Age of Information Aware UAV Network Selection

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***Abstract*—For the command and control in unmanned aerial vehicles (UAVs), it is important to limit the latency of the real-time status updates. Previously proposed network selection schemes mainly select the closest or the strongest-signal base station (BS) for data rate maximization, thus neglecting the BSs' queueing and handover delays. In this paper, we aim to minimize the *age of information* (AoI) in both the network access and handover. Specifically, with the BS' load and UAVs' flight plan information, each UAV needs to choose between uncongested BSs for low-latency updates or BSs along its trajectory for less frequent handovers. As the UAVs' decisions are coupled towards the BSs' load, we formulate the UAVs' interactions as a non-cooperative game, where each UAV aims to minimize its cost as the summation of the associated BSs' average AoI and the handover penalties. We show that it is a *potential game* by characterizing its exact potential function. It leads to the design of a distributed BS association (DBA) algorithm, whose output is guaranteed to converge to a Nash equilibrium within a finite number of iterations. Simulation results show that the DBA scheme's load-aware handover leads to a lower AoI cost than two benchmark schemes.**

I. Introduction

A. Motivations

Recently, numerous innovative unmanned aerial vehicle (UAV) applications, such as search-and-rescue and package delivery, have emerged that rely on the cellular network to support their remote operations [1], [2]. Along its flight path, each UAV associates with and handovers among different ground base stations (BSs) to maintain its network connectivity. Due to the time-critical requirements of UAVs' command and control (such as autonomous operation, flight authorization, and navigation database update) [1], it is important to ensure the *freshness* of the flight status updates [3]. A relevant metric to characterize the information freshness is the *age of information* (AoI) [4], which is defined as the time elapsed between the last update and the present time. For an AoI-aware network selection, it is important to jointly consider the delay incurred during the BS association and handover procedures.

First, in *BS association*, a UAV can experience a lower queueing delay by connecting with an uncongested BS with less data traffic. Traditional UAV network selection policy usually recommends connecting with the closest BS [5] or strongest-signal BS [6], so as to ensure a good wireless channel and thus a high data rate. However, the flight status updates' latency, instead of data rate, matters more for the UAVs' safe operations. Thus, an AoI-aware network selection policy should favor lightly loaded BSs with low queueing delays [4]. However, if all the UAVs nearby simply choose the same BS with the lowest latency, they will overwhelm the BS and significantly increase its AoI at the end. In other words, to balance the BSs' traffic load for a low-AoI network access, a proper *coordination* mechanism is needed among UAVs.

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Besides, the *handover* procedure may lead to service disruption in the form of delay or packet loss during network switching [7]. As UAVs are flying with a high mobility (in the order of 100 km/h [2]), simply adopting the closest BS or the strongest-signal BS policies without considering their future trajectories may result in frequent network handovers (known as ping-pong effect [1]), and thus significantly increases the idle intervals without any network connectivity. One way to reduce the unnecessary handovers is to leverage the *flight plan* information to identify available BSs in the next few time slots and associate with them. In fact, the 3rd Generation Partnership Project (3GPP) has launched a study in Release 15 to leverage the flight plan information to facilitate the handover procedure [1]. However, the detailed network association policy is not specified in the study.

Considering the BS association and handover procedures jointly, we need to achieve a good *tradeoff* between choosing uncongested BSs for low-latency updates or BSs along the UAV's trajectory for less frequent handovers. Overall, we seek to answer the following question: *Given the UAVs' trajectory information, how should they coordinate their network selections in multiple time slots to reduce the AoI due to queueing delay and handover?*

B. Contributions

In this paper, we aim to leverage the UAVs' flight plan to coordinate their network selections and reduce the ping-pong effect over a finite horizon. As the UAVs' aggregate decisions are coupled towards the BSs' traffic loads, we formulate their interactions as a non-cooperative game, where each UAV's cost is defined as the total AoI of the selected BSs plus the handover penalties. We show that it is a *potential game* [8], which guarantees that the network selection of our proposed distributed BS association (DBA) algorithm will converge to a pure strategy Nash equilibrium (NE) within a finite number of iterations.

To the best of our knowledge, this is the first paper that studies AoI-aware network selection in UAVs. Our major contributions are:

- *AoI-aware network selection*: We study how the UAVs should coordinate their network access to reduce the AoI due to queueing delay and handover. Thus, we define a UAV-dependent cost as the summation of the selected BSs' AoI and the handover penalties.

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- *Distributed algorithm with nice convergence property*: Based on the potential game characterization, we design the DBA algorithm whose network selection is guaranteed to converge to a stable equilibrium within a finite number of iterations.
- *Load-aware adaptive handover*: Simulation results show that the DBA scheme adjusts its handover tendency based on the BSs' traffic load to achieve a lower cost than the benchmark closest BS [5] and greedy distributed schemes.

C. Related Works

Depending on the UAVs' roles in the communication system, we can classify the applications into either adopting the server or client model [9]. In the *server model*, the UAVs serve as flying *base stations* (BSs) in enhancing the network capacity or providing Internet connectivity for rural areas and disaster zones. By contrast, in the *client model*, a UAV is an aerial *user equipment* (UE) requesting communication services. Despite the research community's growing interest in studying UAVs in recent years (as documented in a few survey papers [2], [9]–[11]), most of these studies are devoted to the server model.

Comparatively, there are only a few studies, such as [5], [6], [12]–[17], on the client model, which can be broadly classified into three research themes. First, the studies in [12], [13] considered the path planning problem of cellular-connected UAVs. Different from these works that the flight plans are the decisions, we consider the UAVs' network selections based on their *given* flight paths in this paper. Second, the studies in [5], [6] focused on the performance analysis of the closest BS and strongest-signal BS policies, respectively. Different from [5], [6], we aim to *design* a network selection policy that takes into account the network congestion and handover penalty. Third, there were a few simulation studies in [14]–[17] on the impact of drone deployment in existing cellular networks. Different from these simulation studies, we aim to study the network selection problem from an *analytical* perspective.

