Matching-Based Resource Allocation and Distributed Power Control Using Mean Field Game in the NOMA-Based UAV Networks

Zihe Zhang*, Lixin Li*, Xiaomin Liu*, Wei Liang*, and Zhu Han†
* School of Electronics and Information, Northwestern Polytechnical University, Xi'an, China
† Department of Electrical and Computer Engineering, University of Houston, Houston, TX, USA
E-mail: zhangzihe@mail.nwpu.edu.cn

***Abstract*—This paper investigates the resource allocation and distributed power control in the dense unmanned aerial vehicle (UAV) networks. Under the considered non-orthogonal multiple access (NOMA)-based UAV networks, we propose a two-stage scheme to alleviate the congestion of date traffic and the interference effects. In the proposed scheme, a high altitude platform (HAP) performs semi-persistent scheduling and allocates time-frequency resources in a non-orthogonal manner while the UAVs autonomously perform distributed power control. We formulate centralized resource allocation problem as a roommate matching problem and develop a novel time slot allocation algorithm to solve it. And the distributed power control of massive UAVs is formulated as a mean field game (MFG), which is solved based on the finite difference method. Simulation results show that the proposed scheme can greatly improve the reliability of communication in the dense UAV networks.**

I. Introduction

Due to the low cost, mobility, and controllability of unmanned aircraft vehicles (UAVs), it has attracted widespread research and attention for the applications of civilian and industry. The deployment of UAVs can potentially take over the cellular transmissions in disastrous situations. Moreover, integrating drones to overloaded terrestrial networks may also offer benefits by offloading traffic, reducing handovers for highly mobile users, etc. With the development of UAV-related technologies, people gradually focus their attention on the application of UAV cluster which is widely used [1], [2]. As the increasing number of UAVs in the future, reliable and efficient air traffic control will be also essential. In safety-critical applications, UAVs need to broadcast to their neighborhood [3]. When a large number of UAVs perform tasks in coordination, there is often a high requirement on the reliability of communication among UAVs, otherwise it may be devastating to the cluster of UAVs. At the same time, as the number of UAVs in a group increases, the demand for spectrum resources becomes much higher.

As resource collision may occur between orthogonal multiple access (OMA)-based UAVs, and the user access rate is difficult guarantee in a dense moving environment. In this context, non-orthogonal multiple access (NOMA) technology, which can allocate one spectrum resource to multiple users, has been introduced as a potential solution to tackle the challenges of access collision reduction and massive connectivity [4], [5].

Game theory has been widely used to facilitate autonomous network management and dynamic resource allocation. However, conventional game theory-based approaches can only deal with simple scenarios. Matching theory is a powerful tool for studying the dynamic and mutually beneficial relationship between different types of rational and selfish agents, which makes matching theory has become a promising technology that can be used to allocate wireless resource. It is particularly effective in developing high performance, low complexity, decentralized and practical solutions in these wireless networks [6], [7].

As one novel method of game, the mean field game (MFG) has been proved to be an effective tool to obtain the distributed power control policies on current communication networks [8]. Due to the computation complexity brought by the large number of agents in ultra dense networks, MFG is applied to model the interactions between a subjective agent and the average effect of the collective behaviors of other agents [9]-[11].

In this paper, we investigate the applicability of NOMA in supporting the UAVs networks to alleviate the congestion of date traffic and the interference effects. A novel two-stage scheme is proposed to improve the reliability of the communication among UAVs. In the proposed scheme, the centralized resource allocation problem is solved through a novel time slot allocation algorithm. Meanwhile the distributed power control of massive UAVs is formulated as a mean field game (MFG).

The main contributions of this paper are as follows:

- We propose a novel two-stage scheme for the dense UAV

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networks combining the centralized semi-static scheduling (SPS) of time-domain resources and the distributed power control of the UAVs.

- The centralized SPS of time-domain resources in NOMA-based UAV networks is formulated as a roommate matching problem, which can be solved by a novel time slot allocation algorithm.
- We model the NOMA-based interference mitigation problem as a MFG, and propose a distributed power control scheme through dealing with the MFG equations with a finite difference method.

