\frac{M}{N}\right\rceil L_1 + NM^{3.5}L_3\log_2\left(\frac{h_{\max}-h_{\min}}{\epsilon}\right)\right)$.

VII. Simulation Results

In this section, we present the simulation results of the proposed joint resource allocation and 3D placement scheme for UAV-enabled IoT communication networks. In the simulations, 120 IoT devices are randomly distributed within an area of $1\text{km} \times 1\text{km}$, and evenly served by 5 UAVs with carrier frequency of 2 GHz. Here we consider an urban area with ρ of 11.95 and ϑ of 0.14 [28]. The other simulation parameters are listed in Table I.

In Fig. 3, we show the 3D placement of 5 UAVs and locations of 120 IoT devices. The devices which associate to different UAVs are indicated by different colors, while the corresponding UAVs are indicated by the same color. The uncommon devices are specially indicated by star marks. It

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2020.3003717, IEEE Internet of Things Journal

TABLE I
SIMULATION PARAMETER

Parameters	Descriptions	Values
$P_{\max}$	Maximum transmission power of IoT devices	200 mW
σ^2	Variance of AWGN	-110 dBm
α	Path loss exponent	2
η_{LoS}	Additional path loss for LoS in free space	3 dB
η_{NLOS}	Additional path loss for NLoS in free space	23 dB
$h_{\min}$	Minimum altitude of UAVs	200 m
$h_{\max}$	Maximum altitude of UAVs	500 m

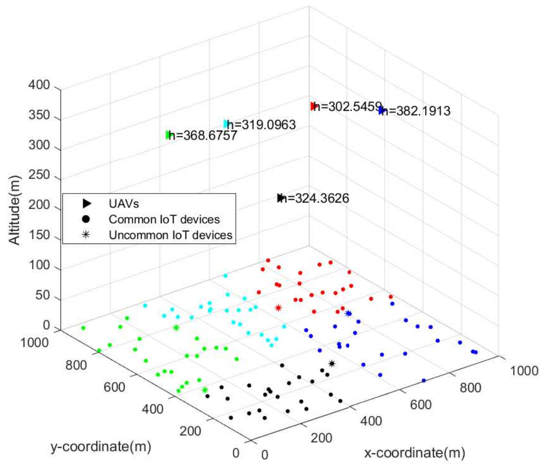

Fig. 3. 3D placement of 5 UAVs serving 120 IoT devices.

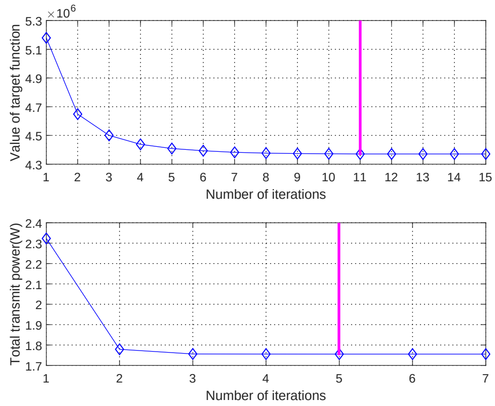

Fig. 4. Convergence performance of Algorithm 1 (up) and Algorithm 3 (down).

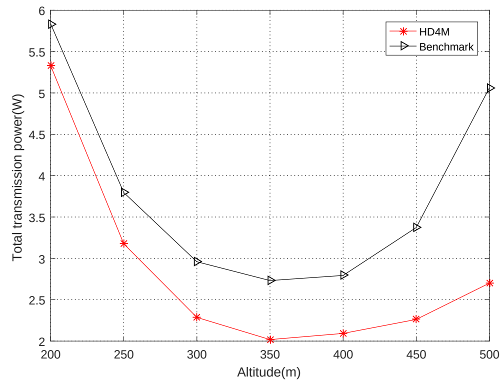

Fig. 5. Total transmission power of devices as the altitude of UAVs varies, where $M = 120$, $N = 5$, $\gamma_0 = 1$ dB, the number of sub-channels $K = M/N$ and UAVs' altitudes are set uniform.

