An Optimal Data Collection Technique for Improved Utility in UAS-aided Networks

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Abstract— **Recent technological advances in electronics, sensors, and communications devices have facilitated the proliferation of Unmanned Aircraft System (UAS)-aided applications. However, the UAS-aided communications networks are yet to receive sufficient research endeavor. In this paper, we address one of the most important research challenges pertaining to UAS-aided networks comprising adaptive modulation-capable nodes, namely how to fairly maximize the energy efficiency (throughput per energy). For the mobility pattern innate to the UAS, we demonstrate how the adaptive modulation behaves. Furthermore, we formulate the problem as a potential game that is played between the UAS and the network-nodes, and prove its stability, optimality, and convergence. Based upon the potential game, a data collection method is envisioned to maximize the energy efficiency with the fairness constraint. Additionally, we analyze the Price of Anarchy (PoA) of our proposed game. Extensive simulations exhibit the effectiveness of our proposal under varying environments.**

I. Introduction

Advances in propulsion systems, energy storage, miniaturized payloads, carbon fiber reinforced plastic materials, and autonomous control have facilitated the development of Unmanned Aircraft Systems (UASs). UASs are miniature unmanned airborne vehicles equipped with wireless transceivers, Global Positioning System (GPS), and superior computational capabilities. UASs can be fixed-winged or rotor-propelled. The UASs with fixed-wings have higher speeds compared with the rotor-propelled ones. We focus on the fixed-winged UASs because their superior speed renders the ability to complete missions in shorter periods of time. Hereafter, we refer to a fixed-winged UAS as a UAS for brevity. UASs have a great potential to forge numerous applications in many domains [1]–[6]. The applications include polar weather monitoring [7], providing communications in disaster struck areas [5], and wildfire management [8]. We aim to use the UAS' abilities to construct an autonomous UAS-aided network, where the UAS flies over the sensor field to collect ambient data from sensor nodes. Those sensor nodes are deployed in various kinds of terrains including dangerous areas that are difficult to reach with conventional vehicles such as helicopters.

We consider a network where the UAS collects data from sensor nodes as it flies over its annular trajectory. Since it is expensive to equip all sensor nodes with functionality to communicate directly with the UAS, special sensor nodes, Cluster Heads (CHs), are deployed in the area. The remaining sensor nodes require only capabilities to communicate with the CHs. The mobility pattern of the UAS causes the distance between a CH and the UAS to vary. The distance between the CH and the UAS affects the Signal-to-Noise Ratio (SNR), which in turn affects the Bit Error Rate (BER) of the CH transmissions. Both SNR and BER affect the modulation scheme. This is because modulation schemes that transmit more bits per symbol require higher values of SNR for a given BER requirement [9]. Moreover, if high levels of BER are acceptable, the achievable number of bits per symbol that a modulation scheme transmits can be increased.

Sensor nodes and CHs powered only by batteries are usually deployed to function unattended for prolonged periods of time [10]. This renders energy efficiency to be very important to ensure the longevity of CHs without the need for battery replacement, especially when they are deployed in hazardous terrains. In such a scenario it is important to make efficient use of the limited battery capacities. Hence, for an amount of consumed energy, the amount of transmitted data should be increased to the utmost. We refer to this metric as energy efficiency. Adaptive modulation is a technology that can transmit more data for the same transmission power given that the channel conditions are favorable, i.e., SNR level is high.

For the considered scenario, the number of bits that can be transmitted per symbol, and consequentially the energy efficiency, defer according to which time slot is used by the CH. As increasing the energy efficiency is of interest, the network designer is inclined to allow CHs with higher SNR to have priority to transmit. This inevitably results in the unfair distribution of time slots between CHs, where the CHs that are far away from the UAS' position transmit less compared to CHs that are close to the UAS' position. Thus, we aim to devise a method to improve the network's energy efficiency while considering fairness between CHs that are close to the UAS' position and the CHs that are faraway from the UAS' position.

Contemporary data collection methods (similar to those employing mobile sinks) fail to consider the challenges associated with the aforementioned energy efficiency issues in UAS-aided networks [11]–[13]. In this paper, we propose a game-theoretic data collection method that improves network energy efficiency while satisfying fairness among CHs. The contributions of this paper can be summarized as follows:

- We show how the modulation scheme is affected by the UAS' trajectory.
- We formulate the problem of maximizing the energy efficiency while satisfying fairness among CHs as a game, where each CH i is interested in increasing its individual utility, U_i, by acting as per its Best Response (BR) correspondence, $BR(a_{-i})$.
- For the formulated game, we prove the properties of stability, optimality, and convergence. These properties give performance guarantees of the formulated game.
- By using the formulated game, we propose a game-theoretic data collection method that improves the energy efficiency while considering fairness in UAS-aided networks.
- We analyze the Price of Anarchy (PoA) of our proposed data collection method.

