Efficient Resource Allocation For UAV Swarm Communication Systems With Awareness of Environmental Interference

Yinfei Qian[1], Linyun Zhou[2], Ziyan Yan[3], Qingjiang Shi[4]
{qyf19800404@163.com[1], 1911561@tongji.edu.cn[2], 1831577@tongji.edu.cn[3]}

School of Info. Sci & Tech, Zhejiang Sci-Tech University, Hangzhou, 310018, China[1]
School of Software Engineering, Tongji University, Shanghai, 201804, China[2,3,4]

Abstract. Unmanned aerial vehicle (UAV) communication has drawn significant interests from the industry and academic due to its low consumption, high maneuverability, and flexible mobility. This paper studies a multi-UAV wireless communication system where UAVs are operated by a ground control center to perform certain task with a planned trajectory. In order to ensure the reliable communication of multiple UAVs, we formulate a mixed-integer problem aimming to maximize the minimum signal-to-noise ratio (SINR) of UAV swarm by jointly optimizing multiuser spectrum access and transmission power. To tackle this problem efficiently, we propose an iterative algorithm based on majorization-minimization method. Extensive simulation results demonstrate that the proposed algorithm can yield substantial gains in terms of communication performance as compared with a baseline scheme.

Keywords: UAV communication, wireless communication, spectrum access, transmission power.

1 Introduction

With many benefits such as low consumption, high maneuverability, and on-demand deployment, multi-UAV formation has received increasing attention in military field. The multi-UAV collaborative operation makes up for the limited capability of single UAV, improves the fault tolerance ability of the system, and makes tasks more efficient. This scheme improves the success probability of single mission, enables its application in military reconnaissance, target strike, electronic countermeasure, battlefield evaluation, etc. Under this background, UAV-aided wireless communication technique is gradually rising [1], [2]. On one hand, leveraging the existing network architecture, UAVs could act as temporary mobile base stations (BSs) to realize the rapid movement of wireless network coverage; on the other hand, the UAV-aided mobile relay system forms virtual multi-antenna array for the communication between remote nodes, which ensures the reliability of emergency communication.

To complete tasks efficiently, the UAV formation needs to interact quickly and safely, especially in highly dynamic, ultra dense wireless network environments. Nonetheless, multi-UAV collaboration brings several challenges. First, UAVs should correctly receive the control signals and quickly follow the instructions from BS. Therefore, the stability and efficiency of communication link will be a critical technical challenge. Furthermore, due to the limited

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available network resources, the reasonable use of network resources can effectively improve communication quality. Finally, in most applications, the external interferences of radiation sources have negative influence on communication system, which we can't ignore. Those above challenges inspire us to study the resource allocation for multi-UAV wireless communication system with awareness of environmental interference in this paper.

Recently, several studies have been devoted to the UAV-based wireless communication network. The authors in [3] proposed a time-frequency resource blocks allocation and power optimization algorithm to promote the reliability of control signals among UAVs. In [4], the authors studied a path planning scheme to minimize the overall inspection time and energy in a specific scenario. The work in [5] addressed the physical-layer security problem in a UAV communication system by jointly optimizing the UAV's trajectory and transmit power under stringent energy constraints. Meanwhile, the authors in [6] jointly considered the multiuser scheduling, power allocation and trajectory optimization problem, which aimmed to realize the fair performance of UAV swarm. Morever, [7] investigated the placement problem in static-UAV enabled networks. Each UAV serves as a static BS to maximum the communication coverage for ground users.

Unlike the existing works [3]-[7], this paper considers resource coordination for efficient control and reliable communication in a BS-controlled-UAV network. In this paper, we study a scenario where a ground BS controls UAV formation, and UAVs should receive the control signals and quickly execute the instructions. The quality of wireless link is mainly affected by the interferences from external radiation sources. Therefore, our goal is to ease the impact of interference and improve the quality of control signals by jointly optimizing multiuser spectrum access and transmission power. To tackle this problem efficiently, we propose an iterative algorithm based on majorization-minimization method. Finally, extensive simulations validate the efficacy of the proposed algorithm.

The remainder of this paper is organized as follows: Section 2 presents the system model and problem formulation. Section 3 introduces our iterative algorithm to solve this problem. The simulation results and performance evaluation are provided in Section 4. In Section 5, we make a conclusion to this paper.