Recently, there were some studies [3], [18]–[20] on the AoI-aware UAV communication design. Specifically, the works in [18]–[20] considered the AoI in the Internet-of-things (IoT) status updates through UAV relays. Thus, they considered the server model, instead of the client model in this paper. Garnaev *et al.* in [3] aimed to maintain the information freshness for UAV control under an adversarial interferer. Although the authors also applied game theory in the design, they mainly focused on the jamming interference, instead of the BS congestion that we consider in this paper.

Overall, our unique contribution is an AoI-aware UAV network selection algorithm design in the client model based on the analytical framework of non-cooperative game theory.

The rest of the paper is organized as follows. We describe our system model in Section II and formulate a BS association game in Section III. We present our simulation results in Section IV and conclude the paper in Section V.

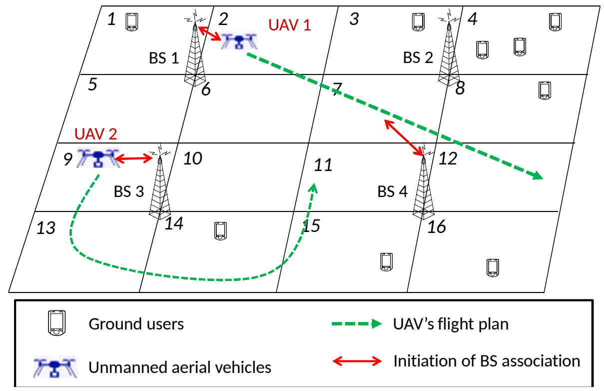

Fig. 1. An example of a flight plan aware UAV network coordination with $I = 2$ UAVs and $N = 4$ BSs in 16 regions. Initially, UAV 1 is associated with BS 1. While flying to region 7, it may associate with the closer BS 2 or a further BS 4, which is possible due to the line-of-sight (LOS) channel condition. (Here, we assume that the coverage radius of each BS for UAV is around 1.5 times the length of the side of a square region in this example.) Aware of its flight plan and the heavy congestion (with five ground users) at BS 2, UAV 1 begins its association with BS 4 for a lower AoI. Similarly, towards the end of UAV 2's trajectory, knowing that three users (i.e., UAV 1 and two other ground users) will be connected with BS 4, UAV 1 decides to associate with BS 3 (instead of BS 4) throughout its course to enjoy a lower AoI without any handover.

II. System Model

In this section, we discuss the system model for the flight plan aware BS association problem. First, we describe the network setting, the air-to-ground (A2G) channel model, and the UAV setting in Sections II-A, II-B, and II-C, respectively. Then we represent a UAV's network access strategy as a network-time route in Section II-D and discuss its cost function in Section II-E.

A. Network Setting

As shown in Fig. 1, we consider a cellular system with a set $\mathcal{N} = \{1, \ldots, N\}$ of base stations (BSs).[1] They provide network access to a set $\mathcal{I} = \{1, \ldots, I\}$ of UAVs and some ground users in a set $\mathcal{T} = \{1, \ldots, T\}$ of time slots, where the length of each time slot is Δ. The parameters of each network are described as follows.

Definition 1 (Network Parameters): Each network $n \in \mathcal{N}$ is associated with the:

- *Average service rate* μ_n: We model each BS $n \in \mathcal{N}$ as a queuing system that handles the data demand of the users (including both UAVs and ground users) at an average service rate μ_n.
- *Handover time* $\delta_i^{n,n'}$: It is the delay incurred by UAV i when it handovers from network $n \in \mathcal{N}$ to network $n' \in \mathcal{N}$, and it accounts for signaling and network switching time during the handover procedure. It is equal to the total number of time slots required to tear down the old connection of network n and setup the new connection of network n'. As there is no handover when a UAV

[1] In this paper, we use the terms "network" and "BS" interchangeably.

keeps using the same network n, we have $\delta_i^{n,n}=0, \forall i \in \mathcal{I}, n \in \mathcal{N}$.

B. Air-to-Ground Channel Model

In this subsection, we define the A2G channel model between a BS-UAV pair. Let $\boldsymbol{l}_i \triangleq (x_i, y_i, h_i) \in \mathcal{L}$ be the three-dimensional coordinates of UAV $i \in \mathcal{I}$, where x_i and y_i together indicate UAV i's horizontal position, h_i represents UAV i's altitude, and $\mathcal{L}$ is the set of feasible positions. Similarly, we let $(x_n, y_n, h_n) \in \mathcal{L}$ be the three-dimensional coordinates of BS $n \in \mathcal{N}$. Thus, when UAV i is at $\boldsymbol{l}_i$, its distance from BS n is

$$d_{i,n}(\boldsymbol{l}_i) = \sqrt{(x_n - x_i)^2 + (y_n - y_i)^2 + (h_n - h_i)^2}. \quad (1)$$

In practice, we assume that $h_i \geq h_n, \forall i \in \mathcal{I}, n \in \mathcal{N}$. The elevation angle $\theta_{i,n}$ [21] of UAV i with respect to BS n is

$$\theta_{i,n}(\boldsymbol{l}_i) = \frac{180}{\pi} \sin^{-1}\left(\frac{h_i - h_n}{d_{i,n}(\boldsymbol{l}_i)}\right). \quad (2)$$

Thus, the LOS probability [21] between UAV i and BS n is

$$p_{i,n}^{\text{LOS}}(\boldsymbol{l}_i) = \frac{1}{1 + a\exp\big(-b(\theta_{i,n}(\boldsymbol{l}_i) - a)\big)}, \quad (3)$$

where a and b are the environment parameters.

Let η^{LOS} and η^{NLOS} be the excessive path loss coefficients in the LOS and non-LOS (NLOS) cases, where $\eta^{\text{NLOS}} > \eta^{\text{LOS}}$. Then the average path loss between UAV i and BS n is [21], [22]

$$\phi_{i,n}(\boldsymbol{l}_i) = \Big(p_{i,n}^{\text{LOS}}(\boldsymbol{l}_i)\eta^{\text{LOS}} + \big(1 - p_{i,n}^{\text{LOS}}(\boldsymbol{l}_i)\big)\eta^{\text{NLOS}}\Big)\Big(\frac{4\pi f}{c} d_{i,n}(\boldsymbol{l}_i)\Big)^{\alpha}, \quad (4)$$

where α is the path loss exponent, f is the carrier frequency, and c is the speed of light.