The rest of this paper is organized as follows. In Section II, we describe the system model. In Section III, we formulate the centralized SPS as a inter-user interference influence minimization problem and solve it by utilizing the matching theory. In Section IV, a scheme based on MFG is designed for the distributed power control problem of UAVs. Simulation results are presented in Section V. We conclude the paper in Section VI.

II. System Model

As shown in Fig. 1, we consider a two-tier UAVs network, which consists of a high altitude platform (HAP) and plenty of UAVs in low altitude. As the HAP has higher power and higher capacity in terms of payload [3], it can assist the air traffic of the low altitude platforms (LAPs) which are under its coverage. In low altitude, UAVs are deployed to assist the cellular networks, where the safety information of each UAV is necessary to broadcast to others. We denote the UAVs in low altitude as $U = \{u_1, ..., u_N\}$. In the system, each transmission period consists of multiple time slots, and the available bandwidth is divided into a number of sub-channels. In each transmission period, the UAV transmits its information to its neighboring UAVs in at least one time slot to meet the need for communication between each other.

Since there are a large number of UAVs in this scenario, when more than one UAVs (e.g., UAV-1 and UAV-2 in Fig. 1) are assigned to the same time-frequency resource to send the message, there will be serious conflicts for those UAVs (e.g., UAV-3 in Fig. 1) that are in the overlapping area of their communication ranges. Therefore, in order to reduce collisions, or to avoid conflict as much as possible, the NOMA technology is used on each sub-carrier so that multiple UAVs can access the same sub-channel at the same time. For conflicting receiver (Rx) UAVs, they can use the successive interference cancellation (SIC) technique to decode the received signal, thereby solve the problem of collision.

Based on the NOMA scheme, for a generic j-th UAV who is allocate to sub-channel m in time slot k, the signal that it receives can be expressed as:

$$y_j^{(k)} = \sum_{i \in N_j} \gamma_{i,m}^{(k)} \sqrt{p_{i,m}^{(k)}} g_{i,j,m}^{(k)} + n_j^{(k)} \tag{1}$$

In the above formula, $N_j = \left\{ 1 \le i \le N \middle| d_{i,j}^{(k)} \le r \right\}$ represents the set of UAVs within the communication range of the i-th UAV when it receives the information. The transmit power of i-th UAV on sub-channel m is denoted by $p_{i,m}^{(k)}$, $n_j^{(k)} \sim \mathrm{N}\left(0,\delta_n^2\right)$ represents the additive white Gaussian noise received by the UAV j, δ_n^2 is the variance of noise. $g_{i,j,m}^{(k)} = h_{i,j,m}^{(k)} r_{i,j}^{(k)}$ is the channel gain between the i-th UAV and the j-th UAV on the sub-channel m in time slot k when the i-th UAV sends the information to j-th UAV. $h_{i,j,m}^{(k)}$ is the Rayleigh fading of subchannel m, $r_{i,j}^{(k)} = \left(d_{i,j}^{(k)}\right)^{-\alpha}$ represents the path loss associated with the sending and receiving parties. The distance between the transmitter and receiver UAV in time slot k is denoted by $d_{i,j}^{(k)}$.

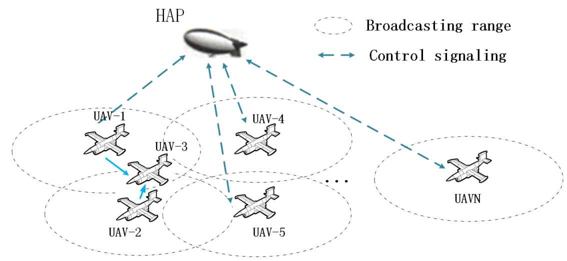

Fig. 1. System model of a two-tier UAVs network.

When the SIC technology is used to decode the superimposed signals received by UAVs, the UAV with a better channel condition is decoded first, that is, the UAV with a relatively higher channel gain is decoded first. So, for a conflicting j-th UAV $(1 \le j \le N)$, the achievable rate it can obtained from i-th UAV $(1 \le i \le N)$ on subchannel m in time slot k can be express as:

$$R_{i,j,m}^{(k)} = \log_2 \left(1 + \frac{p_j^{(k)} \rho_{i,j,m}^{(k)}}{1 + \sum\limits_{j' \in S_{i,j,m}^{(k)}} p_{j'}^{(k)} \rho_{i,j',m}^{(k)}} \right), \tag{2}$$

where $\rho_{i,j,m}^{(k)} = \left| g_{i,j,m}^{(k)} \right|^2 \Big/ \left(n_j^{(k)} \right)^2$ represents the signal-to-noise ratio of the link between i-th UAV and j-th UAV in time slot k. $S_{i,j,m}^{(k)}$ is the set of UAV users that can cause interference to the j-th UAV, when j-th UAV decodes the signals that transmitted from i-th UAV.

