Distributed Mission and Charging Scheduling for UAV Swarm to Maximize Service Coverage

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***Abstract*—In recent decades, unmanned aerial vehicles (UAVs) have been widely adopted such as serving as flying base stations. Compared to traditional solutions, the deployment of UAVs is fast and low-cost. However, due to UAVs' limited energy capacity, efficiently utilizing UAVs' energy is a matter of concern. One solution is to use rechargeable UAVs, but the challenge of charging schedule comes in the wake of it. In this paper, this problem is modeled as a non-cooperative game where a UAV can choose a strategy in order to maximize its payoff. Also, we have proved that the proposed game is an exact potential game (EPG) which ensures a Nash equilibrium (NE) with best-response dynamics. Numerical results show that the proposed algorithm has a larger coverage ratio and is more flexible than other algorithms in most environments; hence, a better performance.**

I. Introduction

Unmanned aerial vehicles (UAVs) are highly mobile and flexible. While deploying sensing or communication services over a large area, UAVs have an advantage over traditional solutions such as convenient and low-cost deployment as base stations. Additionally, without a person on board, UAVs can act autonomously or be controlled remotely. Thus, UAVs are embraced in wireless communication as wireless base stations [1], [2]. For example, UAVs can be an ideal solution to provide network service over a area [1]. And when it comes to a natural disaster or a military activity occurs that destroys the network infrastructure, a temporary network environment can be quickly set up by deploying UAVs. Moreover, in [3], UAVs are used to collect information in inaccessible areas and an approach is proposed to support crowdsourcing missions.

Although UAVs have many benefits, owing to UAVs' limited energy capacity, energy consumption is one of the chief factors that impacts the deployment of UAVs. For this reason, many energy-aware designs (e.g., path planning [4], [5] and transmissions [6], [5]) have been proposed to improve energy efficiency of UAV.

Yet another way to prolong UAV service time is to exploit rechargeable UAVs [7]. Many such applications demand two or more UAVs, one active and the rest standby, to seamlessly cover a specific spot or target. The objective is to minimize the number of demanded UAVs [8], [9] or maximize the battery level [10]. However, it may not be necessary or possible to provide every spot or target in the serving area with full, seamless coverage. We consider the problem of using a fixed number of rechargeable UAVs to collectively cover a target area where different subareas may demand different levels of coverage intensity. The goal is to maximize the accumulated coverage intensity before all UAVs fail for battery exhaustion. The problem can be viewed in both spatial and temporal domains. In spatial domain, we may not have sufficient UAVs to provide a full coverage over the whole area, but a sophisticated deployment plan of UAVs could provide a highest possible coverage intensity. In temporal domain, a UAV contributes no coverage when it flies back to a ground charging station for energy replenishment. On the other hand, a UAV no longer provides any coverage if it runs out of its battery. Therefore, we need a trade-off between serving and charging in scheduling UAV actions to maximize the accumulated coverage.

In this paper, we see each UAV as an independent decision maker and construct a distributed approach where each UAV autonomously decides its own action (e.g., serving, charging, and moving). We model this approach as a non-cooperative game where UAVs as game players act to maximize their own utilities. We carefully design the UAV utility function so that UAVs can balance their serving-charging actions to maximize the accumulated coverage. The main difference between our proposal and prior work [11] is that our work allows heterogeneous coverage demands and considers overlapping coverage among UAVs on the same spot. We show that the proposed game is an exact potential game, so the convergence of player's decisions can be ensured by player's best-response dynamics. We also conducted simulations to evaluate the proposed approach with various numbers of UAVs, charing stations, charing slots, and coverage demands. The results show that the proposed approach can have a higher accumulated coverage than greedy approaches.

The remainder of this paper is organized as follows. Section II provides an overview of related works, describes the system models, and formulates the problems. Sec. III presents the proposed approach and proves its stability. Sec. IV evaluates the performance of the proposed approach and explains the result of each experiment. Sec. V concludes the paper.

II. Background and Related Work

A. Related Work

There are several ways to charge UAVs [7]. Most researches assumed UAV swapping, where a standby, full-charged UAV takes over the duty of an energy-exhausted UAV when the latter UAV must return to a charging station for battery charging. For this scenario, multiple standby UAVs should line up at the same charging station to provide long-term yet seamless coverage services. The minimum number of UAVs that are needed to provide a full, seamless coverage has been studied [12], [13]. Some studies were to plan a flying tour for a swarm of UAVs to visit a sequence of spots and then return to a charging station. The goal is to maximize energy efficiency [8], [9] or battery level [10] yet provide a seamless coverage on these spots.