can be seen that each UAV serves an equal number of devices, and 5 clusters are separated relatively far from each other, which can effectively mitigate the interference. There are 5 uncommon devices, which distribute in 4 clusters and are located at the border areas of the clusters. Here, the uncommon devices are not associated to their nearest UAVs, because these UAVs cannot serve any more device due to the limitation of their task and sub-channels. On the contrary, the common devices are associated to their nearest UAVs. The horizontal location of each UAV is set at the center of each cluster. The altitude of each UAV is optimized based on the distribution of the devices to further reduce the total transmission power.

The results in the following Figs. 4-9 are the average performance over 2000 device distributions and channel realizations without infeasible solutions. In Figs. 5-9, the performance of the proposed HD4M algorithm is compared with a benchmark scheme, in which the sub-channels are randomly assigned to devices and the altitudes of the UAVs are fixed at 300 m. In Figs. 7-9, the grid search method is also applied for optimizing the 3D locations of UAVs instead of the altitudes in Algorithm 3, which is referred to as the 3D grid search. The precision of the search step is 10 m and the search accuracy is 0.2 in the simulations.

In Fig. 4, we present the convergence performance of the proposed algorithms. The values of the objective functions in Algorithm 1 and Algorithm 3 show no variance after 11 and 5 iterations, respectively. The results demonstrate the fast convergence of the proposed algorithms. Specifically, the value of the target function in Algorithm 1 decreases 13.1% in the beginning 3 iterations, and then shows little variance. The value of the target function in Algorithm 3 decreases 18.9% in the first iteration, and then shows minor variance.

Fig. 5 shows the total transmission power as the altitude of UAVs changes. Here the altitudes of UAVs for both the HD4M algorithm and the benchmark scheme are set uniform. We can see a decrease followed by an increase for the total transmission power as the altitude increases. Therefore, optimizing the altitude of each UAV can significantly improve the performance of the system. Specifically, the total transmission power of IoT devices in the proposed algorithm decreases from 5.33 W to 2.02 W and then grows to 2.7 W. In comparison, the transmission power of the benchmark scheme decreases from 5.84 W to 2.73 W and then raises to 5.06 W, with 0.96 W more than the proposed HD4M algorithm on average. This phenomenon reveals a similar fundamental trade-off as shown in [23]. Specifically, by increasing the altitude of UAVs, the probability of establishing LoS link increases as well, and thus the total transmission power decreases. However, as the altitude goes up, the distances between devices and UAVs

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2020.3003717, IEEE Internet of Things Journal

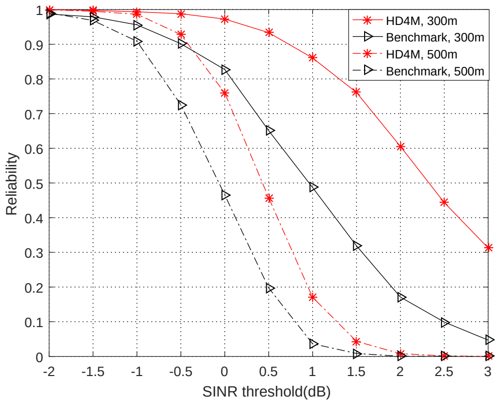

Fig. 6. Reliability comparison between the proposed algorithm and the benchmark scheme for different SINR thresholds and different altitudes, where $M = 120$, $N = 5$, the number of sub-channels $K = M/N$ and UAVs' altitudes are set uniform.