For the considered NOMA-based dense UAVs network, our goal is to design a scheme where each UAV can successfully broadcast to as many neighboring UAVs as possible. Based on the above NOMA manner for reducing the collision, the system performance relies on transmitter (Tx)-Rx selection and power-domain resource allocation. The following sections will introduce the time-domain resource allocation and the distributed power control, respectively.

III. Centralized Scheme based on the Matching Theory

As the path loss has a major influence on the channel gains, the Tx-Rx selection is essential to alleviate the collision and reduce the interference effects. Compared with the distributed scheme, making the decisions of Tx-Rx selection by a HAP, which can obtain the global position information of UAVs, can have a more stable performance in latency and reliability. However, as the acquisition of the global information is still expensive due to the number of the UAVs, we propose a centralized SPS scheme based on matching theory to solve the problem. At the beginning of each transmission period, the HAP collects all UAVs location information and adopts a SPS method to determine how to allocate the time slots, and the scheduling scheme remains unchanged in one transmission period.

We mainly implement this scheme by matching theory, and solve the problem of allocation between UAVs and time slots by considering this problem as a roommate matching problem, where the UAVs and time slots are considered as two sets of students and rooms such that multiple students can occupy the same room. By treating the sets of UAVs $U = \{u_1, ..., u_N\}$ and time slots $K = \{k_1, ..., k_M\}$ as two disjoint agent sets, a many-to-one matching is eventually formed between them. If a UAV is matched with one time slot, we say that it acts as a Tx UAV in this time slot; otherwise it acts as a Rx UAV in this time slot.

If two UAVs within each other's communication ranges, they cannot be assigned to the same time slot. Therefore, we treat them as the forbidden pair. For UAVs that matching to the same time slot, we name them matching peers. For each UAV, it is certainly willing to choose a UAV that is far away from itself as its matching peer, so the overlapping area of the communication ranges between them will be relatively small, and the inter-user interference influence caused by the collision will be reduced. To make the problem more specific, we describe the inter-user interference influence to the UAV in the overlapping area between any UAV i and UAV i' as follows:

$$I_{i,i'}^{(k)} = \begin{cases} (2d_r - d_{i,i'})^2 & if\, 2d_r > d_{i,i'}^{(k)} \\ 0 & otherwise \end{cases}. \tag{3}$$

where d_r denotes the communication range of UAVs. We assume all UAVs have the same communication range. The average inter-user interference influence caused by i-th UAV is:

$$Q_i^{(k)} = \begin{cases} \frac{1}{|\Psi(k)|} \sum\limits_{i' \in \Psi(k)} I_{i,i'}^{(k)} & if\ |\Psi(k)| > 1 \\ 0 & if\ |\Psi(k)| = 1 \end{cases}, \tag{4}$$

where $Q_i^{(k)}$ represents the average interference caused by the UAV i, $|\Psi(k)|$ denotes the matching set of time slot k.

Therefore, the matching problem between the UAVs and the time slots can be expressed as follows:

$$OP_1 : \min Q_{sum} \tag{5a}$$

$$s.t.\ \gamma_{i,m}^{(k)} + \gamma_{i',m}^{(k)} \le 1, \forall \{i, i'\} \in \left\{ 1 \le i, i' \le N \,\middle|\, d_{i,i'}^{(k)} < d_r \right\}, \tag{5b}$$

$$\sum_{k=1}^{K} \gamma_{i,j}^{(k)} = 1, 1 \le i \le N, \tag{5c}$$

where $Q_{sum} = \sum\limits_{k=1}^{K} \sum\limits_{i=1}^{N} |\psi(k)|\, Q_i^{(k)}$ represents the total inter-user interference influence of the system, Optimizing it can greatly improve the reliability of system communication, while reduce the delay of the system. In formula (5b), $\gamma_{i,m}^{(k)}$is a binary variable to indicate whether UAV i is a Tx transmitting over subchannel m in time slot K. (5b) indicates that if any two UAVs within each others communication ranges, they cannot be assigned to the same time slot because they will never receive each others message while transmitting due to the half duplex mechanism. It is indicated from (5c) that each UAV can occupy one time slot to transmit information at the same time.