Unlike the above-mentioned studies, we do not demand full, seamless coverage on very spot/subarea/target. Instead, we aim to maximize the coverage provided by a fixed number of UAVs for as long as possible considering both the benefit and cost of energy replenishment. To this end, we propose a distributed, game-theoretic approach. Although several game-theoretic approaches have been proposed for UAV deployment problems in the literature [14], [15], [16], these approaches did not consider energy replenishment. Our work is most closely-related with that proposed by Trotta et al. [11], who studied UAV serving-charging schedule (which also involves the deployment of UAVs to each spot) to ensure a satisfactory coverage ratio. The goal is to maximize network lifetime, which ends at time when the first UAV runs out of battery. Besides a centralized algorithm, they also proposed a distributed game-theoretic approach. Though our approach shares some similarities with that of Trotta et al., our approach differs in that different subareas may demand different intensities of coverages (i.e., the number of UAVs needed for a satisfactory coverage) and that neighboring UAVs may have overlapping coverage on the same subarea.

B. System Model

We assume p rechargeable UAVs $P = \{1, 2, \ldots, p\}$ and t working time slots $T = \{1, 2, \ldots, t\}$. For each UAV $i \in P$, let k_i denote UAV i's charging rate. Over the whole serving area, A and M denote the set of coverage subareas and the set of charging station locations, respectively. For each $a \in A$, d_a is the number of UAVs required to attain the service coverage. Also, each charging station $m \in M$ has s_m charging slots. Here, p UAVs are considered aerial base stations which provide access services to user equipment across A and charge at the charging stations in M. Notice that a has at most one charging station within; therefore, $M \subseteq A$.

Assuming that UAV $i \in P$ is located in subarea a, it also provide services for neighboring subareas rested on UAV i's coverage radius r_i. Let $l_{a,a'}$ represent the distance between subarea a and a'. At the first time slot, each UAV is always located in the center of a subarea.

Alongside this, $\forall j \in T$ and $\forall i \in P$, let b_i^j denote UAV i's residual energy at time slot j and UAV i has its own consumption rate. In our system, only serving and flying are involved so we let e_i^{fly} and e_i^{ser} denote the energy consumption of flying per unit of distance and the energy consumption of serving in a time slot, respectively. The energy level must be in $[0,\ b_i^{\max}]$ while $b_i^{\max}$ is the capacity of UAV i's battery. When i decides to leave a subarea for another one, it must spend at least one time slot on flying at the average flying speed v. As a result, the maximum flying distance of i in a time slot is defined as $l_i^{\max} = v\rho$ while ρ is the length of a time slot.

C. Problem Formulation

We assume our UAVs will never crash or malfunction. For subarea $a \in A$, a function $O(a)$ is defined as follows:

$$O(a) = \begin{cases} 1, & \text{a charging station in subarea } a \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Further, $\forall i \in P, \forall j \in T$, we define three decision variables x_i^j, y_i^j and Loc_{ia}^j. $x_i^j = 1$ if i is charging at time slot j; otherwise, 0. $y_i^j = 1$ if i is on duty at time slot j; otherwise, 0. $Loc_{ia}^j = 1$ if i is located in subarea a at time slot j; otherwise, 0. Following Loc_{ia}^j, an additional auxiliary function $Loc(j,i) = a$ if and only if $Loc_{ia}^j = 1$. In addition, since an UAV can neither serve nor charge while moving from one area to another, $x_i^j + y_i^j \le 1$. Another auxiliary variable f_i^j is defined as follows:

$$f_i^j = \sum_{a \in A} \left(|Loc_{ia}^j - Loc_{ia}^{j+1}|/2 \right) \in \{0, 1\} \tag{2}$$

$f_i^j = 1$ if and only if UAV i changes to another subarea at time slot $j+1$ while $f_i^j = 0$ if and only if UAV i stays. With the above variables and functions, i's battery power at time slot j is calculated as below:

$$b_i^j = b_i^{j-1} - y_i^j e_i^{\text{ser}} + x_i^j k_i - f_i^j l_{Loc(j-1,i),Loc(j,i)} e_i^{\text{fly}} \tag{3}$$

On the right-hand side of (3), from the first to the fourth terms are UAV i's remaining power at time slot $j-1$, the energy that UAV i spends on serving, that gets from charging and that spends on flying, respectively.