We consider orthogonal[2] uplink transmissions from UAVs to BSs, where a dedicated frequency band is allocated for each pair of UAV-BS communication link [13]. When UAV i is at location $\boldsymbol{l}_i$, we assume that BS n is available for data uploading if the BS's received signal-to-noise ratio (SNR) is no less than a predefined threshold γ_n^{th}. That is,

$$\gamma_{i,n}(\boldsymbol{l}_i) = \frac{P_i}{\phi_{i,n}(\boldsymbol{l}_i)\Psi} \geq \gamma_n^{\text{th}}, \quad (5)$$

where P_i is UAV i's transmit power and Ψ is the noise power.

C. UAV Setting

Definition 2 (UAV's Flight Plan and Network Availability): Each UAV $i \in \mathcal{I}$ is associated with:

- *Flight plan* $\boldsymbol{\theta}_i = (\boldsymbol{l}_i[t] \in \mathcal{L}, \forall t \in \mathcal{T})$: It contains UAV i's position $\boldsymbol{l}_i[t]$ at each time slot $t \in \mathcal{T}$, which is determined by the UAV's flight control system.
- *Location dependent network availability* $\mathcal{N}_i[t] \subseteq \mathcal{N}$: The set of networks available for UAV $i \in \mathcal{I}$ at its location at time $t \in \mathcal{T}$. Based on the flight plan $\boldsymbol{\theta}_i$ and (5),[3] we can define it as

$$\mathcal{N}_i[t] = \Big\{n \in \mathcal{N} : \gamma_{i,n}(\boldsymbol{l}_i[t]) \geq \gamma_n^{\text{th}}\Big\}. \quad (6)$$

[2]This can be achieved using various medium access control protocols, such as time or frequency division multiple access.

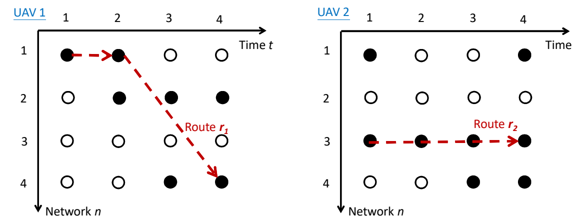

Fig. 2. The network availability and network-time routes of both UAVs in Fig. 1. Here, a solid black dot indicates that the network is available (i.e., $n \in \mathcal{N}_i[t]$), while an empty dot indicates otherwise. The two UAVs have different network availabilities due to their heterogeneous flight plans.

For the example in Fig. 1, we illustrate $\mathcal{N}_i[t]$ in Fig. 2. As an example, we have $\mathcal{N}_2[3] = \{3, 4\}$ for UAV 2 at time $t = 3$.

D. Network-Time Route as UAV's Strategy

Next, we define a UAV's *strategy* as its network selections across multiple time slots, which is referred to as a *network-time route* define below. We further define $\mathcal{R}_i$ as the set of all UAV i's *feasible* network-time routes.

Definition 3 (Feasible Network-Time Route): Given UAV i's flight plan $\boldsymbol{\theta}_i$, its *feasible network-time route* is a sequence

$$\boldsymbol{r}_i = \Big((n_i^1, t_i^1), (n_i^2, t_i^2), \ldots, (n_i^{M_i}, t_i^{M_i})\Big) \in \mathcal{R}_i, \quad (7)$$

which indicates UAV i's network selections in different time slots. It satisfies the following conditions:

1) Causality: $1 = t_i^1 < t_i^2 < \ldots < t_i^{M_i} \leq T$.
2) Network availability based on the flight plan: $n_i^m \in \mathcal{N}_i[t_i^m]$, for each $m \in \{1, \ldots, M_i\}$.
3) Handover time: $t_i^{m+1} - t_i^m \geq \delta_i^{n_i^m, n_i^{m+1}} + 1$,[4] for each $m \in \{1, \ldots, M_i - 1\}$.

Condition 1) accounts for the fact that time is always increasing. Condition 2) ensures that the network is available for the UAV based on its flight plan. Condition 3) ensures that the duration between network switching is sufficient for the handover.

To facilitate the introduction of the UAV's cost function in the next subsection, we define the network-time points of a feasible network-time route as follows.

Definition 4 (Network-time points): Given a feasible route $\boldsymbol{r}_i \in \mathcal{R}_i$ in (7), we define its network-time points as the set

$$\mathcal{V}(\boldsymbol{r}_i) = \Big\{(n_i^1, t_i^1), (n_i^2, t_i^2), \ldots, (n_i^{M_i}, t_i^{M_i})\Big\}. \quad (8)$$

[3]We want to emphasize that our later analysis is not restricted to the A2G channel model in Section II-B. As long as we can characterize $\mathcal{N}_i[t]$ (e.g., through actual channel measurement), our game theoretic analysis and proposed DBA algorithm in Section III remain valid.

[4]Note that it is an inequality constraint. The reason is that some networks may not be available at certain locations, which results in the time difference between two adjacent network-time points to be larger than the handover time.

The set can also be represented as the $M_i - 1$ network-time point pairs

$$\mathcal{E}(\boldsymbol{r}_i) = \Big\{ \big((n_i^m, t_i^m), (n_i^{m+1}, t_i^{m+1}) \big) : m = 1, \ldots, M_i - 1 \Big\}, \tag{9}$$

which are the consecutive pairs of network-time points visited by UAV i in route $\boldsymbol{r}_i$.

Example 1: An example of the feasible network-time routes is illustrated in Fig. 2. In this example, we have $\boldsymbol{r}_1 = \big((1,1),(1,2),(4,4)\big)$, so $\mathcal{V}(\boldsymbol{r}_1) = \{(1,1),(1,2),(4,4)\}$ and $\mathcal{E}(\boldsymbol{r}_1) = \Big\{ \big((1,1),(1,2)\big), \big((1,2),(4,4)\big) \Big\}$. The pair of network-time points $\big((1,1),(1,2)\big)$ denotes that UAV 1 associates with BS 1 at time slot 1, and keeps connecting with BS 1 at time slot 2. The pair of network-time points $\big((1,2),(4,4)\big)$ means that UAV 1 then associates with BS 4 at time slot 4 after taking one time slot of handover time.