To solve this problem, we develop a novel rotation matching algorithm. There are two phases in this algorithm. In phase one, the list of forbidden pair of each UAV is formed by the information of the UAVs position acquired by the HAP. Then through the greedy algorithm, a feasible matching set is obtained. Each unmatched UAV detects whether there is a forbidden pair of itself in the set of each matched time slot, if there is not any forbidden pair, then it can match with this time slot, otherwise, it cannot. Thus a feasible matching set AU_i of the UAV i can be obtained:

$$AU_i = \left\{ k \in Tmatched \,|\psi(k) \cap F_i^{(k)} = \emptyset \right\}. \tag{6}$$

In the formula (6), $Tmatched$ represents the set of time slots that have been matched, $F_i^{(k)}$ represents the set of the UAVs that can form forbidden pairs with UAV i in time slot k.

If AU_i is an empty set, then a time slot from unmatched time slots is selected to match with the UAV i. If all time slots have been matched, then select one time slot that the inter-user interference influence caused by UAV i is smallest when the UAV i matches with it, that is:

$$T(k^*) = \arg\min_k Q_i^{(k)}. \tag{7}$$

Until all UAVs have matched the time slots, finally, a many-to-one matching between a UAVs and time slots is formed, i.e.,

$$Tmatched = \{(u_1, \psi(u_1)), ..., (u_i, \psi(u_i)), ..., (u_N, \psi(u_N))\}, \tag{8}$$

where $(u_i, \psi(u_i))$ represents the matching pair formed by UAV i and the time slot it matches. In phase two, it is mainly based on the matching set formed in phase one. A rotation matching is performed on the matching sequence to minimize the total inter-user interference influence of the UAVs system Q_{sum}.

The so-called rotation matching means that for the matching of each UAV in phase one, a rotary exchange is performed by a rotation factor l so that a new matching set can be obtained, that is a rotation sequence:

$$R = \{(u_1, \psi(u_{l+1})), (u_2, \psi(u_{l+2})), ..., (u_N, \psi(u_l))\}, \tag{9}$$

Algorithm 1 Time Slot Allocation Algorithm Based on Matching Theory (TSAA)

```
Input:Set of UAVs U; Set of time slots T;location of all the UAVs.
Iitialization:
Record current matching as Tmatched, and construct the list Tunmatched and the forbidden pair list F_i^(k) .
Phase 1: Obtaining a feasible matching
for j=1:N do
    Obtaining a feasible set of matched time slots as AU_i according to (6) .
    if AU_i = ∅ and Tunmatched ≠ ∅ then
        Randomly select a time slot from Tunmatched ;
    else
        Obtain T(k*) according to (7) .
    end if
end for
Phase 2: Rotation Matching
for l=1:L do
    Obtain the rotation sequence according to (9) .
    Obtain the optimal matching set R* according to R* = arg min_{1≤l≤N} Q_sum.
end for
Output: the optimal matching set.
```

As can be seen from (9), each UAV's corresponding matching object is not the one it was assigned to in stage one, but the one obtained after a rotary exchange with the other UAVs. It can be found that when the rotation factor $l = N$ the matching sequence obtained after the rotation is the same as the matching sequence obtained in the original stage. Therefore, we make the rotation factor $1 \leq l \leq N$.

For the rotation sequence obtained after each rotation, if there is no forbidden pair in the set $Tmatched$ of matching object for each time slot, then the set obtained by this rotation is valid. For all valid sets that after rotation matching, by comparing the total inter-user interference influence of them, finally, a set with the smallest value is selected among all valid sets that after rotation matching, which is: $R^* = \underset{1\leq l\leq N}{\arg} \min Q_{sum}$.

IV. NOMA-based Distributed Power Control of Massive UAVs

In this section, we address the NOMA-based distributed power control scheme as a MFG, where UAVs performing SIC decoding.

