Resource Allocation for Multi-UAV Assisted Energy-Efficient IoT Communications With Co-Channel Interference*

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Abstract. Due to the superiority of high mobility, low labor cost and line of sight (LOS) prominent links of unmanned aerial vehicles (UAVs), UAV-assisted communications are increasingly attractive in emerging Internet of Things (IoT) networks. In this paper, we study the resource (including node association, channel and transmit power) allocation for the multi-UAV assisted IoT network in the uplink, considering the co-channel interference, limited task and channel capacity for the UAV-BSs. To provide long-term services for the IoT nodes, the total transmit power of the IoT nodes is minimized. We decouple the original nonconvex problem into three subproblems, i.e., node clustering, channel assignment, and transmit power control. To find the suboptimal solutions of the first two challenging subproblems, a balanced node clustering algorithm and a *Hungarian-based Channel Assignment* (HCA) algorithm are proposed, respectively. Then, the transmit power control problem turns into a convex problem, which can be calculated within polynomial time. Simulation results are provided to demonstrate the reliability and effectiveness of the overall strategy.

Keywords: Multi-UAV · energy-efficient Internet of Things · uplink · resource allocation · matching theory.

1 Introduction

The Internet of Things (IoT) has been widely applied to many fields, such as military, intelligent transportation, agricultural production and environmental monitoring [1]. Numerous IoT devices which are always small and battery-limited, are usually widely distributed in a big area. Moreover, the transmit power of each device is usually small, such that the devices may not communicate with the common ground base stations (BSs) which are far away. Unmanned aerial vihicles (UAVs) have significant advantages including high mobility, low labor cost

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and line of sight (LOS) predominant channel [2, 3]. Therefore, deploying UAVs as aerial BSs is an efficient and cost-effective approach for providing ubiquitous and long-term services. In the state-of-the-arts, energy-efficient wireless communication has attracted a lot of attention, not only to decrease the operation cost and be greener but also to prolong the battery life of devices [4]. Therefore, it is a crucial challenge to design an effective resource allocation strategy in UAV-assisted IoT networks.

Recently, UAV-assisted IoT communications have been widely investigated [5–8], where UAVs act as a flexible aerial BSs for data collecting or transferring data to the ground sensors. Wu *et al.* [5] aimed at maximizing the throughput of the ground devices with delay and minimal achievable rate consideration, by optimizing the resource allocation and trajectory of a single UAV-BS. Using denoising autoencoder (DAE) neural network strategy, Yu *et al.* [6] studied a spatial data sampling scheme for the UAV-assisted large-scale IoT system for sampling and reconstructing accurate and efficient data. Samir *et al.* [7] investigated the single-UAV routing and the radio resource allocation for collecting data from time-constrained IoT nodes. Considering multi-UAV enabled mobile IoT architecture, Mozaffari *et al.* [8] developed an energy-efficient transmission scheme in order to guarantee the long-term work of the IoT devices, where dynamic clustering and optimal transport theory were exploited.

From the above works, we can see that many works (e.g., [5–7]) only consider a single UAV, which may cannot adapt to latency-sensitive and dense scenarios. Moreover, although some consider multiple UAVs, the abundant spectrum resource is usually assumed and thus there is no inter-cell interference. Besides, load balancing is always neglected.

Therefore, in this paper, we model the uplink transmission problem in a multi-UAV assisted IoT network, considering the balanced task of UAVs, limited channel resource and co-channel interference. To deal with the original nonconvex problem, we design a three-step resource allocation strategy to find a suboptimal solution, including node clustering, channel assignment and transmit power control. Compared with the relevant works, the study in this paper has contributions as follows. First, considering a large-area IoT network with a huge number of nodes, we investigate a multi-user multi-UAV scenario. Second, since massive access to a UAV with the limited capacity will cause network congestion, we consider the task balance of UAVs and proposed a balanced node clustering algorithm leveraging the idea of the K-means method. Besides, since wireless frequency is a scarce resource and the inter-cell interference is serious, we design a heuristic dynamic channel assignment algorithm inspired by matching theory, namely, *Hungarian-based Channel Assignment* (HCA) algorithm, in order to mitigate the inter-cell interference. Furthermore, simulation results display the superiority of the overall solution compared with the random allocation (RA) scheme in terms of convergence, reliability and effectiveness.