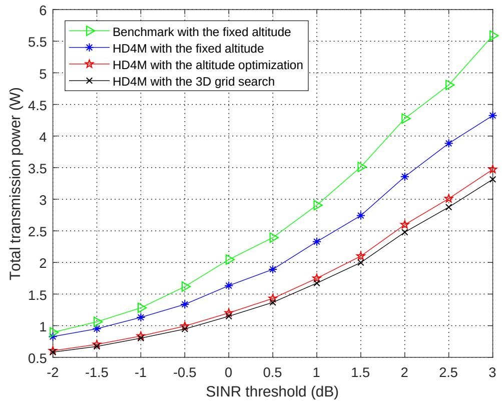

Fig. 7. Total transmission power for different SINR thresholds, where $M = 120$, $N = 5$, the number of sub-channels $K = M/N$ and fixed altitude 300 m.

become the main factor that affects the transmission power. In other words, when UAVs are higher than a certain altitude, IoT devices would have to spend much more power to compensate the path loss of signals.

In Fig. 6, we show the probability of obtaining feasible solution using the proposed algorithms and the benchmark scheme as the SINR threshold changes. The altitudes of the UAVs are set uniform. We define reliability as the percentage of obtaining feasible solutions in 2000 independent simulations. Note that in the given IoT network, all the devices may not be successfully served due to the contradiction between the SINR and the interference. A higher SINR requires more transmission power of a device, while the interference will also become more serious for other co-channel nodes. In fact, it is challenging to achieve the high SINR for devices in large-scale multi-user multi-UAV scenarios, since the sub-channels are heavily multiplexed. As the SINR threshold increases, the feasible region of problem (8) becomes smaller, leading to a decrease of reliability of the proposed solution. From Fig. 6, we can see that at the altitude of 300 m, the reliability of the proposed solution decreases from 1 to 0.31 as the SINR threshold increases from -2 dB to 3 dB. However, the reliability of the benchmark scheme decreases from 0.99 to 0.04. With an SINR threshold of 2 dB, the proposed solution has a 46% reliability improvement compared with the benchmark scheme. The reliability is also related to the altitude of UAVs. Fig. 6 shows that both the proposed solution and the benchmark scheme achieve a higher probability of feasible solution at 300 m than that at 500 m, with any SINR threshold in the simulations. The results indicate that by optimizing the altitudes of UAVs, the reliability of the proposed solution can be further improved.

Fig. 7 shows the total transmission power of all IoT devices as the SINR threshold varies. As the SINR threshold increases, each device needs more transmission power to meet the requirement. By implementing the proposed algorithms, IoT devices can always transmit their data with a lower power compared with the benchmark scheme. For instance, considering UAVs at 300 m altitude, by increasing SINR threshold from -2 dB to 3 dB, the total transmission power increases from 0.89 W to 5.59 W for the benchmark scheme, while it increases from 0.62 W to 3.47 W with our proposed approach. We can see an up to 23% performance improvement in Fig. 7 by implementing the HD4M algorithm, and an extra 25% improvement on average if the altitudes optimization is also applied. What's more is that the performance of the proposed solution for 3D positions of UAVs is very close to that of the 3D grid search method.

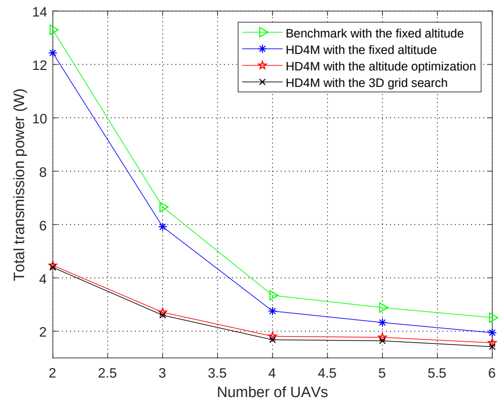

Fig. 8. Total transmission power for different numbers of UAVs, where $M = 120$, $\gamma_0 = 1$ dB, the number of sub-channels $K = M/N$ and fixed altitude 300 m.