To perform SIC decoding, necessary prior knowledge needs to be provided to the conflicting Rx UAVs. Each conflicting Rx j-th UAV decodes the received signals in an order of channel gains which obtained from the control signalings. We formulate the power control problem as a MFG. According to [8], one general setting of MFG is that all other agents just individually introduce infinitesimal interactions to the generic agent. While in our system, we can observe that there exists at least one interference dominator, which should not be aggregated in the interference mean field. Specifically, all the Tx UAVs who transmit signals to the same conflicting Rx j-th UAV occupying the sub-channel m in the time t will introduce much more interference power to each other. While the other UAVs occupying the sub-channel m just introduce infinitesimal interference due to the sub-channel allocation scheme above.

A. Mean Field Game Framework

The interference mitigation problem of massive UAVs, which modeled as a MFG can be represent as a 4-tuple, $G = \{\mathcal{N}_m, \{p_i\}_{i\in\mathcal{N}_m}, \{S_i\}_{i\in\mathcal{N}_m}, \{c_i\}_{i\in\mathcal{N}_m}\}$, where $\mathcal{N}_m$ denotes the set of UAVs occupying the m-th sub-channel. The $\{p_i\}_{i\in\mathcal{N}_m}$, $\{S_i\}_{i\in\mathcal{N}_m}$ and $\{c_i\}_{i\in\mathcal{N}_m}$ are the power control policy, the dynamic state space and cost function of UAV i, respectively.

We consider a generic Tx UAV i who will transmit to Rx UAV j during the considered period. Here, we define the perceived aggregate interference introduced by the set of UAVs $\mathcal{N}_{m,-j}$ transmit to UAV j with lower channel gains than UAV i as the dominator aggregate interference, which can be expressed as

$$\mu_d(t) = \sum_{l}^{l\in\mathcal{N}_{m,j,-l}} p_l(t) g_{l,i}(t), \tag{10}$$

where $p_l(t)$ is the transmit power of the UAVs causing dominating interference and $g_{l,i}(t)$ is the channel gain. According to [9], we assume that the channel gain dynamics can be seen as Ornstein-Uhlenbeck (OU) dynamics as

$$dg_{i,d}(t) = \frac{1}{2}(\mathcal{K}_g - g_{i,d}(t))dt + \sigma_g^2 dW_i(t), \tag{11}$$

where $\mathcal{K}_g$ and σ_g^2 are non-negative real values, thus leading to the stationary distribution of $dg_{i,d}(t)$ as Gaussian with mean $\mathcal{K}_g$ and variance σ_g^2. The $W_i(t)$ is a Brownian motion introduced to denote the stochastic fluctuation. All the channel gain dynamics are independent OU dynamics with different values of mean and variance. Then the perceived aggregate interference of the generic Tx UAV i is given by

$$\mu_i(t) = \sum_{l}^{l\in\mathcal{N}_{m,j,-l}} p_l(t) g_{l,i}(t) + \sum_{n}^{n\in\mathcal{N}_{m,-j}} p_n(t) g_{n,i}(t), \tag{12}$$

where the set $\mathcal{N}_{m,-j}$ consists of the UAVs occupying the m-th sub-channel at time t whose receivers are not Rx UAV j.

As a large number of channel state information (CSI) are need to be estimated for obtaining the optimal transmit power control policies, which will give rise to heary overhead. Hence, in a MFG scheme, we employ a mean field approximation (MFA) method to obtain the aggregate interference, as described in [9]. Note that in this NOMA-based UAV network, more than one UAVs occupying the same sub-channel can transmit to one Rx UAV at the same time, so the channel gains $g_{i,d}(t)$ and $g_{n,i}(t)$ should be approximated as $m_{i,d}(t)$ and $m_{i,n}(t)$, respectively.

The approximate aggregate interference $m_{i,d}(t)$ and $m_{i,n}(t)$ are the average channel gains, which are in the similar form of the OU dynamics. Hence, we have

$$dm_{i,d}(t) = \frac{1}{2}(\mathcal{K}_{m,d} - m_{i,d}(t))dt + \sigma_{m,d}^2 dW_{i,d}(t), \quad (13)$$

$m_{i,n}(t)$ has the same form as (11) with $\mathcal{K}_{m,d}$ and $\sigma_{m,d}$.