The rest of this paper is organized as follows. In Section 2 and Section 3, we model the system and formulate the problem, respectively. Section 4 propose the solutions to the three subproblems. In Section 5, numerical simulation results are presented and discussed. Finally, Section 6 concludes the paper.

2 System Model

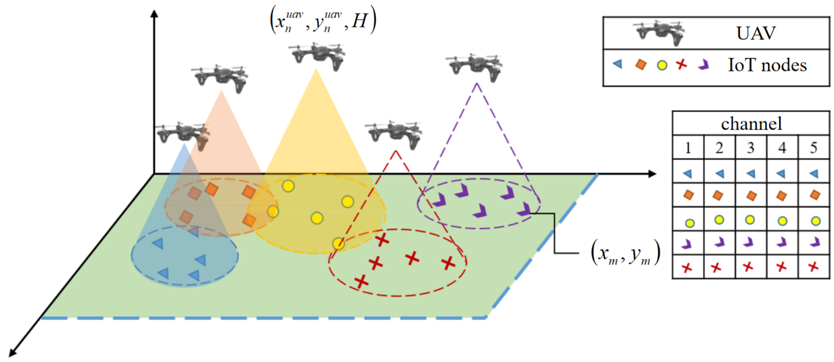


Fig. 1. System model of communications between multi-UAV and IoT nodes in K channels.

The UAV-assisted IoT uplink system is shown in Fig. 1, where M homogeneous and static ground IoT nodes transfer data to N UAVs through . UAVs hover at the same altitude H. The location information of M nodes is already known. Without loss of generality, we allow that several nodes can associate to a same UAV. UAVs utilize the same frequency spectrum to communicate with ground nodes and there are $K \geq \lceil \frac{M}{N} \rceil$ orthogonal channels. The horizontal locations of nodes $m \in \{1, 2, \ldots, M\}$ and UAVs $n \in \{1, 2, \ldots, N\}$ are expressed as $\boldsymbol{x}_m = (x_m, y_m)$ and $\boldsymbol{v}_n = (x_n^{uav}, y_n^{uav})$, respectively. We assume that a UAV is able to communicate with $\lfloor \frac{M}{N} \rfloor$ or $\lceil \frac{M}{N} \rceil$ nodes, and this balanced scheduling can avoid channel waste and network congestion. Thus, the association between UAVs and nodes as well as orthogonal channels should be scheduled. Assume that a channel can be allocated to a node. In the following, we consider the worst condition, i.e., $K = \lceil \frac{M}{N} \rceil$ and the proposed strategy can be applied in the other cases.

2.1 Channel Model

According to [9], we consider a probabilistic LOS channel model, i.e., elevation angle-dependent probabilistic LOS model in an urban environment. The probability of having the LOS link can be modeled as [9]

$$P_{m,n}^{LoS} = \frac{1}{1 + a \exp\left[-b\left(\theta_{m,n} - a\right)\right]} \quad (1)$$

where a and b are modeling parameters. $\theta_{m,n}$ is the elevation angle which is given by $\theta_{m,n} = \frac{180}{\pi} \tan^{-1}\left(\frac{H}{r_{m,n}}\right)$ with the horizontal distance between UAV n and node m expressed as $r_{m,n} = \sqrt{(x_m - x_n^{uav})^2 + (y_m - y_n^{uav})^2}$. Thus, non line of sight (NLOS) probability is $P_{m,n}^{NLoS} = 1 - P_{m,n}^{LoS}$.