E. AoI-aware Cost Function

For the low-latency control, a UAV needs to select BSs with small AoI and reduces the handover delay. In this subsection, we define an AoI-aware cost function that captures these two components.

To define a BS n's AoI at a particular time t, we need to first define its *load level* as

$$\omega[(n,t),\boldsymbol{r}] = \Big| j \in \mathcal{I} : (n,t) \in \mathcal{V}(\boldsymbol{r}_j), \boldsymbol{r}_j \in \mathcal{R}_j \Big| + \omega^{\text{GUE}}[(n,t)], \tag{10}$$

which represents the number of users (including both the UAVs and ground users) it needs to serve. The first term on the right hand side counts the number of *UAVs* that connect with network $n \in \mathcal{N}$ at time $t \in \mathcal{T}$ under strategy profile $\boldsymbol{r} = (\boldsymbol{r}_1, \ldots, \boldsymbol{r}_I)$. The second term $\omega^{\text{GUE}}[(n,t)]$ represents the number of *ground users* that associate with network $n \in \mathcal{N}$ at time $t \in \mathcal{T}$.

Let $a_n(\omega)$ be the *average AoI* through BS n when its load level is ω. Define $\rho(n,t) = \frac{\lambda\,\omega[(n,t),\boldsymbol{r}]}{\mu_n}$ as the *utilization* of BS n at time t, where λ is the average traffic demand rate per user. We notice that when $\rho(n,t) \geq 1$, BS n will be overloaded such that the average queueing delay is infinite [23]. As a result, the UAVs cannot update their status in the whole time slot, so we set the AoI of BS n at time slot t to be equal to the time slot length Δ. Suppose that BS n can be modeled as a M/M/1 queue,[5] BS n's average AoI at time t can be expressed as

$$a_n(\omega[(n,t),\boldsymbol{r}]) = \min\left\{ \frac{1}{\mu_n}\left(1 + \frac{\mu_n}{\lambda\omega[(n,t),\boldsymbol{r}]} + \frac{\lambda^2\omega[(n,t),\boldsymbol{r}]^2}{\mu_n(\mu_n - \lambda\omega[(n,t),\boldsymbol{r}])}\right), \Delta \right\}, \tag{11}$$

where the first term in the minimization function is the AoI when the utilization $\rho(n,t) < 1$ [24].

While targeting for low-AoI BSs, a UAV also needs to reduce the handover time, when it does not associate with any BSs. Specifically, for a feasible switching from network $n \in \mathcal{N}$ at time $t \in \mathcal{T}$ to network $n' \in \mathcal{N}$ at $t' \in \mathcal{T}$ such that $\boldsymbol{e} = \big((n,t),(n',t')\big) \in \mathcal{E}(\boldsymbol{r}_i)$, we define its *handover penalty* as

$$g_i[\boldsymbol{e}] = g_i\big[(n,t),(n',t')\big] = \psi_i(t' - t - 1), \tag{12}$$

where $\psi_i(\epsilon) \geq 0$ is the penalty function for a handover delay $\epsilon \geq 0$. As it is undesirable to lose connectivity for an extended period of time, we assume that it is a nondecreasing function in ϵ with $\psi_i(0) = 0$.

Overall, given the strategy profile $\boldsymbol{r}$ of all UAVs, if $\boldsymbol{r}_i \in \mathcal{R}_i$, UAV i's *cost function* is

$$c_i(\boldsymbol{r}) = \sum_{(n,t)\in\mathcal{V}(\boldsymbol{r}_i)} a_n(\omega[(n,t),\boldsymbol{r}]) + \sum_{\big((n,t),(n',t')\big)\in\mathcal{E}(\boldsymbol{r}_i)} \psi_i(t'-t-1). \tag{13}$$

which is the summation of the average AoI of the connected BSs and the aggregate handover penalties of UAV i. It models the UAV's tradeoff between choosing uncongested BSs for low-latency updates or BSs along its trajectory for less frequent handovers.

III. Distributed Base Station Association Game

In this section, we first formulate the UAVs' BS association as a non-cooperative game in Section III-A. Next, we show that it is a potential game by deriving its exact potential function in Section III-B. We then propose a DBA algorithm to coordinate the UAVs' network selections in Section III-C.

A. BS Association Game Formulation

We first formulate the UAVs' BS association interactions as a non-cooperative game [8] as follows.

Definition 5 (BS Association Game): A BS association game is a tuple $\Omega = (\mathcal{I}, \mathcal{R}, \boldsymbol{c})$ defined by:

- Players: The set $\mathcal{I}$ of UAVs.
- Strategies: The set of strategy profiles of all the UAVs is $\mathcal{R} = \mathcal{R}_1 \times \ldots \times \mathcal{R}_I$, where the strategy $\boldsymbol{r}_i \in \mathcal{R}_i$ of UAV i is its network-time route.
- Costs: The vector $\boldsymbol{c} = (c_i, \forall\, i \in \mathcal{I})$ contains the cost functions of the UAVs defined in (13).

Let $\boldsymbol{r}_{-i} = (\boldsymbol{r}_1, \ldots, \boldsymbol{r}_{i-1}, \boldsymbol{r}_{i+1}, \ldots, \boldsymbol{r}_I)$ be the strategies of all the UAVs except UAV i. A strategy profile can be written as $\boldsymbol{r} = (\boldsymbol{r}_i, \boldsymbol{r}_{-i})$. We define the pure strategy NE [8] as follows.

Definition 6 (Nash equilibrium): The strategy profile $\boldsymbol{r}^*$ is a pure strategy Nash equilibrium (NE) if

$$c_i(\boldsymbol{r}_i^*, \boldsymbol{r}_{-i}^*) \leq c_i(\boldsymbol{r}_i, \boldsymbol{r}_{-i}^*),\ \forall\, \boldsymbol{r}_i \in \mathcal{R}_i, i \in \mathcal{I}. \tag{14}$$

In other words, a NE is a strategy profile that no UAV has the incentive to unilaterally deviate from its strategy to obtain a lower cost.

B. Potential Game

In general, it is difficult to establish the analytical results of the NE. Nevertheless, we are able to show that Ω is a *potential game* [8], which exhibits the *finite improvement property* [25]. It thus implies the *existence* of and the *convergence* to the NE.