D. Objective Function

To start with an indicator variable z_a^j defined as follows:

$$z_a^j = \begin{cases} 1, & \sum_{i \in U^j(a)} y_i^j \ge d_a \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

$z_a^j = 1$ signifies that subarea a's demand is met at time slot j and $U^j(a)$ denotes the set of the UAVs which are able to cover subarea a at time slot j as below:

$$U^j(a) = \{ i \mid i \in P, a \in Cov_i(Loc(j,i)) \}, \tag{5}$$

where $Cov_i(a) = \{a' \mid a' \in A, l_{aa'} \le r_i\}$ is the set of the subareas where UAV i can provide its service confined by its coverage radius r_i. Hence, to maximize the total profit from all the subareas over the span of T, our objective function is defined as follow:

$$\max_{x_i^j, y_i^j, Loc_{ia}^j} \sum_{j \in T} \sum_{a \in A} d_a z_a^j \tag{6}$$

subject to the following constraints:

$$\sum_{a\in A} Loc_{ia}^{j} = 1, \forall i \in P, \forall j \in T \tag{7}$$

$$\sum_{p\in P} (x_i^j \times Loc_{ia}^j) \le s_a, \forall a \in M, \forall j \in T \tag{8}$$

$$(y_i^j \times b_i^j) - \epsilon \times (y_i^j - 1) > 0, \forall i \in P, \forall j \in T \tag{9}$$

$$f_j^i \times e_i^{\text{fly}} \times l_{Loc(j,i),Loc(j+1,i)} \le b_i^j, \forall i \in P, \forall j \in T \tag{10}$$

$$x_i^j + y_i^j + f_i^j \le 1, \forall i \in P, \forall j \in T \tag{11}$$

$$x_i^j + y_i^j + f_i^j \ge 1 - O(Loc(j,i)), \forall i \in P, \forall j \in T \tag{12}$$

$$x_i^j \le O(Loc(j,i)), \forall i \in p, \forall j \in T \tag{13}$$

$$l_{Loc(j,i),Loc(j+1,i)} \le l_i^{\max}, \forall i \in P, \forall j \in T \tag{14}$$

Constraint (7) implies that an UAV can only appear in one subarea in any time slot. Constraint (8) implies that the number of UAVs charging at the charging station of subarea a must not exceed s_a. Constraint (9) specifies that if an UAV's runs down its battery, it cannot serve. Constraint (10) specifies that only if UAV i's remaining power is enough can it moves from $Loc(j,i)$ to $Loc(j+1,i)$. Constraint (11) signifies that an UAV can either serve, charge, fly or stay idle. Constraint (12) forbids an UAV to rest in a subarea without a charging station. Constraint (13) signifies that an UAV cannot charge in a subarea without a charging station. Constraint (14) limits the maximum distance which an UAV can fly in a time slot.

III. Proposed Mechanism

A. Game Mechanism

To model our problem into game theory, a *non-cooperative dynamic* game Γ is defined as $\Gamma = (P, \{Z_i\}_{i=1}^{p}, \{u_i(\cdot)\}_{i=1}^{p})$ where all the UAVs in P are considered as players. Strategy set Z_i and strategy z_i are defined as follows:

$$z_i \in Z_i = A \times S \times C, \forall i \in P, \tag{15}$$

where sets S and C are both $\{0,1\}$ which signify whether an UAV is serving and is charging, respectively.

The utility function $u_i(\mathbf{z}, j) = u_i(z_i, \mathbf{z}_{-i}, j)$ is UAV i's payoff concerning an n-tuple *strategy profile* $\mathbf{z} = (z_1, z_2, ..., z_p)$ in time slot j. Note that each player is considered selfish and only maximizes her/his payoff despite other players', that is to say, each UAV will take its best-response strategy. Next, we will embark on two gain functions.

The *serving gain function* on subarea a is defined as below:

$$G_a(\mathbf{z}, j) = \begin{cases} \alpha, & \text{if } \sum_{i\in U^j(a)} y_i^j \le d_a \\ 0, & \text{otherwise.} \end{cases} \tag{16}$$

The idea behind $G_a(\mathbf{z}, j)$ is that subarea a keeps luring other UAVs into filling the vacancies with a profit $\alpha \ge 0$ until d_a is reached. Once reached, $G_a(\mathbf{z}, j) = 0$ so no further UAVs would want to join a. Instead, they turn to other subareas where the payoff > 0.

Next, the charging gain function is defined as below:

$$R_a(\mathbf{z}, j) = \begin{cases} \gamma, & \text{if } \sum_{i\in P} x_i^j Loc_{ia}^j \le s_a \\ -\theta, & \text{otherwise,} \end{cases} \tag{17}$$

where θ and γ are both constants. The purpose of $R_a(\mathbf{z}, j)$ is to strictly limit the amount of charging UAVs to s_a. Any UAV which attempts to charge in a full charging station will get a penalty $\theta \gg \gamma$. In the following, we will delve into the utility function $u_i(\mathbf{z}, j)$ case by case.