2 System Model and Problem Formulation

2.1 System Model

As shown in **Figure 1**, we consider an uplink communication scenario where multiple UAVs controlled by a ground BS performing some tasks with a planned trajectory. In this scenario, the BS sends control signals through a limited spectrum to multiple UAVs at each time slot. We assume that many external radiation sources spread across the region and cause interference. In addition, we assume that the central processing unit at the ground BS can not only acquire the flight dynamics of UAV swarm, but also perceive channel state information (CSI). Due to the shortage of spectrum resources, the available frequency spectrum is usually limited. Moreover, we assume that the external interference can be sensed by enabling cognitive radio function and the received interferences of each UAV on different channels are very different. Under the above assumptions, the goal of this paper is to jointly design spectrum access and power control to combat the external interference and improve the reliability of control signals.

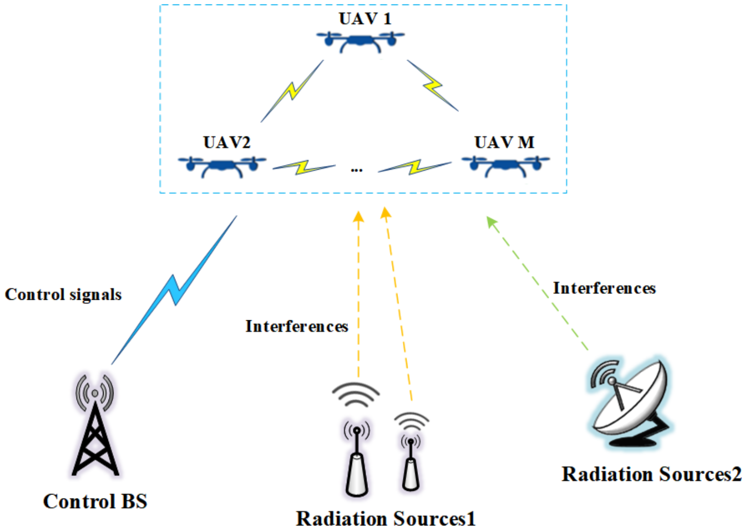

Fig. 1. The flight scenario of UAV swarm.

We use $\mathcal{M} \triangleq \{1, ..., M\}$ to denote the set of UAVs, $\mathcal{N} \triangleq \{1, ..., N\}$ the set of communication channels, and $\mathcal{S} \triangleq \{1, ..., S\}$ the set of time slots. We assume that the length of time slot is set to be sufficiently small such that the UAV's location seems to be unchange within every time slot. In the considered scenario, the ground-to-air link is mainly affected by the probability of line-of-sight (LoS) and non-line-of-sight (NLoS). According to [8], at time slot s the channel gain between the BS and UAV k on channel i can be expressed as

$$g_{s,k}^{i} = c_{s,k}(F + f_{s,k}^{i})^{-2} \tag{1}$$

with

$$c_{s,k} = \begin{cases} 10^{-32.4-\eta_{LoS}} \times d_{s,k}^{-2}, & \text{LoS link} \\ 10^{-32.4-\eta_{NLoS}} \times d_{s,k}^{-2}, & \text{NLoS link} \end{cases}$$

where F denotes the baseline carrier frequency, $f_{s,k}^{i} \in \{\Delta f_1, ..., \Delta f_N\}$ denotes the frequency interval between the F and the channel i that UAV k uses in time slot s, $d_{s,k}$ is the distance between the UAV swarm and BS. What's more, η_{LoS} and η_{NLoS} indicate the additional attenuation index for LoS and NLoS links, respectively.