[5] Note that our results (e.g., Theorems 1 and 2) are general and they are not restricted to the specific AoI function in (11) of the M/M/1 example here.

Algorithm 1 *Distributed BS association (DBA) algorithm for UAV $i \in \mathcal{I}$.*

Initialization

1: User's input: Flight plan $\boldsymbol{\theta_i} = (\boldsymbol{l}_i[t], \forall\, t \in \mathcal{T})$.
2: Query network availability $\mathcal{N}_i[t], \forall\, t \in \mathcal{T}$ from the operator by reporting $\boldsymbol{\theta_i}$.
3: Query network setting from the operator's database: BS AoI function $a_n(\omega), \forall\, n \in \mathcal{N}$ and average demand rate λ.
4: Define the user-dependent penalty function $\psi_i(\epsilon)$ and handover time $\delta_i^{n,n'}, \forall\, n, n' \in \mathcal{N}, n \neq n'$.
5: Determine the set $\mathcal{R}_i$ of feasible network-time routes from $\mathcal{N}_i[t], \forall\, t \in \mathcal{T}$ and handover time $\delta_i^{n,n'}, \forall\, n, n' \in \mathcal{N}$ by Definition 3.

Planning Phase: BS Association Game

6: **repeat**
7: **if** $\tau \in \Gamma_i$
8: Obtain network load level $q_{-i}[(n,t)]$ for all $(n,t) \in \mathcal{N} \times \mathcal{T}$ from the operator
9: Perform a best response update by identifying a route $\boldsymbol{r}_i \in \mathcal{R}_i$ that minimizes UAV i's cost:

$$\tilde{c}_i(\boldsymbol{r}_i) := \sum_{(n,t)\in\mathcal{V}(\boldsymbol{r}_i)} a_n(q_{-i}[(n,t)]+1) + \sum_{\big((n,t),(n',t')\big)\in\mathcal{E}(\boldsymbol{r}_i)} \psi_i(t'-t-1). \tag{17}$$

10: Report the BS association plan $\boldsymbol{r}_i$ to the operator.
11: **end if**
12: Set $\tau := \tau + 1$.
13: **until** $\tau \geq \tau^{\max}$.

BS Association Phase

14: Associate with BSs in different time slots based on strategy $\boldsymbol{r}_i$.

Definition 7 (Potential Game): Game Ω is a *potential game* if there exists an exact potential function $\Phi(\boldsymbol{r})$ such that

$$c_i(\boldsymbol{r}_i,\boldsymbol{r}_{-i}) - c_i(\boldsymbol{r}'_i,\boldsymbol{r}_{-i}) = \Phi(\boldsymbol{r}_i,\boldsymbol{r}_{-i}) - \Phi(\boldsymbol{r}'_i,\boldsymbol{r}_{-i}), \quad \forall\, \boldsymbol{r}_i, \boldsymbol{r}'_i \in \mathcal{R}_i, i \in \mathcal{I}. \tag{15}$$

Theorem 1: Game Ω is a potential game with the exact potential function given by

$$\Phi(\boldsymbol{r}) = \sum_{(n,t)\in\mathcal{N}\times\mathcal{T}} \sum_{q=1}^{\omega[(n,t),\boldsymbol{r}]} a_n(q) + \sum_{i\in\mathcal{I}} \sum_{\big((n,t),(n',t')\big)\in\mathcal{E}(\boldsymbol{r}_i)} \psi_i(t'-t-1). \tag{16}$$

The proof of Theorem 1 is given in Appendix A.

1) Properties of the Potential Game: Before stating the convergence properties, let us recall some definitions.

Definition 8 (Best response update): Starting from $\boldsymbol{r} = (\boldsymbol{r}_i, \boldsymbol{r}_{-i})$, a *best response update* [8] is an event where a single UAV i changes its strategy from $\boldsymbol{r}_i \in \mathcal{R}_i$ to $\boldsymbol{r}'_i \in \mathcal{R}_i$ to minimize its cost. That is, $\boldsymbol{r}'_i = \arg\min_{\boldsymbol{r}_i \in \mathcal{R}_i} c_i(\boldsymbol{r}_i, \boldsymbol{r}_{-i})$.

Definition 9 (Finite improvement property): A game possesses the *finite improvement property* (FIP) [25] when asynchronous best response updates always converge to a NE within a finite number of steps, irrespective of the initial strategy profile or the UAVs' updating order.

The FIP implies that best response updating always leads to a pure strategy NE, which implies the existence of a pure strategy NE. From [26], every finite game with a potential function has the FIP, which leads to the following result.

Theorem 2: Game Ω possesses the FIP.

Algorithm 2 *Information update algorithm for the mobile operator.*

Initialization

Establish network parameter database for UAVs: BS AoI function $a_n(\omega), \forall\, n \in \mathcal{N}$ and average demand rate λ.
Synchronize the clock timer $\tau := 1$ with all the UAVs.

Network availability information update

if UAV i queries for network availability by reporting $\boldsymbol{\theta}_i$
Calculate $\mathcal{N}_i[t], \forall\, t \in \mathcal{T}$ based on (6) and send to UAV i.
end if

BS load information update

repeat
if UAV i queries for BS load
Calculate the network load level $q_{-i}[(n,t)]$ for all $(n,t) \in \mathcal{N} \times \mathcal{T}$ and send it to UAV i:

$$q_{-i}[(n,t)] := \Big| j \in \mathcal{I}\backslash\{i\} : (n,t) \in \mathcal{V}(\boldsymbol{r}_j) \Big| + \omega^{\text{GUE}}[(n,t)]. \tag{18}$$

end if
Set $\tau := \tau + 1$.
until $\tau \geq \tau^{\max}$.

C. Algorithm Design

With the nice FIP, we propose a DBA algorithm (i.e., Algorithm 1) for the UAVs to make their BS association decisions autonomously. It relies on the operational information obtained from the mobile operator[6] in Algorithm 2.