The remainder of the paper is organized as follows. Section II commences with a literature review. Section III gives details on the system assumptions and definitions. In Section IV, we propose our data collection method for UAS-aided networks. In Section V, we analyze the PoA of our proposed game. Section VI presents the performance evaluation of our proposed data collection technique. We finalize this paper in Section VII with a conclusion.

II. Related works

In this section, we elucidate the works relevant to the UAS-aided networks research direction, which include the investigations of UAS-aided networks, mobile sink-based Wireless Sensor Networks (WSNs), network partitioning known as clustering, channel adaptive modulation techniques, and communication network optimization based on Game Theory.

UASs have been incorporated into many applications across many domains that include those of civilian and military [1]–[6]. The applications include polar weather monitoring [7] and wildfire management [8]. Daniel *et al.* [2] considered using multiple UASs equipped with sensing capabilities to sense data from hostile environments. Using the UAS' abilities for communications applications has recently attracted much attention. Bekmezci *et al.* [1] surveyed communication problems of ad hoc networks composed of multiple UASs referred to as Flying Ad-Hoc Networks (FANETs). Freitas *et al.* [3] considered using UASs as relays to link disconnected ad hoc networks. Varakliotis *et al.* [5] proposed providing communications in disaster areas with UASs equipped with cognitive radio technology. Goddemeier *et al.* [6] investigated communication-aware steering algorithms for exploration applications in UAS swarms. The considered communication-aware steering algorithms maximize exploration coverage with the simultaneous ability to self-optimize the communication links among UASs and the ground base station by exploiting controlled mobility.

Unlike the existing works on UAS-aided networks, we aim to use the UAS' abilities to construct an autonomous UAS-aided network, where the UAS flies over the sensor field to collect ambient data from ground nodes, which are in various kinds of terrains including dangerous areas that are difficult to reach with conventional vehicles like helicopters. Among all the existing works on UAS-aided networks, to the best of our knowledge, there have not been any research that exploits the UAS' unique abilities to collect data from nodes on the ground. Indeed, we aim to explore how to collect data from ground nodes while considering the unique characteristics of the UAS, of which we consider the UAS' inability to be stationary in the air. Additionally, the UAS quintessentially wheels in a trajectory. This constantly changes the communication distance and the SNR between UAS and the ground nodes. Since the SNR of transmissions is of varying levels, adaptive modulation [9], [14] can be incorporated to capitalize on favorable SNR levels to increase energy efficiency and throughput.

The closest proposals to the research direction of this paper are data collection techniques for mobile sink nodes in WSNs [11]–[13]. However, they do not consider the circular trajectory akin to the UAS' movement pattern and the inability of UAS to remain stationary in air. Furthermore, they do not exploit favorable channel conditions by incorporating adaptive modulation. Most notable of which is the work of Shah *et al.* [11], where the authors proposed a scheme in which mobile sinks visit sensor nodes to collect data.

Equipping all nodes with the ability to communicate with the UAS is cost prohibitive in terms of hardware and energy consumption. Network partitioning is a suitable solution. Many studies have been carried out that partition the network layer into smaller components, known as clusters, most notably is Low-Energy Adaptive Clustering Hierarchy (LEACH) and its many variants [10]. Clusters decrease the deployment cost of sensor nodes, since only a special subset of nodes, referred to as CHs, need to be able to communicate with the UAS while the remaining nodes only need to have simple communication functionalities to communicate with the CHs.

Researches conducted in [9], [14] have explored adaptive M-ary Quadrature Amplitude Modulation (M-QAM). Adaptive transmission techniques can exploit the number of degrees available for communications to improve throughput by adapting the modulation scheme according to channel conditions, i.e., SNR levels. Without this technology the transceivers on the CHs can only transmit at a constant number of bits per symbol regardless of the SNR level.

Our method aims to maximize the energy efficiency of the UAS-aided network, where CHs with different SNR levels at different geographical locations exist. Hence, we need to employ a method that optimizes the allocation of time slots to CHs such that the network's energy efficiency is at its maximum while maintaining a particular degree of fairness. Game Theory is a suitable solution for such a problem. Game Theory has been applied to a wide range of research areas, most notably of which are economic problems [15], [16]. Using the game theoretical framework to solve complex issues has greatly attracted the attention of many researchers in the last decade and its applicability has been abound ever since. In particular, Game Theory has been applied to many research issues in the context of network communications, which