Let us denote by $a_{s,k}^{i}$ a binary variable, which indicates channel i is occupied by UAV k at time slot s if $a_{s,k}^{i} = 1$ and $a_{s,k}^{i} = 0$ otherwise. Since the BS needs to transmit control signals to the UAV formation in each time slot, sufficient frequency bands is necessary for UAVs. Due to the shortage of available frequency spectrum, we assume that each UAV only assigns one channel, and different UAVs must select different channels, which yields the following constraints

$$\begin{cases} M \le N \\ \sum_{i=1}^{N} a_{s,k}^{i} = 1, \quad \forall k \in \mathcal{M}, \quad \forall s \in \mathcal{S}, \\ f_{s,k}^{i} \ne f_{s,m}^{j}, \quad \forall k \ne m, \quad \forall i \ne j, \end{cases} \tag{2}$$

Now we are ready to write down the expression of SINR of each UAV at time slot s. Specifically, the corresponding received SINR of UAV k can be expressed as follows

$$r_{s,k} = \frac{\sum_{i=1}^{N} a_{s,k}^{i} p_{s,k} c_{s,k} (F + f_{s,k}^{i})^{-2}}{\sum_{i=1}^{N} a_{s,k}^{i} (\sigma_{s,k}^{i})^{2}} \tag{3}$$

Here, the uplink transmission power of the BS for UAV k is denoted by $p_{s,k}$, which is subject to the constraint $\sum_{k=1}^{M} p_{s,k} \le P_{\max}$, with $P_{\max}$ denoting the maximum transmission power of ground BS. Furthermore, the numerator of (3) represents the useful signal, and the denominator is the external interferences from radiation sources, where $(\sigma_{s,k}^{i})^{2}$ denotes the power of interference (plus noise) on channel i received by UAV k at time slot s and it is assumed to be sensed through enabling cognitive radio function [9].

2.2 Problem Formulation

We denote $\mathbf{A} \triangleq \{a_{s,k}^{i} | s \in \mathcal{S}, k \in \mathcal{M}, i \in \mathcal{N}\} \in \mathbb{R}^{S \times M \times N}$. For time slot s, the matrix $\mathbf{A}_s \triangleq [\boldsymbol{a}_{s,1}, ..., \boldsymbol{a}_{s,M}]$ denotes the channel selection scheme of multi-UAV formation, where $\boldsymbol{a}_{s,k} \triangleq [a_{s,k}^{1}, ..., a_{s,k}^{N}]^{T}$. Obviously, only one element in each column of matrix $\mathbf{A}_s$ is 1 and others are 0. Similarly, we define $\mathbf{P} \triangleq \{p_{s,k} | s \in \mathcal{S}, k \in \mathcal{M}\} \in \mathbb{R}^{S \times M}$ as the power allocation matrix. $\mathbf{p}_s \triangleq [p_{s,1}, ..., p_{s,M}]^{T}$ represents transmission power at time slot s. Next, we consider control instructions and interference signals. Let $\mathbf{\Phi} \triangleq \{\Phi_{s,k}^{i} | s \in \mathcal{S}, k \in \mathcal{M}, i \in \mathcal{N}\} \in \mathbb{R}^{S \times M \times N}$, where $\Phi_{s,k}^{i} = (F + f_{s,k}^{i})^{-2}$. The matrix $\mathbf{\Phi}_s \triangleq [\mathbf{\Phi}_{s,1}, ..., \mathbf{\Phi}_{s,M}]$ denotes the channel frequency coefficient of multi-UAV swarm and $\mathbf{\Phi}_{s,k} \triangleq [\Phi_{s,k}^{1}, ..., \Phi_{s,k}^{N}]^{T}$. In addition, we also define $\mathbf{C} \triangleq \{c_{s,k} | s \in \mathcal{S}, k \in \mathcal{M}\} \in \mathbb{R}^{S \times M}$ and $\mathbf{c}_s \triangleq [c_{s,1}, ..., c_{s,M}]^{T}$ to represent distance factor of channel gain. Then, we define $\mathbf{\Sigma} \triangleq \{(\sigma_{s,k}^{i})^{2} | s \in \mathcal{S}, k \in \mathcal{M}, i \in \mathcal{N}\} \in \mathbb{R}^{S \times M \times N}$ as the external interference matrix. For time slot s, the matrix $\mathbf{\Sigma}_s \triangleq [\boldsymbol{\sigma}_{s,1}, ..., \boldsymbol{\sigma}_{s,M}]^{T}$ represents the external interference of UAVs, where $\boldsymbol{\sigma}_{s,k} \triangleq [(\sigma_{s,k}^{1})^{2}, ..., (\sigma_{s,k}^{N})^{2}]^{T}$. Define $\mathbf{e}_k$ as a unit column vector with the k-th element being 1. Therefore, for expression (3), we have the following transformations:

$$p_{s,k} = \mathbf{p}_s^T \mathbf{e}_k \tag{4}$$

$$c_{s,k} = \mathbf{c}_s^T \mathbf{e}_k \tag{5}$$

$$\sum_{i=1}^{N} a_{s,k}^i (F + f_{s,k}^i)^{-2} = \mathbf{e}_k^T \mathbf{\Phi}_s^T \mathbf{A}_s \mathbf{e}_k \tag{6}$$

$$\sum_{i=1}^{N} a_{s,k}^i (\sigma_{s,k}^i)^2 = \mathbf{e}_k^T \mathbf{\Sigma}_s^T \mathbf{A}_s \mathbf{e}_k \tag{7}$$

In general, the higher SINR indicates better communication quality of the UAV network, we hope to improve the corresponding SINR level of whole wireless communication system. Hence, the paper introduces the max-min-fairness index of the SINR in order to maintain the reliable communication for each UAV. The optimization problem of the whole flight process is formulated as follows

$$\max_{\{\mathbf{A},\,\mathbf{P}\}} \sum_{s=1}^{S} \min_k \left(\frac{\mathbf{p}_s^T \mathbf{e}_k \mathbf{c}_s^T \mathbf{e}_k \mathbf{e}_k^T \mathbf{\Phi}_s^T \mathbf{A}_s \mathbf{e}_k}{\mathbf{e}_k^T \mathbf{\Sigma}_s^T \mathbf{A}_s \mathbf{e}_k} \right) \tag{8a}$$

$$\text{s.t.}\quad \mathbf{1}^T \mathbf{A}_s \mathbf{e}_k = 1, \quad \forall k \in \mathcal{M},\ \forall s \in \mathcal{S}, \tag{8b}$$

$$\mathbf{1}^T \mathbf{A}_s \mathbf{e}_i \leq 1, \quad \forall i \in \mathcal{N},\ \forall s \in \mathcal{S}, \tag{8c}$$

$$a_{s,k}^i \in \{0,1\}, \quad \forall k \in \mathcal{M},\ \forall i \in \mathcal{N},\ \forall s \in \mathcal{S}, \tag{8d}$$

$$\mathbf{1}^T \mathbf{p}_s \leq P_{\max}, \quad \forall s \in \mathcal{S}, \tag{8e}$$

$$0 \leq p_{s,k}, \quad \forall k \in \mathcal{M}, \quad \forall s \in \mathcal{S}. \tag{8f}$$

The purpose of our optimal model (8) is to maximize the minimum SINR of UAV swarm by jointly optimizing multiuser channel access and transmission power at each time slot. (8b-8f) are the channel asssignment constraints, i.e., each UAV is only assigned with one channel and any two UAVs access different channels. Note that the inequality in (8c) is due to that the number of UAVs is less than the number of available channels. Obviously, problem (8) is a Mixed-Integer Nonlinear Program (MINLP), which belongs to NP-Hard problem.

3 Proposed Solution

In this section, we propose a simple and efficient iterative algorithm to solve problem (8) by adopting majorization-minimization (MM) method.

First, we can see that problem (8) is separable across s. As a result, we only need to focus on the problem of each time slot, i.e.,

$$\max_{\{\mathbf{A},\,\mathbf{P}\}} \ \min_{k}\left(\frac{\mathbf{p}_s^T\mathbf{e}_k\mathbf{c}_s^T\mathbf{e}_k\mathbf{e}_k^T\mathbf{\Phi}_s^T\mathbf{A}_s\mathbf{e}_k}{\mathbf{e}_k^T\mathbf{\Sigma}_s^T\mathbf{A}_s\mathbf{e}_k}\right) \tag{9a}$$

$$\text{s.t. } \mathbf{1}^T\mathbf{A}_s\mathbf{e}_k = 1, \quad \forall k\in\mathcal{M}, \tag{9b}$$

$$\mathbf{1}^T\mathbf{A}_s\mathbf{e}_i \le 1, \quad \forall i\in\mathcal{N}, \tag{9c}$$

$$a_{s,k}^i \in\{0,1\}, \quad \forall k\in\mathcal{M}, \quad \forall i\in\mathcal{N}, \tag{9d}$$