1) Algorithm 1: The key operations of Algorithm 1 are as follows:

- *Initialization*: The user of UAV i first needs to input its flight plan (line 1), so that the UAV can automatically query the operator's database for the network availability (line 2) and other network parameters (line 3). He also needs to define the penalty function $\psi_i(\epsilon)$ and handover time $\delta_i^{n,n'}, \forall\, n, n' \in \mathcal{N}, n \neq n'$ (line 4). Then UAV i initializes the set $\mathcal{R}_i$ of feasible network-time routes (line 5).
- *Iterative best response update*: We apply an iterative best response update for UAV i to plan its network association (line 6-13). Let Γ_i be the set of time slots (line 7) when UAV i updates its strategy. First, UAV i queries the operator on the network load level $q_{-i}[(n,t)]$ (from Algorithm 2) excluding UAV i itself for each network-time point (n,t) (line 8). Next, UAV i computes the best response by applying a shortest path algorithm [27], such as Dijkstra's algorithm (line 9). This process can be performed in an asynchronous manner until reaching the iteration limit $\tau^{\max}$ (line 13).
- *Strategy update*: After each round of best response update, UAV i reports its network association plan $\boldsymbol{r}_i$ to the operator (line 10).
- *BS association*: When UAV i is flying according to its planned trajectory $\boldsymbol{\theta}_i$, it can then associate with the BSs based on its network association strategy $\boldsymbol{r}_i$ (line 14).

[6]Notice that with this architecture, the UAVs can coordinate their network selections through the mobile operator. Thus, it is not required that the UAVs are located in proximity or able to connect with all the BSs.

TABLE I
SIMULATION PARAMETERS

Parameters	Values
Number of BSs N	9
BS antenna height h_n	25 m [1]
Carrier frequency f	2 GHz [1]
Transmit power P_i	49 dBm
Noise power Ψ	-96 dBm
Path loss exponent α	2.2 [2]
Environment parameters a, b	$11.95, 0.14$ [22]
Excessive path loss coefficients $\eta^{\text{LOS}}, \eta^{\text{NLOS}}$	2.3 dB, 34 dB [21]
Receive SNR threshold γ_n^{th}	10 dB

Regarding the computational complexity of Algorithm 1, we can show that each best response update (i.e., line 9) can be computed efficiently in polynomial time.

Proposition 1: Each best response update of UAV i can be computed in $\mathcal{O}(N^2T^2)$ time.

The proof of Proposition 1 is given in Appendix B. In Section IV, we will further discuss the average number of best response iterations required for convergence.

2) Algorithm 2: In Algorithm 2, the operator needs to provide some network parameters to the UAVs (line 1) and two key information:

- *Time dependent network availability* (in response to Algorithm 1 line 2): With flight plan $\boldsymbol{\theta}_i$, the operator can determine UAV i's time dependent network availability set $\mathcal{N}_i[t]$ based on (6) related to the A2G channel model or channel measurement (line 3-5).
- *BS load* (in response to Algorithm 1 line 8): The operator calculates $q_{-i}[(n,t)]$ in (18) for each UAV i based on other UAVs' planned network usage $\boldsymbol{r}_{-i}$ (line 6-11).

IV. PERFORMANCE EVALUATIONS

In this section, we evaluate the performance of our proposed DBA scheme by comparing it with the benchmark closest BS scheme [5] and greedy distributed scheme under various system parameters. We show that the DBA scheme takes advantage of the BS load information to select less congested BSs and adaptively adjust its handover tendency to reduce its cost.

A. Simulation Setting

1) Network Setting: We consider a 1.5 km by 1.5 km square region. There are $N = 9$ BSs deployed in a grid topology (similar to Fig. 1 but with a larger scale) and the inter-site distance between the closest pair of BSs is 500 m [1]. For each BS $n \in \mathcal{N}$, we consider that the average service rate μ_n is a normally distributed random variable with mean equals to 1000 packets/second and standard deviation equals to 10 packets/second. We adopt the M/M/1 BS queueing model such that the BS's AoI is given by (11). To model the dissatisfaction of a prolonged idle period without any network connectivity in UAV command and control, we assume the same increasing and convex handover penalty function for all the UAVs such that $\psi_i(\epsilon) = \epsilon^2, \forall\, i \in \mathcal{I}$. The handover time $\delta_i^{n,n'} = 1$ for all $n \neq n', i \in \mathcal{I}$. To focus on the impact of UAVs' network association, we do not consider any ground users such that $\omega^{\text{GUE}}[(n,t)] = 0, \forall\, n \in \mathcal{N}, t \in \mathcal{T}$. Other simulation parameters are listed in Table I unless specified otherwise.

2) UAV Setting: For each UAV i, we assume that its initial horizontal coordinates, x_i and y_i, are randomly generated within the square region. Its altitude h_i is uniformly distributed between 50 and 300 m [1]. Then, it flies at a constant speed and height in a straight line along a randomly generated horizontal direction [1]. Its speed is uniformly distributed between 100 and 160 km/hr [1], [2]. When it reaches the boundary of the square region, it will bounce back in a random direction.

3) Benchmark Schemes: We compare our DBA scheme with the following two benchmark schemes:

- *Closest BS* scheme [5]: At a given time $t \in \mathcal{T}$, each UAV i aims to associate with the nearest BS $\tilde{n} \in \mathcal{N}$ that is available (i.e., $\tilde{n} = \arg\min_{n \in \mathcal{N}_i[t]} d_{i,n}(\boldsymbol{l}_i[t])$). In case no BS is available (i.e., $\mathcal{N}_i[t] = \emptyset$), it will remain idle and does not associate with any BS.
- *Greedy distributed* (GD) scheme: At a given time $t \in \mathcal{T}$, each UAV aims to associate with an available BS with the lowest initial AoI without considering the demand from other UAVs. That is, it aims to connect with BS $\breve{n} = \arg\min_{n \in \mathcal{N}_i[t]} a_n(1)$ by assuming that it is the sole user of the network with $\omega = 1$. Similar to the closest BS scheme, it will remain idle when no BS is available.

B. Performance Evaluations

For each set of system parameters, we run the simulations 10000 times in MATLAB with randomized UAV flight plans and BS service rates to obtain the following results.