The channel power of the LOS and NLOS links are formed as [9]

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

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

where α is path loss exponent, $d_{m,n}$ is the Euclidean distance between IoT node m and UAV n, η_{LoS} and η_{NLoS} are excessive path loss coefficients, λ is carrier wavelength. Thus, the expected channel power from node m to UAV n is expressed as

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

2.2 Interference Model

Then, we model the co-channel interference. Here a set $\{a_{m,n,k}\}$ is defined to indicate the association among node m, UAV n and channel $k \in \{1, 2, \ldots, K\}$. When UAV n associate node m through channel k, $a_{m,n,k} = 1$, otherwise $a_{m,n,k} = 0$. Let $\{p_1, ..., p_M\}$ and σ^2 denote the transmit powers of IoT nodes and the variance of additive white Gaussian noise (AWGN), respectively. Thus, the existing interference for UAV n and node m through channel k can be expressed as

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

Then, the signal-to-interference-and-noise ratio (SINR) of node m is given by

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

3 Problem Formulation

The total transmit power minimization problem of IoT nodes is formulated as

$$\min_{\substack{\{a_{m,n,k}\},\\ \{p_m\},\{v_n\}}} \sum_{m=1}^{M} p_m \tag{7}$$

$$s.t. \quad \sum_{n=1}^{N}\sum_{k=1}^{K} a_{m,n,k}\gamma_{m,n,k} \geq \gamma_0, \forall m \tag{7a}$$

$$\left\lfloor \frac{M}{N} \right\rfloor \leq \sum_{m=1}^{M}\sum_{k=1}^{K} a_{m,n,k} \leq \left\lceil \frac{M}{N} \right\rceil, \forall n \tag{7b}$$

$$\sum_{n=1}^{N}\sum_{k=1}^{K} a_{m,n,k} = 1, \forall m \tag{7c}$$

$$\sum_{m=1}^{M}\sum_{n=1}^{N} a_{m,n,k} \leq N, \forall k \tag{7d}$$

$$a_{m,n,k} \in \{0,1\}, \forall m,n,k \tag{7e}$$

$$0 \leq \sum_{n=1}^{N}\sum_{k=1}^{K} a_{m,n,k}p_m \leq P_{\max}, \forall m \tag{7f}$$

where (7a) demands the minimal limitation of the SINR threshold γ_0 for each node, i.e., the SINR constraint. (7b) is the task capability constraint. (7c) requires that each node communicates with a UAV in a channel, i.e., the association constraint. (7d) indicates that Up to N nodes occupy one channel, i.e., the co-channel node number constraint. Moreover, (7f) constrains the transmit power of each node not exceeding $P_{\max}$.

4 Proposed Solution

In the original problem (7), $\{c_{m,n,k}\}$ is a integer set, and thus all the constraints are integer constraints. In addition, constraint (7a) is nonconvex. Therefore, the problem (7) is a mixed-integer nonconvex problem.

In the following, we decouple problem (7) into three subproblems and find an overall sub-optimal solution. Firstly, a balanced node clustering problem is modeled and an corresponding algorithm is developed inspired by the K-means method. At the same time, the horizontal locations of UAVs are determined. Secondly, based on matching theory, channels are assigned to nodes with the proposed HCA algorithm. Lastly, the transmit power optimization problem transfers into a convex problem and can be solved within polynomial time.

4.1 Node Clustering

Due to homogeneous nodes and distance-based channel power, the K-means method is an efficient strategy in user clustering [8, 10]. However, in practical scenario, uneven distribution of nodes with the K-means method may lead to massive access or few access from nodes to a UAV. Correspondingly, there will be the stringent co-channel interference or the idle channel in a cell. Therefore, we propose the balanced clustering algorithm to ensure the full utilization of spectrum resources as well as mitigate the inter-cell interference, and meanwhile, each UAV balances the load.

Without loss of generality, we assume that in the horizontal direction, UAVs are deployed at centers of clusters [10]. Thus, n can denote both "UAV" and "cluster center". Then, we define the association between node m and UAV n as

$$c_{m,n} = \sum_{k=1}^{K} a_{m,n,k}, \tag{8}$$

where we have $c_{m,n} \in \{0,1\}$ according to the model. Thus, the balanced node clustering subproblem can be fomulated as

$$\min_{\{c_{m,n}\},\{\boldsymbol{v}_n\}} \sum_{m=1}^{M} \sum_{n=1}^{N} c_{m,n} r_{m,n}^2 \tag{9}$$

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

$$\sum_{n=1}^{N} c_{m,n} = 1, \forall m \tag{9b}$$

$$c_{m,n} \in \{0,1\}, \forall m, n \tag{9c}$$

with $r_{m,n}^2 = \|\boldsymbol{x}_m - \boldsymbol{v}_n\|^2$. In [11], the clustering problem was proven NP-hard. In the following, an three-step algorithm inspired by the K-means method is proposed for the sub-optimal solution of problem (9).