First, $z_i = (a, 1, 0)$ means i intends to serve subarea a and $u_i(\mathbf{z}, j)$ is defined as follows:

$$\begin{aligned} u_i(\mathbf{z}, j) = \sum_{\tau=0}^{\eta} \sum_{a'\in Cov_i(a)} & G_{a'}(\mathbf{z}, j + F_i(k,a) + \tau) \\ & - \nu e_i^{\text{hov}} l_{ka} - \theta H_i^j(k,a), \end{aligned} \tag{18}$$

where $k = Loc(j,i)$ and $F_i(k,a)$ denotes the time it takes for i to fly from subareas k to a. i will get $\sum_{\tau=0}^{\eta} \sum_{a'\in Cov_i(a)} G_{a'}(\mathbf{z}, j + F_i(k,a) + \tau)$ from serving a and its neighboring subareas in $Cov_i(a)$ for exactly η time slots, where η is a constant. However, the cost on flying from k to a is considered, which is $\nu e_i^{\text{hov}} l_{ka}$. Besides, function $H_i^j(k,a)$ tells whether or not the battery is ample enough as follows:

$$H_i^j(k,a) = \begin{cases} 1, & \text{if } b_i^j < \eta e_i^{\text{ser}} + e_i^{\text{hov}} l_{ka} + e_i^{\text{hov}} D(a) \\ 0, & \text{otherwise,} \end{cases} \tag{19}$$

where function $D(a)$ is the distance to the nearest charging station from a. $H_i^j(k,a) = 0$ signifies the residual energy of i in time slot j is enough to support both the coverage mission in a and the travel to the nearest charging station. On the other hand, i gets a penalty θ if its battery comes flat.

Second, when i opts for charging in subarea a, $z_i = (a, 0, 1)$ and $u_i(\mathbf{z}, j)$ is defined as follows:

$$\begin{aligned} u_i(\mathbf{z}, j) = \sum_{\tau=0}^{\mu} & R_a(\mathbf{z}, t + F_i(k,a) + \tau) + \lambda B(j,i) \\ & - \nu e_i^{\text{hov}} l_{ka} - \theta I_i^j(k,a) - \theta \Lambda^j(i). \end{aligned} \tag{20}$$

Over the span of μ time slots, i receives $\sum_{\tau=0}^{\mu} R_a(\mathbf{z}, t + F_i(k,a) + \tau)$ from charging in a. Also, function $B(j,i)$ with a weighting factor λ specifies the lower power i has, then the larger $B(j,i)$ is and the more i benefits from this term.

However, in order to make sure $O(a) = 1$ and i has enough power to fly there, a function $I_i^j(k,a)$ is defined as below:

$$I_i^j(k,a) = \begin{cases} 1, & \text{if } b_i^j < e_i^{\text{hov}} l_{ka} \text{ or } O(a) \ne 1, \\ 0, & \text{otherwise.} \end{cases} \tag{21}$$

Furthermore, to prevent a fully-charged UAV from occupying a charging slot, function $\Lambda^j(i)$ is defined as below:

$$\Lambda^j(i) = \begin{cases} 1, & \text{if } b_i^j = b_i^{\max}, \\ 0, & \text{otherwise.} \end{cases} \tag{22}$$

Third, i decides to rest in a if $z_i = (a, 0, 0)$ and $u_i^j(\mathbf{z})$ is defined as follows:

$$u_i(\mathbf{z}, j) = \beta + \lambda B(j,i) - \nu e_i^{\text{hov}} l_{ka} - \theta I_i^j(k,a). \tag{23}$$

It is worth noticing that if i can charge for μ time slots without violating Constraint (8), $\sum_{\tau=0}^{\mu} R_a(\mathbf{z}, t + F_i(k,a) + \tau) = \mu\gamma >$

$\beta > 0$. In other words, i profits more from charging than resting so it will not choose to rest unless the charging station in a is full.

Finally, i will receive a penalty θ if it chooses $z_i = (a, 1, 1)$ since i cannot charge and serve simultaneously.

B. Proof of Self-Stabilization

We will prove that our game is an *exact potential game* (EPG) [17] which guarantees at least one Nash equilibrium (NE), that is, $\forall i \in P, \forall z_i \in Z_i, u_i(z_i^*, \mathbf{z}_{-i}^*) \geq u_i(z_i, \mathbf{z}_{-i}^*)$.