Then the state equation of dominator UAVs $d \in \mathcal{N}_{m,j,-i}$ and the generic UAV i can be given by

$$s_d(t) = p_i(t)\varpi_{i,j}(t)dt + p_i(t)\sigma_{m,i}^2 dW_{i,d}(t), \quad (14)$$

$$\begin{aligned} s_i(t) = p_d(t)\varpi_{d,j}(t)dt + p_d(t)\sigma_{m,d}^2 dW_{d,j}(t) \\ +p_l(t)\varpi_{i,j}(t)dt + p_l(t)\sigma_{m,i}^2 dW_{i,j}(t), \end{aligned} \quad (15)$$

respectively, where $\varpi_{i,d}(t) = \frac{1}{2}(\mathcal{K}_{m,i} - m_{i,j}(t))$ and $\varpi_{d,j}(t) = \frac{1}{2}(\mathcal{K}_{m,d} - m_{d,j}(t))$. The UAV l belong to the set $\mathcal{N}_{m,-j}$.

So we define system state dynamics $s(t) = [s_d(t), s_i(t)]$ for the dominating UAV set $\mathcal{N}_{m,-j}$ and generic UAV i, respectively. They will individually update the dynamics during the distributed implementation of optimal control. There exists the necessary strategic information exchange which give the Tx UAVs of Rx UAV j different power ranges. However, it is largely reduced.

Given system state dynamics $s(t) = [s_d(t), s_i(t)]$, we define the mean field $m(t,s)$ as

$$m(t,e) = \lim_{N\to\infty} \frac{1}{N} \sum_{\forall i \in N} \mathbb{1}_{\{s(t)=s\}}, \quad (16)$$

where $\mathbb{1}$ denotes an indicator function which returns 1 if the given condition is true, 0 otherwise. For a given time instant, the mean field is the probability distribution of the states over the set of players.

In our proposed MFG, each Tx UAV obtain the optimal power control policy minimizing the cost $c(t,s,p)$. In this work, UAVs aim to mitigate the interference, so the system cost function is given by

$$c(t) = \mu_d^2(t) + \mu_i^2(t), \quad (17)$$

where $\mu_d(t) = |\mathcal{N}_{m,j}|\, p_i(t) m_{i,j}(t)$ and $\mu_i(t) = |\mathcal{N}_{m,j,-i}|\, p_d(t) m_{d,j}(t)$, respectively.

B. MFG Equilibrium and MFG Equations

For the continuous stochastic dynamics of UAVs, we can derive the Hamilton-Jacobi-Bellman (HJB) partial differential equation to obtain the optimal value function following the Bellman's optimality principle as

$$\partial_t u(t,s) + \frac{\sigma_d^2}{2}\Delta_{s_d} u(t,s) + \frac{\sigma_i^2}{2}\Delta_{s_i} u(t,s) = H(c, \nabla_s u(t,s)), \quad (18)$$

where the Hamiltonian is given by

$$\begin{aligned} H(c, \nabla_s u(t,s)) = \\ -\min_{p_d(t),p_i(t)} \left[c(t,s,p) + \tfrac{\partial_{s_d}}{\partial_t}\nabla_{s_d} u(t,s) + \tfrac{\partial_{s_i}}{\partial_t}\nabla_{s_i} u(t,s) \right]. \end{aligned} \quad (19)$$

And the Fokker-Planck-Kolmogorov (FPK) equation is derived as

$$\begin{aligned} \partial_t m(t,s) + \tfrac{\sigma_d^2}{2}\Delta_{s_d} m(t,s) + \tfrac{\sigma_i^2}{2}\Delta_{s_i} m(t,s) \\ -\tfrac{\partial_{s_d}}{\partial_t}\nabla_{s_d} m(t,s) - \tfrac{\partial_{s_i}}{\partial_t}\nabla_{s_i} m(t,s) = 0. \end{aligned} \quad (20)$$

The MFG is defined as the combination of the derived HJB and FPK equations. The HJB equation governs the computation of the optimal control policy with time, while the FPK equation evolves forward in time that governs the evolution of the density function of the agents' states. With the given final value of the value function, the HJB equation is solved backward in time. Then the solutions of the HJB equation are used to evolve the mean field in the FPK equation. The interactive evolution finally leads to the mean field equilibrium.