1) ***Center Initialization:*** First, we initialize centers of clusters by K-means++ to separate centers far from each other.
2) ***Association Initialization:*** Second, we allocate the M nodes association in sequence to the closest UAV. We define $R = \mathrm{mod}\,(M,N)$. According to constraint (9a), $\lceil \frac{M}{N} \rceil$ and $\lfloor \frac{M}{N} \rfloor$ nodes are served by R and $(N-R)$ UAVs, respectively. We define the node that is assigned to its closest UAV as *good node*. If a node is going to be assigned to its closest UAV whereas there have been $\lceil \frac{M}{N} \rceil$ nodes served by this UAV, the node will turn to connect the second closest UAV and we call the node *bad node*. In the end, several nodes may be assigned to UAVs which are not the closest UAVs. Furthermore, the execution sequence of nodes affect the association result. Therefore, next we further update clusters to adjust the association from good and bad nodes to UAVs.
3) ***Cluster update:*** An iterative process is developed to adjust clusters. In each process, we first recalculate each cluster center, which is given by

$$\boldsymbol{v}_n = \frac{\sum_{m=1}^{M} c_{m,n} \boldsymbol{x}_m}{\sum_{m=1}^{M} c_{m,n}}, \tag{10}$$

Algorithm 1: Balanced Node Clustering Algorithm

Input: N, M, $\{\boldsymbol{x}_m\}$.
Output: $\{\boldsymbol{v}_n\}$, $\{c_{m,n}\}$.
Initialize $R_{clu} = 0$ as the real number of clusters which own $\lceil \frac{M}{N} \rceil$ nodes. Initialize $\hat{N}_n = 0$ and $\{c_{m,n}\} = 0$. Initialize $\mathcal{L} = \varnothing$ as the bad node set. Initialize R. Compute $\{r_{m,n}\}$;
Utilizing K-means++ to initialize cluster center locations $\{\boldsymbol{v}_n\}$;
for $m = 1$ *to* M **do**
  if $R_{clu} < R$ **then**
    Get the closest UAV $n^* = \arg\min_n \{r_{m,n}\}, n \in \{n \mid \hat{N}_n < \lceil \frac{M}{N} \rceil\}$ and set $c_{m,n^*} = 1$. Update R_{clu};
  else
    Get the closest UAV $n^* = \arg\min_n \{r_{m,n}\}, n \in \{n \mid \hat{N}_n < \lfloor \frac{M}{N} \rfloor\}$ and set $c_{m,n^*} = 1$. Update R_{clu};
while *objective function in problem (9) decreases* **do**
  Update $\{\boldsymbol{v}_n\}$ and $\mathcal{L}$;
  for $i \in \mathcal{L}$ **do**
    Get UAV $n_1 = \arg_n \{c_{i,n} = 1\}$ and UAV $n_2 = \arg\min_n \{r_{i,n}\}$. Set $\{r_j\} = \varnothing$;
    if $\hat{N}_{n_1} \le \hat{N}_{n_2}$ **then**
      Compute (11) to get $\{r_j\}$;
      Compute (12) to get j^*;
      if $r_{j^*} > 0$ **then**
        Set $c_{i,n_1} = 0$, $c_{i,n_2} = 1$, $c_{j^*,n_1} = 1$ and $c_{j^*,n_2} = 0$;
    else
      Set $c_{i,n_2} = 1$ and $c_{i,n_1} = 0$;
return $\{\boldsymbol{v}_n\}$, $\{c_{m,n}\}$.