$$\mathbf{1}^T\mathbf{p}_s \le P_{\max}, \tag{9e}$$

$$0\le p_{s,k}, \quad \forall k\in\mathcal{M}. \tag{9f}$$

We rewrite (9) as

$$\max_{\{\mathbf{A},\,\mathbf{P}\}} \ \min_{k}\left(\frac{\mathbf{p}_s^T\mathbf{e}_k\mathbf{c}_s^T\mathbf{e}_k\mathbf{e}_k^T\mathbf{\Phi}_s^T\mathbf{A}_s\mathbf{e}_k}{B\sum_{m=1,m\ne k}^{M}\mathbf{e}_k^T\mathbf{A}_s^T\mathbf{A}_s\mathbf{e}_m + \mathbf{e}_k^T\mathbf{\Sigma}_s^T\mathbf{A}_s\mathbf{e}_k}\right) \tag{10a}$$

$$\text{s.t. } \mathbf{1}^T\mathbf{A}_s\mathbf{e}_k = 1, \quad \forall k\in\mathcal{M}, \tag{10b}$$

$$a_{s,k}^i \in\{0,1\}, \quad \forall k\in\mathcal{M}, \quad \forall i\in\mathcal{N}, \tag{10c}$$

$$\mathbf{1}^T\mathbf{p}_s \le P_{\max}, \tag{10d}$$

$$0\le p_{s,k}, \quad \forall k\in\mathcal{M}. \tag{10e}$$

As compared to (9), we have cancel the constraint (9c) in (10) but introduce an extra term $B\sum_{m=1,m\ne k}^{M}\mathbf{e}_k^T\mathbf{A}_s^T\mathbf{A}_s\mathbf{e}_m$ in the objective of (10). It is readily known that when the parameter B is sufficiently large, we have $B\sum_{m=1,m\ne k}^{M}\mathbf{e}_k^T\mathbf{A}_s^T\mathbf{A}_s\mathbf{e}_m=0$, $\forall k\in\mathcal{M}$ to maximize the objective. As a result, problems (9) and (10) are equivalent when a sufficiently large B is used.

Furthermore, it is seen that, fixing $\mathbf{A}_s$, the power control can ensure that all the SINR values are the same. Let γ be the optimal objective value. Then we have

$$p_{s,k} = \mathbf{p}_s^T\mathbf{e}_k = \gamma\frac{B\sum_{m=1,m\ne k}^{M}\mathbf{e}_k^T\mathbf{A}_s^T\mathbf{A}_s\mathbf{e}_m + \mathbf{e}_k^T\mathbf{\Sigma}_s^T\mathbf{A}_s\mathbf{e}_k}{\mathbf{c}_s^T\mathbf{e}_k\mathbf{e}_k^T\mathbf{\Phi}_s^T\mathbf{A}_s\mathbf{e}_k}, \quad \forall k \tag{11}$$

Considering that the power constraint (10d) must be satisfied with equality at the optimality, (11) leads to

$$\frac{P_{\max}}{\gamma}=\sum_{k=1}^{M}\frac{B\sum\limits_{m=1,m\neq k}^{M}\mathbf{e}_k^T\mathbf{A}_s^T\mathbf{A}_s\mathbf{e}_m+\mathbf{e}_k^T\mathbf{\Sigma}_s^T\mathbf{A}_s\mathbf{e}_k}{\mathbf{c}_s^T\mathbf{e}_k\mathbf{e}_k^T\mathbf{\Phi}_s^T\mathbf{A}_s\mathbf{e}_k} \tag{12}$$

Therefore, problem (10) is equivalent to

$$\min_{\mathbf{A}_s}\ \sum_{k=1}^{M}\frac{B\sum\limits_{m=1,m\neq k}^{M}\mathbf{e}_k^T\mathbf{A}_s^T\mathbf{A}_s\mathbf{e}_m+\mathbf{e}_k^T\mathbf{\Sigma}_s^T\mathbf{A}_s\mathbf{e}_k}{\mathbf{c}_s^T\mathbf{e}_k\mathbf{e}_k^T\mathbf{\Phi}_s^T\mathbf{A}_s\mathbf{e}_k} \tag{13a}$$

$$\text{s.t. } \mathbf{1}^T\mathbf{A}_s\mathbf{e}_k=1,\quad \forall k\in\mathcal{M}, \tag{13b}$$

$$a_{s,k}^i\in\{0,1\},\quad \forall k\in\mathcal{M},\quad \forall i\in\mathcal{N}. \tag{13c}$$