Impact of the number of UAVs on cost: In Fig. 3, we plot the average cost (defined in (13)) per UAV against the total number of UAVs I for the average traffic demand rate $\lambda = 200$. First, we can see that the average costs of all the schemes increase with I, as the increasing traffic demand increases the BSs' loads and thus their AoI. Second, we observe that the average cost of the DBA scheme is much lower than that of the two benchmark schemes. The reason is that DBA balances the load across different BSs to significantly reduce their AoI. Also, we see that the GD scheme results in a higher cost than the closest BS scheme. It is because under the GD scheme, the UAVs in a neighbourhood may tend to associate with the same BS with a low initial AoI without any coordination, which leads to a higher chance of network congestion and thus a higher average AoI.

Scalability of DBA algorithm: To evaluate the complexity of the DBA scheme, besides deriving the best response's polynomial time complexity in Proposition 1, we need to further study the number of best response iterations required for convergence. In Fig. 4, we plot the average number of best response updates required for convergence per UAV against I for $\lambda = 200$. We observe the diminishing increase rate of the required iterations over I and reaches only 5.90 iterations for $I = 50$, which suggests the scalability of the DBA algorithm.

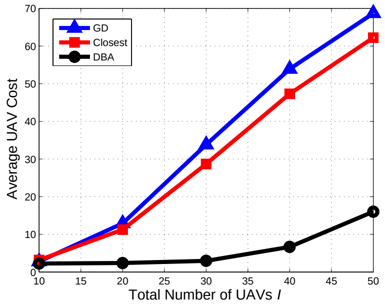

Fig. 3. The average UAV cost versus the total number of UAVs I for $\lambda = 200$.

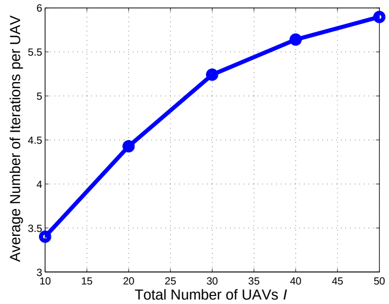

Fig. 4. The average number of best response iterations per UAV for convergence of the DBA scheme with $\lambda = 200$.

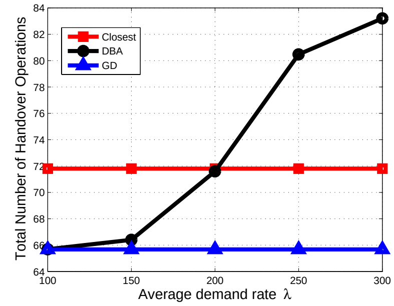

Fig. 5. The total number of handovers versus the average demand rate λ for $I = 30$.

Adaptive handover with respect to demand rate: In Fig. 5, we plot the total number of handover operations (i.e., the number of network switchings to different BSs) against the average demand rate λ for $I = 30$. First, we notice that the operations of both the closest BS and GD schemes are independent of λ, as they always suggest connecting with the closest BS or the lowest-AoI BS, respectively, regardless of the traffic load. Second, the handover tendencies of the DBA and GD schemes are similar for small λ, when the BSs are not congested. Interestingly, when λ increases, the DBA scheme handovers more often. The reason is that each UAV is generating more traffic as λ increases, which becomes easier to overwhelm BSs surrounded by plenty of UAVs and increase their AoI significantly from (13). Thus, it is better to handover more often in search of some less congested BSs to prevent the sharp increase in AoI.

V. Conclusion

In this paper, we proposed an AoI-aware network selection algorithm to support the UAV command and control, which has not been explored in the literature to the best of our knowledge. Specifically, we exploited the flight plan information to coordinate multiple UAVs' network selections by balancing the BSs' loads. Through the potential game formulation, we proposed the distributed BS association (DBA) algorithm, whose network selection is guaranteed to converge to a Nash equilibrium within a finite number of iterations. Simulation results showed that our proposed DBA algorithm handovers more often under the high traffic regime to lower its cost as compared with two benchmark schemes.

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APPENDIX

A. Proof of Theorem 1

In the proof, we want to show that the cost function in (13) and the potential function in (16) satisfy (15). First, starting from the original strategy profile $\boldsymbol{r} = (\boldsymbol{r}_i, \boldsymbol{r}_{-i})$, we define a new strategy profile $\boldsymbol{r}'$, where $\boldsymbol{r}'_j = \boldsymbol{r}_j$ if $j \neq i$ and $\boldsymbol{r}'_j \neq \boldsymbol{r}_j$ if $j = i$. In other words, only UAV i changes its strategy from $\boldsymbol{r}_i$ to $\boldsymbol{r}'_i$ in the new strategy profile $\boldsymbol{r}' = (\boldsymbol{r}'_i, \boldsymbol{r}_{-i})$.

Next, we define a partition of set $\mathcal{N} \times \mathcal{T}$, which consists of four non-overlapping sets of the network-time points

$$\begin{aligned}
\mathcal{B}^{(1)} &= \{(n,t) : (n,t) \in \mathcal{V}(\boldsymbol{r}_i), (n,t) \notin \mathcal{V}(\boldsymbol{r}'_i)\},\\
\mathcal{B}^{(2)} &= \{(n,t) : (n,t) \notin \mathcal{V}(\boldsymbol{r}_i), (n,t) \in \mathcal{V}(\boldsymbol{r}'_i)\},\\
\mathcal{B}^{(3)} &= \{(n,t) : (n,t) \in \mathcal{V}(\boldsymbol{r}_i), (n,t) \in \mathcal{V}(\boldsymbol{r}'_i)\},\\
\mathcal{B}^{(4)} &= \{(n,t) : (n,t) \notin \mathcal{V}(\boldsymbol{r}_i), (n,t) \notin \mathcal{V}(\boldsymbol{r}'_i)\},
\end{aligned} \tag{19}$$

where $\mathcal{B}^{(1)} \cup \mathcal{B}^{(2)} \cup \mathcal{B}^{(3)} \cup \mathcal{B}^{(4)} = \mathcal{N} \times \mathcal{T}$. As a result, by considering the difference in congestion level in network-time point (n,t) between strategy profiles $\boldsymbol{r}$ and $\boldsymbol{r}'$, we have

$$\omega[(n,t),\boldsymbol{r}] - \omega[(n,t),\boldsymbol{r}'] = \begin{cases} 1, & \text{if } (n,t) \in \mathcal{B}^{(1)},\\ -1, & \text{if } (n,t) \in \mathcal{B}^{(2)},\\ 0, & \text{if } (n,t) \in \mathcal{B}^{(3)} \cup \mathcal{B}^{(4)}. \end{cases} \tag{20}$$

For example, in the first line in (20), we have one more UAV (i.e., UAV i) choosing the network-time point $(n,t) \in \mathcal{B}^{(1)}$ in the strategy profile $\boldsymbol{r} = (\boldsymbol{r}_i, \boldsymbol{r}_{-i})$ than in $\boldsymbol{r}' = (\boldsymbol{r}'_i, \boldsymbol{r}_{-i})$, since UAVs other than i choose the same strategy profile $\boldsymbol{r}_{-i}$.