C. Distributed Optimal Power Control Policy Based on the Finite Difference Method

As derived above, the HJB and FPK equations will result in the solutions of the proposed MFG. We utilize the finite difference method with Upwind scheme to obtain the numerical solutions of these partial differential equations. The solution space is firstly discretized, where the investigated time intercal $[0,T]$ and the interference state space $[0, S_i max]$ and $[0, S_d max]$ are discretized into $X \times Y \times Z$ spaces. The step sizes of time and state space are $\delta_{\mathrm{t}} = \frac{T}{X}$, $\delta_{S_i} = \frac{S_{i\max}}{Y}$ and $\delta_{S_d} = \frac{S_{d\max}}{Z}$, respectively. The operators of the Upwind scheme are given as

$$\partial_t u(t,s_i,s_d) = \frac{u(t+1,s_i,s_d) - u(t,s_i,s_d)}{\delta_{\mathrm{t}}}, \quad (21)$$

$$\nabla_{S_i} u(t,s_i,s_d) = \frac{u(t,s_i,s_d) - u(t,s_i-1,s_d)}{\delta_{S_i}}, \quad (22)$$

$$\begin{aligned} \Delta_{S_i} u(t,s_i,s_d) = \\ \tfrac{1}{\delta_{S_i}^2}\left[u(t,s_i+1,s_d) - 2u(t,s_i,s_d) + u(t,s_i-1,s_d) \right]. \end{aligned} \quad (23)$$

Due to the Hamiltonian, it is not able to solve the HJB equation through the finite difference method. Like [9], we reformulate a optimal problem to deal with the HJB euqation as

$$\begin{aligned} &\min_{p_d(t),p_i(t)} E\left[\textstyle\int_0^T c(t)dt + c(T) \right], \\ &s.t. \quad \partial_t m(t,s) + \tfrac{\sigma_d^2}{2}\Delta_{s_d} m(t,s) + \tfrac{\sigma_i^2}{2}\Delta_{s_i} m(t,s) \\ &\qquad -\tfrac{\partial_{s_d}}{\partial_t}\nabla_{s_d} m(t,s) - \tfrac{\partial_{s_i}}{\partial_t}\nabla_{s_i} m(t,s) = 0. \end{aligned} \quad (24)$$

Assuming $c(T) = 0$ we can derive the Lagrangian $L\left(m(t,s), p_i(t,s), p_d(t,s), \lambda(t,s)\right)$ as (25), where $\lambda(t,s)$ is the Lagrangian multiplier.

As the FPK equation can be discretized and solved with Upwind scheme, the optimal decision variables (P^* and λ^*) can be obtained according to the Karush-Kuhn-Tucker (KKT) conditions. The interactive evolution finally leads to the mean field equilibrium.

$$L\left(m(t,s),p_i(t,s),p_d(t,s),\lambda(t,s)\right)=\\ \int_{t=0}^{T}\int_{s_i=0}^{S_{i\max}}\int_{s_d=0}^{S_{d\max}} c(t,s)m(t,s)+\lambda(t,s)\Big(\partial_t m(t,s)+\frac{\sigma_d^2}{2}\Delta_{s_d}m(t,s)+\frac{\sigma_i^2}{2}\Delta_{s_i}m(t,s)-\frac{\partial_{s_d}}{\partial_t}\nabla_{s_d}m(t,s)-\frac{\partial_{s_i}}{\partial_t}\nabla_{s_i}m(t,s)\Big)dtds_ids_d. \tag{25}$$

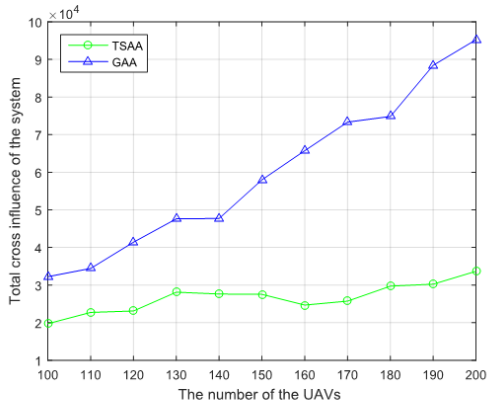

Fig. 2. Total inter-user interference influence of the system

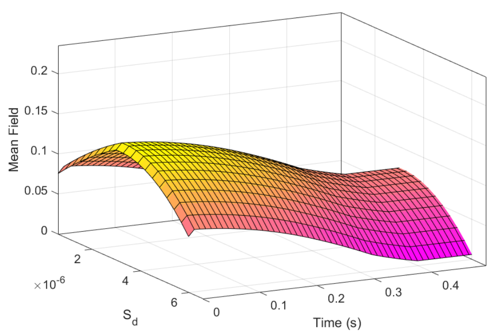

Fig. 3. Interference mean field distribution with S_d.