Note that for a binary variable a, we always have $(a-0.5)^2=0.25$ which is a constant. Moreover, it holds true that $0.25=\max_{0\le a\le 1}(a-0.5)^2$. Hence, we can relax the binary constraint (13c) to $0\le a_{s,k}^i \le 1$ with a penalty term $-\mu\|\mathbf{A}_s-0.5\mathbf{E}\|_F^2$, where $\mathbf{E}$ denotes the matrix of all one. That is, we consider the following problem

$$\min_{\mathbf{A}_s}\ f_\mu(\mathbf{A}_s) \tag{14a}$$

$$\text{s.t. } \mathbf{1}^T\mathbf{A}_s\mathbf{e}_k=1,\quad \forall k\in\mathcal{M}, \tag{14b}$$

$$0\le a_{s,k}^i\le 1,\quad \forall k\in\mathcal{M},\quad \forall i\in\mathcal{N}. \tag{14c}$$

where

$$f_\mu(\mathbf{A}_s)=\sum_{k=1}^{M}\frac{B\sum\limits_{m=1,m\neq k}^{M}\mathbf{e}_k^T\mathbf{A}_s^T\mathbf{A}_s\mathbf{e}_m+\mathbf{e}_k^T\mathbf{\Sigma}_s^T\mathbf{A}_s\mathbf{e}_k}{\mathbf{c}_s^T\mathbf{e}_k\mathbf{e}_k^T\mathbf{\Phi}_s^T\mathbf{A}_s\mathbf{e}_k}-\mu\|\mathbf{A}_s-0.5\mathbf{E}\|_F^2 \tag{15}$$

Two observation can be made as follows. First, problem (14) is equivalent to (13) when μ is sufficiently large. Second, if μ is large enough, the objective function (15) can be shown to be concave. Hence, we can use MM method [10] to solve problem (14). In the r-th iteration of MM, we find a upper bound of (15) by using Taylor approximation and instead minimize the upper bound, i.e., equivalently solve the following problem

$$\min_{\mathbf{A}_s}\ \ Trace(\mathbf{W}\mathbf{A}_s) \tag{16a}$$

$$\text{s.t. } \mathbf{1}^T\mathbf{A}_s\mathbf{e}_k=1,\quad \forall k\in\mathcal{M}, \tag{16b}$$

$$0\le a_{s,k}^i\le 1,\quad \forall k\in\mathcal{M},\quad \forall i\in\mathcal{N}. \tag{16c}$$

where $\mathbf{W} \triangleq \nabla_{\mathbf{A}_s} f_\mu(\mathbf{A}_s^{r-1})$. Note that (16) can be decomposed into M independent subproblems in the form of

$$\min_{a_{s,k}^i} \quad \sum_{i=1}^{N} a_{s,k}^i w_{i,k} \tag{17a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} a_{s,k}^i = 1, \tag{17b}$$

$$0 \le a_{s,k}^i \le 1, \quad \forall i \in \mathcal{N}. \tag{17c}$$

where $w_{i,k}$ is the (i,k)-th element of $\mathbf{W}$. Obviously (17) has a closed-form solution, i.e. $a_{s,k}^{i_k} = 1$ and $a_{s,k}^i = 0, \forall i \ne i_k$ with $i_k = \arg\min_i w_{i,k}$.