and the bad nodes is updated. After that, two operations are designed, namely, *exchange operation* and *supply operation* for uncommon nodes in order to improve the clustering performance. Assume that for an bad node i, n_1 and n_2 denote the associated UAV and closest UAV, respectively. Assume node j associates to UAV n_2 The number of nodes associated to UAV n is denoted as $\hat{N}_n$. In the exchange operation, if $\hat{N}_1 \le \hat{N}_2$, objective function value in (9) may minish with the exchange for association between UAVs n_1, n_2 and nodes i, j. Furthermore, a fitness set $\{r_j\}$ with $j \in \{m|a_{m,n_2} = 1\}$ is defined as

$$r_j = \left(r_{i,n_1}^2 + r_{j,n_2}^2\right) - \left(r_{i,n_2}^2 + r_{j,n_1}^2\right), \tag{11}$$

which show the decrease of the objective function. Then, the optimal exchange node j^* with a maximal reduction is got, which is computed as

$$j^* = \arg\max_j \{r_j\}. \tag{12}$$

Note that only when $r_{j^*} > 0$, the association for nodes i and j^* are exchanged. In the supply operation, if $\hat{N}_1 > \hat{N}_2$, node i will be assigned to UAV n_2. The iterative process is stopped when the objective function in (9) does not decrease.

The above process is summarized in Algorithm 1. ***Center Initialization*** is conducted in Step 2. ***Association Initialization*** is conducted in Steps 3-7. ***Cluster update*** is conducted in Steps 8-18. The exchange and supply operations are conducted in Steps 13-16 and Step 18, respectively. In ***Cluster update*** stage, only if the objective function value decreases, both of the two operations are executed, which guarantee the convergence. The ***Cluster update*** stage determines the algorithm complexity, which is given by $\mathcal{O}\left(M \left\lceil \frac{M}{N} \right\rceil L_1\right)$, where L_1 is the number of iterations.

4.2 Channel Assignment

With the fixed association scheduling $\{c_{m,n}\}$ between UAVs and nodes as well as the horizontal location $\{\boldsymbol{v}_n\}$, the original problem (7) is still nonconvex with uncertain channel scheduling and power control. Thus, in order to minimizing the co-channel interference and get $\{c_{m,n,k}\}$, a channel assignment strategy is designed in the following.

In practical multi-user multi-UAV networks, the co-channel interference is a tricky issue. Specifically, each node can increase the transmit power to improve its SINR, while the SINRs of other co-channel nodes in different cells will decrease. Therefore, a reasonable channel assignment strategy plays a vital part in improving the network performance. Matching theory has been proved to be an effective method for the future wireless communications, especially in channel allocation [12]. Inspired by matching theory, the channel assignment problem in the multi-user multi-UAV network can be modeled as a many-many matching process between channels and nodes. In the following, we design an HCA algorithm to address the channel assignment problem.

Define $\mathcal{P}_k$ as a node set in which the nodes utilize the same channel k and initialize $\mathcal{P}_k = \varnothing$. We assign channels to N clusters (denoted as $\{\pi_n\}$ in which $\pi_n \in \{1, 2, \ldots, N\}$) in sequence. Because of stringent interference between neighbouring clusters, we select the first two clusters as π_1 and π_2, whose centers are cloest. According to the nearest distance to the previous clusters, the next cluster π_n, $3 \le n \le N$, is selected by

$$\pi_n = \arg\min_{\pi_n} \left\{ \sum_{i=1}^{n-1} \|\boldsymbol{v}_{\pi_n} - \boldsymbol{v}_{\pi_i}\| \right\}. \tag{13}$$

First, we assign nodes in cluster π_1 initially with channels in random, which does not affect the optimality, and $\{\mathcal{P}_k\}$ is updated. Then, we assign channels from cluster π_2 to π_N. The objective cluster is denoted as the cluster where the nodes are required to be allocated channels. Thus, we can model the assignment problem for each objective cluster as a bipartite matching problem, and a heuristic design for the qualification matrix below.

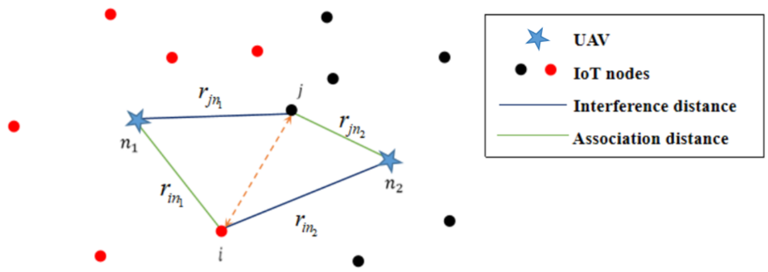


Fig. 2. Interference and association links between two co-channel nodes.