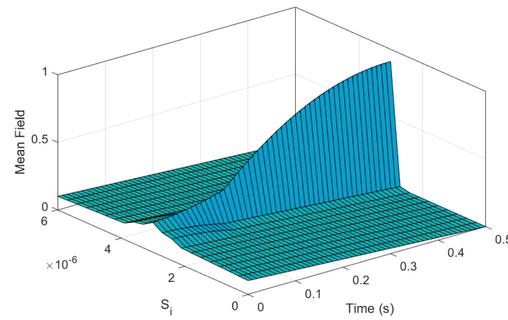

Fig. 4. Interference mean field distribution with S_i.

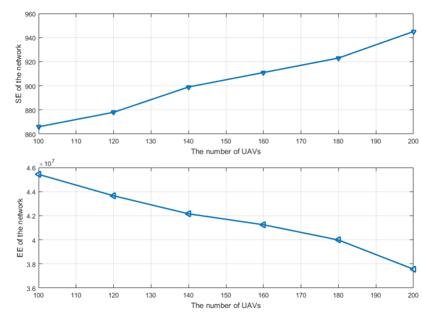

Fig. 5. Network spectrum and energy efficiency with the increasing number of UAVs.

V. Simulation and Discussion

In this section, we demonstrate the superior performance of our proposed algorithm in multiple UAVs scenarios through simulation results. It is assumed that the speed UAV is 100km/h in this scenario, and the communication range of UAV is r=200m, furthermore, in every transmission period consisting of 10 time slots, there are 5 sub-channels in eachtime slot.

As shown in Fig. 2, in order to evaluate the superiority of our proposed algorithm, we compare the performance of the time slot allocation algorithm (TSAA) and the geometric greedy algorithm (GAA) in the UAV scenario. With the increase in the number of UAVs, we find that the total inter-user interference influence of system obtained from the TSAA is less than GAA, indicating that the two-stage matching between the time slot and the UAV can reduce the inter-user interference influence among UAVs. At the same time, it can be found that the gap between the two curves becomes more and more obvious as the number of UAVs increases, indicating that the proposed algorithm is more suitable for the UAV scenario that is denser.

We simulate the distributed power control problem in the UAV network obtained above. In the considered MFG, we jointly consider the interference effects of the dominator and generic UAV. As we set $M_{\max}$ is 2, which resulting to a 4-dimensional space of mean field. Without loss of generality, we illustrate the mean field with the fixed interference state of the generic UAV in Fig. 3 and the interference mean field with the fixed state of dominator UAV in Fig. 4. We can conclude that with some fixed interference of generic UAVs, there is small difference in the interference state of dominator UAVs. And the interference state of generic UAVs tend to be consistent with the same interference state of dominator UAVs. The interference state of the generic UAV have a bigger influence on the mean field.

We illustrate the network spectrum and energy efficiency (SE and EE) with the increasing number of UAVs in Fig. 5.

The network SE and EE are the average SE and EE of all UAVs during the whole transmission period. We can see that the proposed method can enhance SE but sacrificing the EE. It is because the SE improvement is much slower than that of power consumption, when the number of small cells keep increasing.

VI. Conclusion

In this paper, we study the collision alleviating and interference mitigation in the dense UAV networks. In order to reduce the interference of system and improve the reliability of the system, we propose a two-phase optimization scheme for the NOMA-based UAVs system. Through a centralized time slot allocation scheme, the system inter-user interference influence can be reduced. And based on a distributed MFG power control scheme, the network spectrum efficiency is optimized. Simulation results show that the proposed algorithm can greatly improve the reliability of communication among UAVs. In the future work, more practical issues such as the precise channel model among UAVs will be discussed.

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