In order to achieve this, our game is decomposed into three sub-games $\Gamma_s = (P, \{Z_i\}_{i=1}^p, \{us_i(\cdot)\}_{i=1}^p), \forall s = 1, 2, 3$. $u1_i(\mathbf{z}, j) = \sum_{\tau=0}^{\eta} \sum_{a' \in Cov_i(a)} G_{a'}(\mathbf{z}, j + F_i(k, a) + \tau)$ if $z_i = (a, 1, 0)$; otherwise, 0. Also, $u2_i(\mathbf{z}, j) = \sum_{\tau=0}^{\mu} R_a(\mathbf{z}, j + F_i(k, a) + \tau)$ if $z_i = (a, 1, 0)$; otherwise, 0. As for $u3_i(\mathbf{z}, j)$, it is shown as below:

$$u3_i(\mathbf{z}, j) = \begin{cases} -\nu e_i^{\text{hov}} l_{ka} - \theta H_i^j(k, a), & \text{if } z_i = (a, 1, 0), \\ -\nu e_i^{\text{hov}} l_{ka} + \lambda B(j, i) - \\ \theta I_i^j(k, a) - \theta \Lambda^j(i), & \text{if } z_i = (a, 0, 1), \\ -\nu e_i^{\text{hov}} l_{ka} + \lambda B(j, i) - \\ \theta I_i^j(k, a), & \text{if } z_i = (a, 0, 0), \\ -\theta, & \text{if } z_i = (a, 1, 1), \end{cases} \tag{24}$$

Hopefully, we want to prove Γ_1 and Γ_2 are two congestion games and Γ_3 is a self-motivated game, which they are classes of EPGs; hence, Γ is also an EPG.

Theorem 1: Suppose that $\mathcal{G}_1 = (N, \{X_n\}_{n \in N}, \{u_a\}_{n \in N})$ and $\mathcal{G}_2 = (N, \{X_n\}_{n \in N}, \{u_a\}_{n \in N})$ are two EPGs and the exact potential functions are $\pi_1(\cdot)$ and $\pi_2(\cdot)$, respectively. Let $\alpha, \beta \in \mathbb{R}$, the game $\mathcal{G} = (N, \{X_n\}_{n \in N}, \alpha\{u_a\}_{n \in N} + \beta\{u_b\}_{n \in N})$ is also an EPG with exact potential function $\alpha\pi_1(\cdot) + \beta\pi_2(\cdot)$. [18]

First of all, we seek to equate Γ_1 to a congestion game defined as $(P, A, \{Z_i\}_{i=1}^p, \{W1_i(\cdot)\}_{i=1}^p)$. On the basis of Equation (16), $G_a(\cdot)$ can be rewritten as follows:

$$G_a(\mathbf{z}, j) = W1_a(ns_a(\mathbf{z}, j)) = \begin{cases} \alpha, & \text{if } ns_a(\mathbf{z}, j) \leq d_a, \\ 0, & \text{otherwise,} \end{cases} \tag{25}$$

where $W1_a(\cdot)$ is subarea a's payoff function and $ns_a(\mathbf{z}, j)$ is the number of UAVs that cover a, i.e., $\sum_{i \in U^j(a)} y_i^j$.

Thus, the payment made by a at time slot j can be interpreted as $\sum_{l=1}^{ns_a(\mathbf{z},j)} W1_a(l)$. Summing up the payment of every subarea $a \in A$ leads to $\pi_{ser}(\mathbf{z}, j)$ as below:

$$\pi_{ser}(\mathbf{z}, j) = \sum_{a \in A} \left(\sum_{l=1}^{ns_a(\mathbf{z},j)} W1_a(l) \right). \tag{26}$$

Evidently, $\sum_{l=1}^{ns_a(\mathbf{z},j)} W1_a(l)$ and $\pi_{ser}(\mathbf{z}, j)$ fit the utility function and the exact potential function of a congestion game, respectively.

Now by Theorem 1, since $u1_i(\mathbf{z}, j)$ is obviously a linear combination of $\sum_{a' \in Cov_i(a)} G_{a'}(\cdot)$, Γ_1 is proved to be a congestion game and hence, an EPG. However, unlike traditional congestion games, UAVs in Γ_1 ask for future resources, i.e., $F_i(k, a)$ time slots before i actually arrives a from k, i has claimed to serve a for η time slots. We let $\epsilon = \max_{i \in P; k, a \in A} F_i(k, a)$ and consequently, exact potential function $\pi_1(\mathbf{z}, j)$ of Γ_1 is a linear combination of $\pi_{ser}(\mathbf{z}, j + \varepsilon + \tau)$ as follows:

$$\begin{aligned} \pi_1(\mathbf{z}, j) &= \sum_{\tau=0}^{\eta} \pi_{ser}(\mathbf{z}, j + \varepsilon + \tau) \\ &= \sum_{\tau=0}^{\eta} \sum_{a \in A} \left(\sum_{l=1}^{ns_a(\mathbf{z}, j+\varepsilon+\tau)} W1_a(l) \right). \end{aligned} \tag{27}$$

Similarly, Γ_2 is proved the same way as Γ_1 to be an EPG with exact potential function $\pi_2(\mathbf{z}, j)$ defined as follows:

$$\pi_2(\mathbf{z}, j) = \sum_{\tau=0}^{\eta} \sum_{a \in A} \left(\sum_{l=1}^{nc_a(\mathbf{z}, j+\varepsilon+\tau)} W2_a(l) \right). \tag{28}$$

According to Equation (17), $R_a(\cdot)$ can be rewritten as follows:

$$R_a(\mathbf{z}, j) = W2_a(nc_a(\mathbf{z}, j)) = \begin{cases} \gamma, & \text{if } nc_a(\mathbf{z}, j) \leq s_a, \\ -\theta, & \text{otherwise,} \end{cases} \tag{29}$$

where $W2_a(\cdot)$ is subarea a's payoff function and $nc_a(\mathbf{z}, j)$ is the number of UAVs which charge in a, that is, $\sum_{i \in U^j(a)} Loc_{ia}^j x_i^j$.