As shown in Fig. 2, assume that the same channel is utilized by nodes i and j which communicates with UAVs n_1 and n_2. r_{i,n_2} and r_{j,n_1} are difined as *interference distance*, as well as r_{i,n_1} and r_{j,n_2} are defined as *association distance*. Apparently, a higher transmit power of device i is required in case of a larger r_{i,n_1} to make up for a larger channel loss and/or a smaller r_{i,n_1} to counter the more serious interference. Thus, to describe the co-channel interference between any two nodes, we define the fitness set $\{w_{i,j}\}$, in which

$$w_{i,j} = \frac{\left(r_{i,n_1}^2 + r_{j,n_2}^2\right)}{\left(r_{i,n_2}^2 + r_{j,n_1}^2\right)}. \tag{14}$$

A small value of $w_{i,j}$ can be obtained by both large interference distance and small association distance, indicating small co-channel interference between n-odes i and j. Thus, in each objective cluster, we can get the qualification set of channels and nodes, i.e.,

$$\lambda_{i,k} = \sum_{j \in \mathcal{P}_k} w_{i,j}, \tag{15}$$

where $\lambda_{i,k}$ actually indicates the total suffered interference of node i from the other co-channel nodes. We can have $\lambda_{i,k} = 0$ for no co-channel nodes, i.e., $\mathcal{P}_k = \varnothing$. Thus, the matching problem between the nodes of present objective cluster and channels can be given by

$$\min_{\boldsymbol{S}} \sum_{j \in \{m | c_{m,n}=1\}} \sum_{k=1}^{K} s_{j,k} \lambda_{j,k} \tag{16}$$

$$s.t. \quad \sum_{k=1}^{K} s_{j,k} = 1, \forall j \in \{m | c_{m,n} = 1\} \tag{16a}$$

$$\sum_{j \in \{m | c_{m,n}=1\}} s_{j,k} = 1, \forall k \tag{16b}$$

$$s_{j,k} \in \{0, 1\}, \forall k, \forall j \in \{m | c_{m,n} = 1\} \tag{16c}$$

Algorithm 2: HCA Algorithm

Input: $\{\boldsymbol{x}_m\}$, $\{c_{m,n}\}$, $\{\boldsymbol{v}_n\}$.
Output: $\{a_{m,n,k}\}$, $\{\mathcal{P}_k\}$.

1 Initialize $\{a_{m,n,k}\} = 0$, $\{\mathcal{P}_k\} = \varnothing$, the objective clustering list $\{\pi_n\}$ and random channel allocation in objective cluster π_1. Update $\{\mathcal{P}_k\}$;
2 **for** $n = 2$ *to* N **do**
3   Get set $\mathcal{I}_n$ whose element is the node in the objective cluster π_n;
4   Compute $\{\lambda_{i,k}\}$ with (15);
5   Solve matching problem (16) with hungarian method to get $\boldsymbol{S}$;
6   Update $\{\mathcal{P}_k\}$;
7   **for** $i \in \mathcal{I}_n$ **do**
8   Find $k^* \in \{k|s_{i,k} = 1\}$ and set $a_{i,\pi_n,k^*} = 1$;
9 return $\{\mathcal{P}_k\}$, $\{a_{m,n,k}\}$.

Where $\boldsymbol{S}$ is the binary matching matrix and $s_{j,k}$ is the element. The optimal solution can be resolved using hungarian method [13]. $s_{i,k} = 1$ denotes that node i utilizes channel k, and we can have $\mathcal{P}_k = \mathcal{P}_k \cup i$. When the nodes in each objective cluster are allocated channels, the process terminates. Finally, we can get the scheduling among UAVs, nodes and channels, i.e., $a_{m,n,k} = c_{m,n} s_{m,k}$.

In Algorithm 2, we summarize the above process. The hungarian method or fitness set computation in Step 4 determine the algorithm complexity, which is given by $\mathcal{O}\left(\left\lceil \frac{M}{N} \right\rceil^2 N\right)$ and $\mathcal{O}\left(\left\lceil \frac{M}{N} \right\rceil^3\right)$ [14], respectively. Therefore, the algorithm complexity is $\max\left\{\mathcal{O}\left(\left\lceil \frac{M}{N} \right\rceil^3 N\right), \mathcal{O}\left(\left\lceil \frac{M}{N} \right\rceil^2 N^2\right)\right\}$.