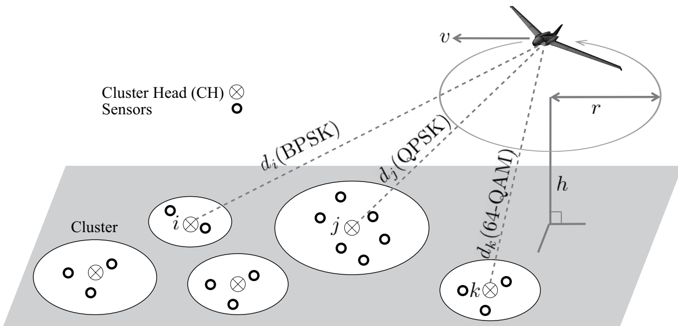


Fig. 1. Considered UAS-aided network topology.

include channel assignment in wireless mesh networks [17] and quality of service in wireless networks [18]. Readers unfamiliar with Game Theory concepts and its applications in wireless communications are encouraged to refer to the works in [15], [19] that contain fundamental results in this research area. In this work, we employ the framework of potential games, which have been used in the context of objective maximization problems such as the problem investigated in this paper.

III. System Assumptions and Definitions

Fig. 1 shows the considered UAS-aided network. Each CH is provisioned with superior hardware that allows it to communicate with the UAS. On the other hand, a normal sensor node is not able to communicate with the UAS, and has to send the data that it collects to the closest CH to it. This architecture lowers the deployment cost of the UAS-aided network because only the CHs need to be able to communicate with the UAS.

Sensor field: Similar to many data collection applications of sensor nodes [20], we assume that sensor nodes sense their surrounding environment and report the data that they have sensed to the CH by using a low energy communications standard such as ZigBee or Bluetooth Low Energy [21]. The CH communicates with the UAS by using the specific time slots assigned to it.

Mobility model: The UAS is designed to collect data from the sensor field. It glides around the sensor field in a circular trajectory. The UAS has varying degrees of mobility, which allow the UAS to achieve its objective of data collection. The UAS' degrees of mobility (characterized by altitude (h), speed (v), and radius (r)) are flexible [1], [22]. The degree of mobility changes according to mission objectives that are influenced by time limitation of mission completion, the terrain that the sensors are deployed in, and so on.

Adaptive modulation: The CHs in the UAS-aided network are equipped with transceivers that are capable of adaptive modulation. We consider that the adaptive modulation scheme can change its modulation level to one of five modes, which include no transmit, Phase-Shift Keying (PSK), Quadrature Phase-Shift Keying (QPSK), 16-Quadrature Amplitude Modulation (QAM), and 64-QAM. For these K-modes ($n = 0, 1, ..., K-1$), the modulation schemes are able to transmit a different number of bits per symbol, b_n, and have M_n possible constellations.

TABLE I
SNR switching levels for five-mode adaptive M-QAM.

SNR	n	M_n	b_n	mode
$\gamma_0 \leq \gamma < \gamma_1$	0	0	0	No Tx
$\gamma_1 \leq \gamma < \gamma_2$	1	2	1	BPSK
$\gamma_2 \leq \gamma < \gamma_3$	2	4	2	QPSK
$\gamma_3 \leq \gamma < \gamma_4$	3	16	4	16-QAM
$\gamma_4 \leq \gamma < \gamma_5$	4	64	6	64-QAM

A. System Model

The network is composed of a set of sensor nodes, CHs, and a UAS. According to [23], the path-loss factor, which reflects the extent of attenuation that the signal transmitted from CH i to the UAS suffers from can be given by

$$G_i = \xi d_i^{-\varphi}, \tag{1}$$

where d_i is the Euclidean distance between CH$_i$ and the UAS, φ denotes the path-loss exponent (it takes values between 2 and 4), and ξ is a constant dependent on factors that include receiver gain, transmitter gain, and wavelength. The received signal suffers from Additive White Gaussian Noise (AWGN) with a normalized one-sided power spectral density, N_0. We assume that the transmission device on each CH transmits with the same symbol-wise average transmit power P. Moreover, CHs can not control the transmission power, which is constant. Also, the network has finite bandwidth B, measured in Hertz. Hence, the network SNR can be defined as [23], [24]:

$$\rho = \frac{P}{N_0 B}. \tag{2}$$

The SNR for a transmission conducted by CH$_i$, ρ_{CH_i}, can be given as:

$$\rho_{CH_i} = \rho G_i. \tag{3}$$

B. Modulation Switching Levels Model

We adopt the fixed switching scheme [9], [14] that determines the switching criterion based on fixed SNR values. In the fixed switching scheme, the assignment of the SNR boundaries is done so that the SNR level at the boundary satisfies the BER requirement with the modulation scheme used in an AWGN channel. According to [9], [14] the criteria used to find the SNR switching levels are shown in Table I. The switching levels, γ_n, can be derived from the equations developed by Alouini and Goldsmith [14]:

$$\begin{aligned} \gamma_0 &= 0 \\ \gamma_1 &= [erfc^{-1}(2BER_0)]^2 \\ \gamma_n &= \frac{2}{3}K_0(M_n - 1); n = 2, 3, ..., K-1 \\ \gamma_K &= +\infty, \end{aligned} \tag{4}$$

where BER_0 is the target BER level, $erfc^{-1}$ is the inverse complementary error function, and $K_0 = -\ln(5BER_0)$. K in our system corresponds to the value of five.