Finally, Equation (24) tells us that utility function $u3_i(\mathbf{z}, j)$ in Γ_3 solely relevant to its own battery so it is not affected by other UAVs' strategies, in consequence, it is a self-motivated game.

All in all, by Theorem 1, Γ_1, Γ_2 and Γ_3 are all EPGs with their own exact potential functions, our proposed game $\Gamma = (P, \{Z_i\}_{i=1}^p, \{u1_i\}_{i=1}^p(\cdot) + \{u2_i\}_{i=1}^p(\cdot) + \{u3_i\}_{i=1}^p(\cdot))$ is also an EFG, i.e., there exists at least one NE in our game.

C. The Proposed Approach

In our decentralized approach, each UAV i is an independent decision maker and keeps a local strategy profile at time slot j defined as $\mathbf{z}_{i,j}^{local}$. All the local strategy profile $\mathbf{z}_{i,0}^{local}, \forall i \in P$ are initialized as $\mathbf{z}$ and the game starts from time slot $j = 1$.

Roughly speaking, in order for the game to converge, all the UAVs must act sequentially. Thus, we equip each UAV i a countdown timer T_i to avoid concurrent decisions and an indicator D_i to indicate whether or not i has multicasted its strategy $z_i^{(j)}$ at time slot j. When a new time slot j begins, we set T_i a random value, update $\mathbf{z}_{i,j}^{local}$ with $\mathbf{z}_{i,j-1}^{local}$ and set D_i false. If i receives a strategy from another UAV x, i may change its strategy. Hence, besides updating its local strategy profile $\mathbf{z}_{i,j}^{local}[x] = z_x^{(j)}$, i reset T_i a random value and D_i false.

Once T_i expires, i first checks D_i. If D_i is false, it means that at least one UAV has changed and multicasted its strategy before T_i expires, i.e., the game has not yet reached a NE. Under the circumstances, i calculates its best response based on $\mathbf{z}_{-i,j}^{local}$ and replaces its current strategy $z_i^{(j)}$ with this best response. Afterwards, i multicasts $z_i^{(j)}$ and resets T_i a random value and D_i true. On the other hand, if D_i is true, it means that no other UAV has changed its strategy. The current strategy is assumed to be the best so i carries out $z_i^{(j)}$.

IV. Simulation Results

Table I shows the major simulation parameters with default setting. We first analyze the various factors in the objective function and Table II shows the most representative values in our simulation.

TABLE I: Parameter Setting

Parameter	Default Value
The length of a time slot ρ	5 s
The number of subareas	61
The hexagon side length	25 m
The whole area size	99000 m^2
The coverage demand of a subarea $d_a, \forall a \in A$	1
The number of charging stations	1
The number of charging slots $s_a, \forall a \in M$	9
The number of UAVs	40
The coverage radius of a UAV r_i	50 m
The flying speed of a UAV v_i	10 m/s
The maximum energy budget $b_i^{\max}$	200 kJ
The average energy consumption for serving e_i^{ser}	1 kJ/time slot
The average energy consumption for hovering e_i^{hov}	0.025 kJ/m
The average charging rate for UAV k_i	0.25 kJ/time slot

TABLE II: Simulation parameters in utility function

Name	Setting 1
α	10
γ	100
β	5
μ	5
η	5
ν	0.5
λ	30
θ	100000

A. Environment Factors Analysis

In order to assess the performance, we compare our approach with a greedy algorithm, where a UAV serves, switches between serving and charging or charges if its residual energy is higher than 80%, between 20% to 80% or lower than 20%. Also, we consider two variants of the greedy algorithm, which are *greedy tight* and *greedy loose*, respectively. In greedy tight, a UAV either serves more than 6 subareas or none; in greedy loose, a UAV either serves more than 2 subareas or none. To further analyze, we consider two settings in Table III. We measured coverage ratio, the ratio of the resulting accumulated coverage intensity to the largest possible result.