Algorithm 1: The proposed algorithm for problem (14)
1. Initialize $\mathbf{A}_s^0$, $T_{\max}$ and $\Delta\mu$
2. Set $r = 0$
3. Repeat
4. Solve for $\mathbf{A}_s^{r+1}$ problem (16) with $\mathbf{W} \triangleq \nabla_{\mathbf{A}_s} f_\mu(\mathbf{A}_s^{r-1})$
5. If $f_\mu(\mathbf{A}_s^{r+1}) - f_\mu(\mathbf{A}_s^r) > 0$
$\mu = \mu + \Delta\mu$
6. Else
$r = r + 1$
7. End
8. Until $f_\mu(\mathbf{A}_s)$ converges, or the maximum iteration number $T_{\max}$ is reached.
9. Compute $\gamma = P_{\max} \Big/ \sum_{k=1}^{M} \frac{\mathbf{e}_k^T \boldsymbol{\Sigma}_s^T \mathbf{A}_s \mathbf{e}_k}{\mathbf{c}_s^T \mathbf{e}_k \mathbf{e}_k^T \boldsymbol{\Phi}_s^T \mathbf{A}_s \mathbf{e}_k}$
10. Compute $p_{s,k} = \gamma \frac{\mathbf{e}_k^T \boldsymbol{\Sigma}_s^T \mathbf{A}_s \mathbf{e}_k}{\mathbf{c}_s^T \mathbf{e}_k \mathbf{e}_k^T \boldsymbol{\Phi}_s^T \mathbf{A}_s \mathbf{e}_k}$, $\forall k$

We summarize the proposed algorithm in Algorithm 1. By increasing μ, we can ensure that μ could be large enough so that the objective (15) becomes concave constantly and the algorithm goes into the phase of MM method with guaranteed convergence. Our algorithm can always keep the objective nonincreasing and guarantee outputting binary variable in each iteration. What's more, when B is large enough, we can also ensure the terms $B\sum_{m=1,m\ne k}^{M} \boldsymbol{e}_k^T \mathbf{A}_s^T \mathbf{A}_s \boldsymbol{e}_m = 0$, $\forall k \in \mathcal{M}$. Hence, once $\mathbf{A}_s$ is obtained, we can find compute $\mathbf{P}_s$ as in the last step of Algorithm 1.

4 Numerical Results

We consider an scene of $5 \times 5\ \text{km}^2$ with the BS located at $\boldsymbol{x}_0 = (0,\ 0,\ 0)$ and the UAV formation flies from the BS to a certain destination at the altitude of $H = 1.0\ \text{km}$. L radiation sources randomly distributed in the network and the power is assumed about -90 dBm. Similarly, the maximum transmission power of the control BS is set to be 30 dBm. The baseline carrier frequency is set to be $F = 500\ \text{MHz}$ and the channel interval is $\Delta f = 5\ \text{MHz}$. For comparison, we introduce the simple algorithm, called Random method as a baseline. The algorithm includes two steps, the first step is to distribute channels to UAVs randomly, then allocate power to ensure that all the SINR values of UAVs are the same.

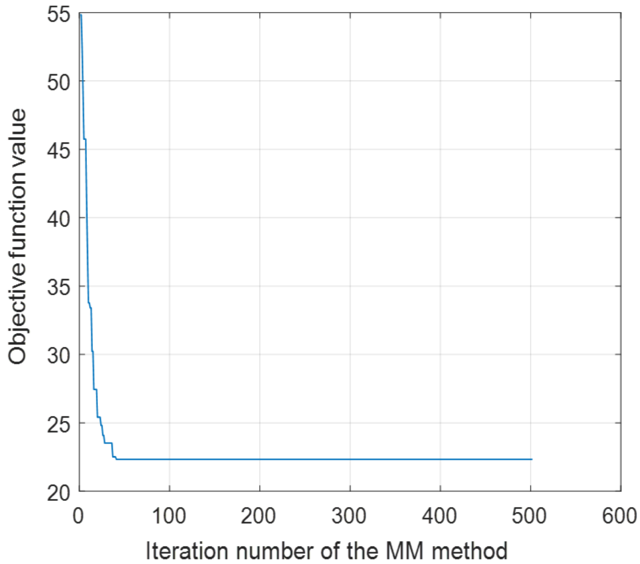

Fig. 2. Convergence of the proposed algorithm.

First, we consider the convergence behaviors of the proposed algorithm. We randomly select one time slot of the MM method, at the scenario of M = 12, N = 25 and L = 3. To avoid the algorithm converging to the undesired local points prematurely, we set the maximum iteration number in Algorithm 1 as $T_{\max} = 500$. From the result of **Figure 2**, we can observe that the MM method makes the objective function descend rapidly, until it converges. As a result, the simulation results verify the effectiveness of the proposed algorithm.