4.3 Transmit Power Control

After the node clustering and channel assignment with the horizontal locations $\{\boldsymbol{v}_n\}$ of UAVs, relation set $\{a_{m,n,k}\}$ as well as co-channel information set $\{\mathcal{P}_k\}$, original problem (7) can be transferred into a transmit power control problem. The simplified problem is given by

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

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

$$0 \leq p_m \leq P_{\max}, \forall m \tag{17b}$$

where $k^{(m)}$ indicates the allocated channel of node m, and $n^{(m)}$ denotes the associated UAV of node m.

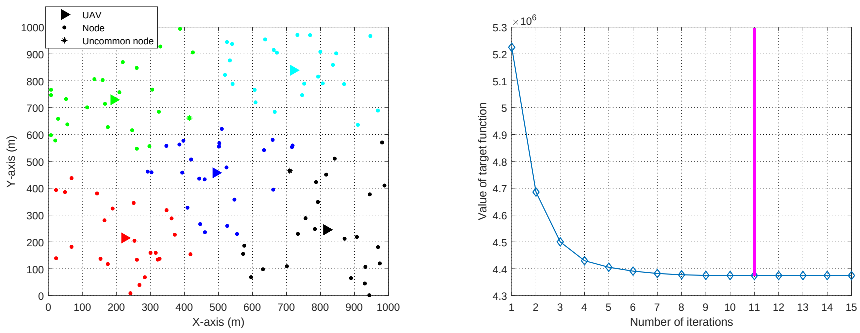
Problem (17) is a linear programming (LP) problem. Through interior point method, problem (17) can be addressed within polynomial time [15].

5 Performance Simulations

In this section, the simulation results are provided to verify the performance of the proposed strategy for multi-UAV assisted IoT communications. In the simulations, we consider an urban area of 1km $\times$ 1km with 120 randomly distributed IoT nodes and 5 UAVs, and a and b are 11.95 and 0.14 [16], respectively. The carrier frequency is 2 GHz, UAVs hover at 300 m, variance of AWGN is -110 dBm, maximal transmit power of IoT nodes is 300 mW, $\alpha = 2$, $\eta_{LoS} = 3$ dB, $\eta_{NLOS} = 23$ dB, respectively. Our proposed strategy is simulated by MATLAB R2018b.

The results in the following Fig. 3(b) and Figs. 4-5 are the average results of 2000 independent running. In Figs. 4-5, a random assignment (RA) strategy, in which channels are randomly assigned to nodes, acts as a benchmark scheme.

In Fig. 3, with Algorithm 1, we show the balanced node clustering result and convergence of Algorithm 1. Specifically, in Fig. 3(a), 120 IoT nodes are evenly divided into 5 clusters (identified by different colors) and the horizontal locations of the UAVs are fixed at the centers of clusters. What's more, there are 2 bad nodes (indicated by star marks) which are on the boundary of two groups and not communicate with their closest UAVs because of the task and channel constraints. The good nodes are scheduled to their closest UAVs. In Fig. 3(b),the objective function value in subproblem (9) does not decrease after 11 iterations, which show the fast convergence of Algorithm 1.

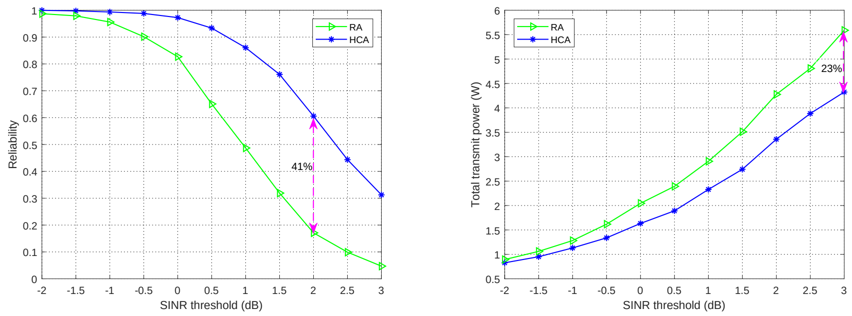


(a) Balanced node clustering using Algorithm 1 with 120 IoT nodes and 5 UAVs.