Fig. 8 shows the total transmission power of all the IoT devices as the number of UAVs changes. Clearly, the total transmission power of IoT devices can be reduced by deploying more UAVs. Furthermore, using the proposed algorithms, the total transmission power of the devices decreases by 51% (on the average) compared to the benchmark scheme. When there is only a small number of UAVs, such as 2 or 3, the total transmission power mostly depends on whether the altitudes optimization is applied. In the case with more UAVs deployed in the system, the total transmission power decreases, and the decrease rate of the transmission power becomes smaller.

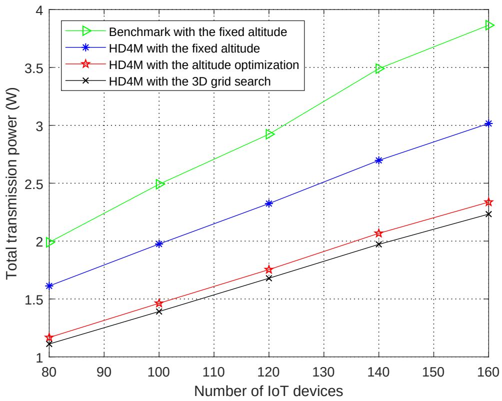

Fig. 9. Total transmission power for different numbers of IoT devices, where $N = 5$, $\gamma_0 = 1$ dB, the number of sub-channels $K = M/N$ and fixed altitude 300 m.

Although optimizing the altitudes still brings good performance, this advantage becomes smaller. Correspondingly, our proposed HD4M algorithm show better performance when the number of UAVs becomes larger. In fact, with more UAVs deployed, the total transmission power decreases dramatically. However, when the number of UAVs is large to a certain degree, with more devices sharing sub-channels, a stronger interference also emerges. This leads to a very low decrease rate of transmission power when the number of UAVs is larger than 4. It indicates that considering the cost of UAVs, it is better to deploy 4 UAVs instead of more UAVs with a very low power consumption gain. In other words, it reveals a fundamental trade-off between the cost of UAVs and the transmission power of IoT devices.

Fig. 9 shows the total transmission power as the number of devices increases. Using our proposed approach, we can see that the total transmission power increases from 1 to 0.31 as the SINR threshold increases from 1.17 W to 2.33 W, while it increases from 1.96 W to 3.85 W for the benchmark scheme. Clearly, the total transmission power linearly increases with more devices introduced into the system. The proposed HD4M algorithm outperforms the benchmark scheme by 21% reduction of the total transmission power, and 41% reduction of the total transmission power if the altitude optimization is applied. It can be seen that our proposed approach is applicable to both small-scale and large-scale IoT systems. From Fig. 7 to Fig. 9, it is a good way that the horizontal position of each UAV is fixed in the average position of the devices in the cluster. We can also see that comparing with the proposed solution, the exhaustive search of the 3D locations of UAVs only brings relatively small increments. The results show the rationality behind the proposed 3D deployment method of UAVs.

VIII. Conclusion

In this paper, we proposed a strategy to optimize the 3D placement and resource allocation of multiple UAV-mounted BSs in an uplink IoT network. It is to minimize the total transmission power, where both the interference between different IoT devices and the limited number of channels of a UAV are taken into consideration. The strategy can be divided to three parts. First, to balance the service task of each UAV, we proposed a clustering method based on K-means algorithm to divide all devices into several clusters/groups, such that each group has approximately the same number of devices and is served by the same UAV. Then, we proposed the HD4M algorithm to determine the sub-channel assignment of the devices to efficiently mitigate possible interference. Finally, we jointly optimized the power control of IoT devices and the altitudes of UAVs by using an alternating optimization method. In each iteration, we first derive the optimal transmission powers of the IoT devices, and then optimize the altitudes of UAVs by using the golden-section search method. The proposed overall strategy was verified by the simulation results, which showed that the proposed strategy achieves higher reliability and effectiveness than the benchmark scheme.

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