1) Number of Charging Slots: In Fig. 1, Setting 1 apparently outperforms Setting 2 when the number of charging slots is small. In Setting 1, α is small. Because an UAV does not benefits much from serving, it would not wait to charge until

TABLE III: Simulation parameters in utility function

Name	Setting 1	Setting 2
α	6.25	18.75
γ	25	25
β	5	200
μ	20	20
η	8	8
ν	100	60
λ	350	200
θ	100000	100000

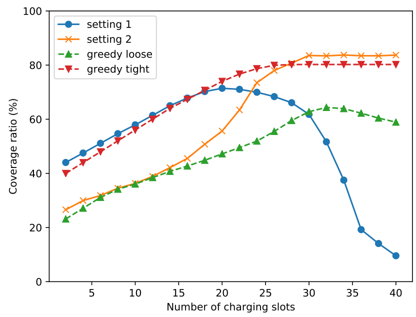
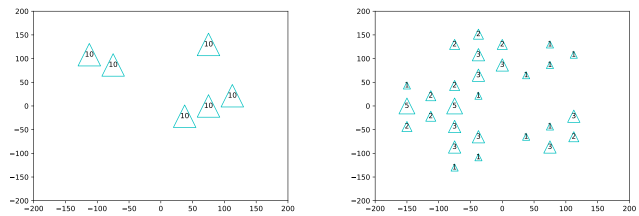


Fig. 1: Coverage ratio with versus the number of charging slots

its battery is almost flat. On the contrary, α is larger in Setting 2 so an UAV would serve as long as it possibly could. When there are few charging stations, Setting 2 may lead to intense competition over charging stations and thus, the performance is worse. On the other hand, when there are ample charging slots, UAVs in Setting 1 instead charge too frequently and hence worse performance. Most importantly, when the number of charging slots is small, Setting 1 is the best and when it increases, Setting 2 becomes the best. Thus, in response to any number of charging slots, our proposed approach can outperform greedy by adjusting α.

2) Coverage Demand in Cluster Distribution: We use 2D Gaussian distribution to generate coverage demands so that coverage demands are clustered in some hot-spot regions as shown in Fig. 2. We randomly choose tne center locations for six clusters and gradually increase the standard deviations along both the x-axis and the y-axis.

Fig. 3 shows that Setting 2 outperforms the greedy algorithm. Under lower standard deviation, there are less than 7 clusters; therefore, UAVs in greedy tight does not serve since



(a) standard deviation 0

(b) standard deviation 30

Fig. 2: Cluster distribution with total 60 coverage demands distributed in 6 clusters

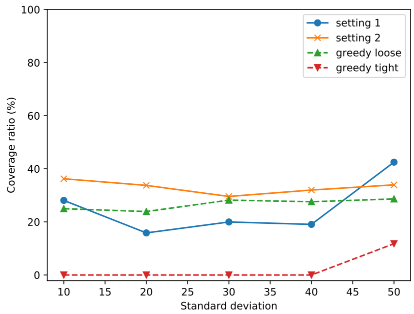


Fig. 3: Coverage ratio with increasing standard deviations in cluster distribution

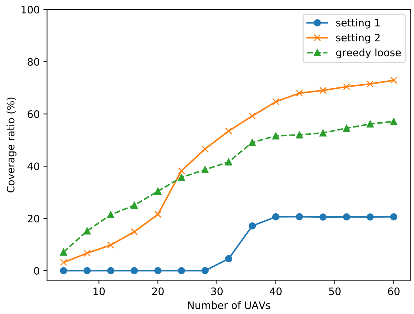


Fig. 4: Coverage ratio with increasing number of UAVs in cluster distribution with 30 standard deviation

they serve either more than 7 subareas at once or none.

Next, we fix the standard deviation at 30. Both Fig. 4 and Fig. 5 are similar to the results under uniform distribution. In consequence, even if we change the distribution, the impacts of the number of charging slots and the number of UAVs are almost the same as in the uniform distribution.

V. Conclusions

In this paper, so as to maximize UAV swarm's service coverage, we model the problem of distributed coverage and charging scheduling as a game. We not only put forward a decentralized solution to solve the problem but also prove that the proposed game is an EPG such that our game always converges to a NE.

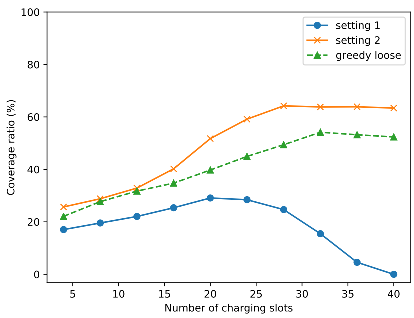


Fig. 5: Coverage ratio with increasing number of charging slots in cluster distribution with 30 standard deviation

In the future, we shall devote to a mechanism where our game can adapt to environment changes by dynamically adjusting the parameters in the utility function. Moreover, we will consider a non-linear energy consumption model which fits real-life situations more.