(b) Convergence performance of Algorithm 1.

Fig. 3. Association assignment and convergence in balanced node clustering.

In Fig. 4, with changing SINR threshold, we show the performance comparison between HCA algorithm and RA strategy, in terms of the system reliability and the transmit power. Reliability denotes the percentage of obtaining feasible solutions. Compared with the RA scheme, we can see that using the HCA algorithm, the reliability is better and the total transmit power is smaller from Fig. 4. As the SINR threshold increases, the reliability becomes worse and more transmit power is needed. With $\gamma_0 = 2\,\text{dB}$, the HCA algorithm has at most 46% improvement of reliability over the RA strategy. In Fig. 4(b), the total transmit power increases by HCA algorithm or RA strategy. In fact, a higher SINR for a node needs more transmit power, but it will produce stronger interference to the co-channel nodes. Therefore, in multi-user multi-cell networks, it is difficult to obtain a very high SINR for nodes with co-channel interference. In Fig. 4(b), there are 23% transmit power reduction at most using HCA algorithm, which verifies the performance.

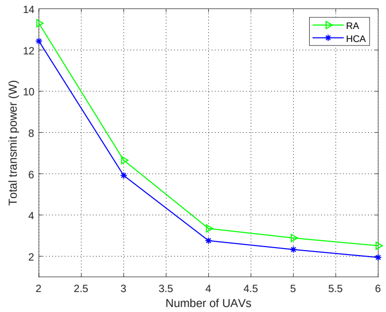


(a) Reliability comparison for different SINR thresholds, where the number of IoT nodes, UAVs and channels is 120, 5 and 24, respectively.

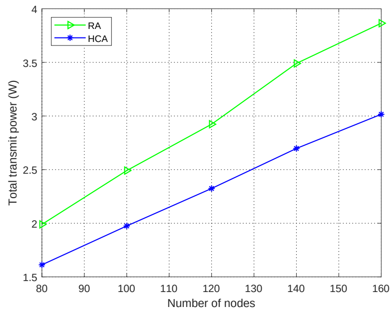
(b) Total transmit power for different SINR thresholds, where the number of IoT nodes, UAVs and channels is 120, 5 and 24, respectively.

Fig. 4. Property with different SINR thresholds.

Fig. 5(a) and Fig. 5(b) show the total transmit power of the IoT nodes as the UAV number and the node number change, respectively. From Fig. 5(a), using HCA algorithm, the total transmit power of nodes is reduced by an average of 15% under different number of UAVs and nodes compared with the RA strategy. Furthermore, we can see that the percentage of the performance improvement by using the HCA algorithm will increases with more UAVs, which means that the HCA algorithm will obtain the better performance than the RA strategy with more UAVs. What's more, when the number of UAVs increases, there will be less performance gain using either the RA stragety or HCA algorithm. It reveals that if we take into account the operation and maintenance cost of UAVs, we should not deploy many UAVs to just reduce the total transmit power of nodes but reasonably deploy the proper number of UAVs in practice. From Fig. 5(b), with the increase of nodes, the total transmit power increases linearly. The total transmit power of nodes is reduced by an average of 15% under different number of nodes compared with the RA strategy. We can see that the proposed scheme works well in IoT networks of all sizes.



(a) Total transmit power for different numbers of UAVs, where the number of IoT nodes and channels is 120 and 24, respectively, as well as the SINR threshold is 1 dB.



(b) Total transmit power for different numbers of IoT nodes, where the number of UAVs and channels is 5 and 24, respectively, as well as the SINR threshold is 1 dB.

Fig. 5. Total transmit power with different number of UAVs and nodes.

6 Conclusion

In this article, a resource allocation strategy for multi-UAV assisted IoT uplink communication was developed. In particular, we considered the co-channel interference, limited channel resource and balanced task of UAVs. First, the balanced node clustering algorithm was designed. Then, we proposed HCA algorithm to assign channels. Finally, we used CVX to resolve the convex problem of the transmit power control. The proposed solution was verified via the simulations, which showed good convergence and obtained better performance than RA strategy.

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