Let

$$A \triangleq \sum_{\big((n,t),(n',t')\big)\in\mathcal{E}(\boldsymbol{r}_i)} \psi_i(t'-t-1) - \sum_{\big((n,t),(n',t')\big)\in\mathcal{E}(\boldsymbol{r}'_i)} \psi_i(t'-t-1). \tag{21}$$

As a result, we have

$$\begin{aligned}
&\Phi(\boldsymbol{r}_i,\boldsymbol{r}_{-i}) - \Phi(\boldsymbol{r}'_i,\boldsymbol{r}_{-i})\\
=&\Big(\sum_{j\in\mathcal{I}} \sum_{\big((n,t),(n',t')\big)\in\mathcal{E}(\boldsymbol{r}_j)} \psi_j(t'-t-1)\\
&- \sum_{j\in\mathcal{I}} \sum_{\big((n,t),(n',t')\big)\in\mathcal{E}(\boldsymbol{r}'_j)} \psi_j(t'-t-1)\Big)\\
&+ \sum_{(n,t)\in\mathcal{N}\times\mathcal{T}} \Big(\sum_{q=1}^{\omega[(n,t),\boldsymbol{r}]} a_n(q) - \sum_{q=1}^{\omega[(n,t),\boldsymbol{r}']} a_n(q)\Big)\\
=&A + \sum_{(n,t)\in\mathcal{B}^{(1)}\cup\mathcal{B}^{(2)}\cup\mathcal{B}^{(3)}\cup\mathcal{B}^{(4)}} \Big(\sum_{q=1}^{\omega[(n,t),\boldsymbol{r}]} a_n(q) - \sum_{q=1}^{\omega[(n,t),\boldsymbol{r}']} a_n(q)\Big)\\
=&A + \sum_{(n,t)\in\mathcal{B}^{(1)}} \Big(\sum_{q=1}^{\omega[(n,t),\boldsymbol{r}]} a_n(q) - \sum_{q=1}^{\omega[(n,t),\boldsymbol{r}']} a_n(q)\Big)\\
&+ \sum_{(n,t)\in\mathcal{B}^{(2)}} \Big(\sum_{q=1}^{\omega[(n,t),\boldsymbol{r}]} a_n(q) - \sum_{q=1}^{\omega[(n,t),\boldsymbol{r}']} a_n(q)\Big)\\
=&A + \sum_{(n,t)\in\mathcal{B}^{(1)}} a_n(\omega[(n,t),\boldsymbol{r}]) - \sum_{(n,t)\in\mathcal{B}^{(2)}} a_n(\omega[(n,t),\boldsymbol{r}'])\\
=&A + \sum_{(n,t)\in\mathcal{B}^{(1)}\cup\mathcal{B}^{(3)}} a_n(\omega[(n,t),\boldsymbol{r}]) - \sum_{(n,t)\in\mathcal{B}^{(2)}\cup\mathcal{B}^{(3)}} a_n(\omega[(n,t),\boldsymbol{r}'])\\
=&A + \sum_{(n,t)\in\mathcal{V}(\boldsymbol{r}_i)} a_n(\omega[(n,t),\boldsymbol{r}]) - \sum_{(n,t)\in\mathcal{V}(\boldsymbol{r}'_i)} a_n(\omega[(n,t),\boldsymbol{r}'])\\
=&c_i(\boldsymbol{r}_i,\boldsymbol{r}_{-i}) - c_i(\boldsymbol{r}'_i,\boldsymbol{r}_{-i}).
\end{aligned} \tag{22}$$

Here, the first equality is due to the definition in (16). The second equality is due to $\boldsymbol{r}'_j = \boldsymbol{r}_j$ for $j \neq i$ and $\mathcal{B}^{(1)} \cup \mathcal{B}^{(2)} \cup \mathcal{B}^{(3)} \cup \mathcal{B}^{(4)} = \mathcal{N} \times \mathcal{T}$. The third equality is due to the fact that from (20), we have

$$\sum_{q=1}^{\omega[(n,t),\boldsymbol{r}]} a_n(q) - \sum_{q=1}^{\omega[(n,t),\boldsymbol{r}']} a_n(q) = 0, \text{ for } (n,t) \in \mathcal{B}^{(3)} \cup \mathcal{B}^{(4)}. \tag{23}$$

The fourth equality is due to the algebraic manipulation based on (20). The fifth equality is due to $a_n(\omega[(n,t),\boldsymbol{r}]) = a_n(\omega[(n,t),\boldsymbol{r}'])$ if $(n,t) \in \mathcal{B}^{(3)}$ from (20). The sixth equality is due to $\mathcal{V}(\boldsymbol{r}_i) = \mathcal{B}^{(1)} \cup \mathcal{B}^{(3)}$ and $\mathcal{V}(\boldsymbol{r}'_i) = \mathcal{B}^{(2)} \cup \mathcal{B}^{(3)}$. The last equality is due to the definition in (13). ■

B. Proof of Proposition 1

As illustrated in Fig. 2, in a network-time graph, the total number of nodes $V = NT$. In the extreme case that every pair of nodes is connected by an edge, the total number of edges $E \approx V^2 = N^2T^2$. In computing the best response update for UAV i, we can applying a shortest path algorithm, such as Dijkstra's algorithm, which has a computational complexity of $\mathcal{O}(E + V^2) = \mathcal{O}(V^2) = \mathcal{O}(N^2T^2)$ [27]. ■