Figure 3 shows the performance of the UAV formation (M = 12, N = 21) for the proposed algorithm with the Random algorithm, for the case of L = 3 and 5. It is observed that the communication quality of UAVs declines gradually with the distance from the BS increases. Morever, with the increasing number of radiation sources, the interference in this system is correspondingly to rise sharply. We can come to the conclusion that the proposed MM method always achieves the higher SINR, compared to the Random algorithm. The main reason is that the MM method makes the channel assignment scheme more reasonable, which can reduce the interference in communication system.

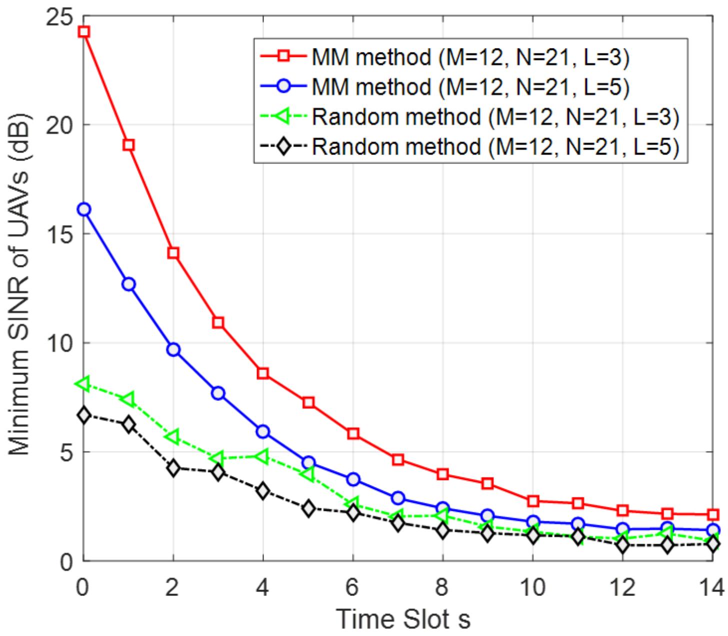

Fig. 3. UAV swarm performance during the flight phase.

In **Figure 4**, we illustrate the system performance obtained by two algorithms under different scenario. For a fair comparison, we assume that there are 5 radiation sources with fixed locations. It is seen that the result of MM algorithm offers superior performance over that of Random algorithm. As a result, for the formation with the same number of UAVs, allocating more bandwidth will get better effect on communication system. Similarly, when the available frequency bands of system is fixed, the network performance will gradually deteriorate with the increase of users.

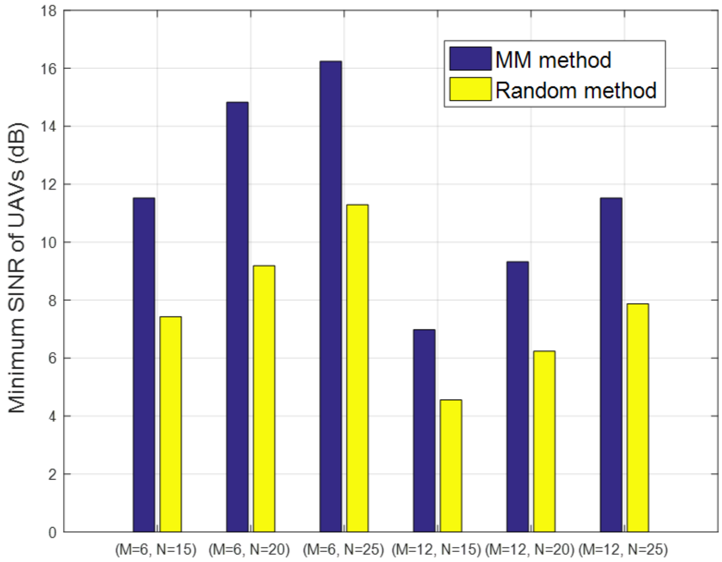

Fig. 4. UAV system performance under different scenario.

5 Conclusion

In this paper, we have studied the reliable communication in a multi-UAV enabled wireless network. The spectrum access and power allocation are jointly optimized by using an iterative algorithm based on majorization-minimization method. The simulation results show that the proposed algorithm substantially outperforms the baseline algorithm in terms of system performance.

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