References

[1] I. Dalmasso, I. Galletti, R. Giuliano, and F. Mazzenga, "WiMAX networks for emergency management based on UAVs," in *2012 IEEE First AESS European Conference on Satellite Telecommunications (ESTEL)*, 2012, pp. 1–6.

[2] M. Mozaffari, W. Saad, M. Bennis, Y. Nam, and M. Debbah, "A tutorial on UAVs for wireless networks: Applications, challenges, and open problems," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2334–2360, 2019.

[3] T. Li, K. Ota, T. Wang, X. Li, Z. Cai, and A. Liu, "Optimizing the coverage via the UAVs with lower costs for information-centric Internet of Things," *IEEE Access*, vol. 7, pp. 15 292–15 309, 2019.

[4] C. D. Franco and G. Buttazzo, "Energy-aware coverage path planning of UAVs," in *2015 IEEE Int'l Conf. on Autonomous Robot Systems and Competitions*, 2015, pp. 111–117.

[5] X. Li, W. Feng, Y. Chen, C. Wang, and N. Ge, "UAV-enabled accompanying coverage for hybrid satellite-UAV-terrestrial maritime communications," in *Proc. 28th Wireless and Optical Communications Conf. (WOCC)*, 2019, pp. 1–5.

[6] L. Zhu, J. Zhang, Z. Xiao, X. Cao, D. O. Wu, and X. Xia, "3-D beamforming for flexible coverage in millimeter-wave UAV communications," *IEEE Wireless Communications Letters*, vol. 8, no. 3, pp. 837–840, 2019.

[7] B. Galkin, J. Kibilda, and L. A. DaSilva, "UAVs as mobile infrastructure: Addressing battery lifetime," *IEEE Communications Magazine*, vol. 57, no. 6, pp. 132–137, 2019.

[8] X. Li, H. Yao, J. Wang, S. Wu, C. Jiang, and Y. Qian, "Rechargeable multi-UAV aided seamless coverage for QoS-guaranteed IoT networks," *IEEE Internet of Things Journal*, vol. 6, no. 6, pp. 10 902–10 914, Dec. 2019.

[9] X. Li, H. Yao, J. Wang, X. Xu, C. Jiang, and L. Hanzo, "A near-optimal UAV-aided radio coverage strategy for dense urban areas," *IEEE Trans. on Vehicular Technology*, vol. 68, no. 9, pp. 9098–9109, Sep. 2019.

[10] L. Amorosi, L. Chiaraviglio, and J. Galán-Jiménez, "Optimal energy management of UAV-based cellular networks powered by solar panels and batteries: Formulation and solutions," *IEEE Access*, vol. 7, pp. 53 698–53 717, 2019.

[11] A. Trotta, M. Di Felice, F. Montori, K. R. Chowdhury, and L. Bononi, "Joint coverage, connectivity, and charging strategies for distributed UAV networks," *IEEE Trans. on Robotics*, vol. 34, no. 4, pp. 883–900, Aug. 2018.

[12] H. Shakhatreh, A. Khreishah, J. Chakareski, H. B. Salameh, and I. Khalil, "On the continuous coverage problem for a swarm of UAVs," in *IEEE 37th Sarnoff Symposium*, 2016, pp. 130–135.

[13] A. Boggio-Dandry and T. Soyata, "Perpetual flight for UAV drone swarms using continuous energy replenishment," in *Proc. 9th IEEE Annual Ubiquitous Computing, Electronics Mobile Communication Conf.*, 2018, pp. 478–484.

[14] T. Fang, H. Tian, X. Zhang, X. Chen, X. Shao, and Y. Zhang, "Context-aware caching distribution and UAV deployment: A game-theoretic approach," *Applied Sciences*, vol. 8, no. 10, Oct. 2018.

[15] L. Ruan, J. Wang, J. Chen, Y. Xu, Y. Yang, H. Jiang, Y. Zhang, and Y. Xu, "Energy-efficient multi-UAV coverage deployment in UAV networks: A game-theoretic framework," *China Communications*, vol. 15, no. 10, pp. 194–209, 2018.

[16] L. Ruan, J. Chen, Q. Guo, H. Jiang, Y. Zhang, and D. Liu, "A coalition formation game approach for efficient cooperative multi-UAV deployment," *Applied Sciences*, vol. 8, Nov. 2018.

[17] D. Monderer and L. Shapley, "Potential games," *Games and Economic Behavior*, vol. 14, no. 1, pp. 124–143, 1996.

[18] G. Facchini, F. van Megen, P. Borm, and S. Tijs, "Congestion models and weighted Bayesian potential games," *Theory and Decision*, vol. 42, no. 2, pp. 193–206, Mar. 1997.