IV. Data Collection Challenges and Proposed Solution

The CHs and the sensor nodes power their operation by limited battery reserves. Energy efficiency (throughput per energy) allows for more transmissions with the limited battery capacities. Energy efficiency is affected by the UAS' mobility. The reason is, as the UAS traverses the sensor field according to its circular trajectory, the displacements between the CHs and the UAS change, effectively the SNR of the transmissions between the CHs and the UAS also change. When the SNR of the transmitted signal is high, the CHs' transmitters can adapt the modulation scheme to allow for more bits to be transmitted per symbol. Inversely, if the SNR of the transmitted signal is low, the CHs adapt the modulation scheme to lower the number of bits transmitted per symbol. Such calibration of the number of bits per symbol (b_n) regulates the BER level so that it is within the predetermined acceptable level, i.e., BER_0. The UAS' time slots assignment (S) should be assigned in a way that allows for better energy efficiency of the UAS-aided network. Assigning time slots to maximize energy efficiency results in unfairness of the distribution of time slots among CHs, as CHs that are close to the UAS' position would have a higher probability of getting the time slots. The fairness criterion (β) should reflect on the fairness of both energy efficiency and throughput among the CHs. Fairness between CHs can be expressed by using the fairness index defined as:

$$Fairness = \frac{(\sum_{i\in(1,2,....,N)} m_i)^2}{N\sum_{i\in(1,2,....,N)} m_i^2}, \tag{5}$$

where N is the number of CHs in the UAS-aided network and m denotes a metric that indicates throughput or energy efficiency. The problem of allocating the UAS' time slots among CHs to maximize the networks energy efficiency such that the fairness criterion is satisfied cannot be solved in real time. The reason is the number of computations behind solving this problem. Consider a hypothetical UAS-aided network that consists of 20 CHs, where 1000 time slots need to be assigned. Working out a slot assignment for the aforementioned problem involves computations of mammoth proportions (20^{1000}). Game Theory can be used to solve this optimization problem without the associated computational burden [25]. Thus, we formulate this problem as a game in Section IV-A. Furthermore, we give proof for the performance of our formulated game in Section IV-B. The results found in Section IV-B are used to propose an game-theoretic method in Section IV-C. The proposed game-theoretic method for assigning time slots to CHs such that network energy efficiency is improved given that the fairness criterion is satisfied.

A. Game-based Interactions

We model the CHs as players in oder to find an optimal time slot assignment using the framework provided by Game Theory. Each CH is considered to be an intelligent decision maker of the game $G(\mathbf{N}, \mathbf{A}_i, U_i)$. Here, $\mathbf{N}$, $\mathbf{A}_i$, U_i refers to the players, their actions, and their utility functions. The players in this game are N CHs defined as follows:

$$\mathbf{N} = \{CH_i; \forall i \in (1, 2, ..., N)\}, \tag{6}$$

where CH_i denotes the CH with index i. The utility function of CH i, U_i, can be expressed as:

$$U_i = \frac{\delta_i}{\eta_i}; \forall i \in (1, 2, ..., N), \tag{7}$$

where δ_i is the amount of transmissions that CH i has completed and η_i is the amount of energy CH i consumed. U_i reflects the energy efficiency of CH i, and is a positive real number. The network utility is formulated as follows:

$$U_{Network} = \sum_{i\in(1,2,....,N)} U_i. \tag{8}$$

Each CH in $G(\mathbf{N}, \mathbf{A}_i, U_i)$ defines a threshold, α_i, which is the farthest distance that the CH is willing to transmit. Consequentially, α_i indicates the lowest SNR that the CH i is willing to transmit at. Hence, the actions of CH i, $\mathbf{A}_i$, are defined as:

$$\mathbf{A}_i = \{\alpha_i; \forall i \in (1, 2, ..., N)\}. \tag{9}$$

The game profile, Ψ, is defined as the Cartesian product of the players' actions

$$\begin{aligned}\Psi &= \times_{\forall i\in(1,2,....,N)} \mathbf{A}_i \\ &= \mathbf{A}_1 \times \mathbf{A}_2 \times \mathbf{A}_3 \times ... \times \mathbf{A}_N.\end{aligned} \tag{10}$$

Define a_{-i} as the action set chosen by all other players except for player i. Thus, a_{-i} can be defined as:

$$a_{-i} = \{a_1, ..., a_{i-1}, a_{i+1}, ..., a_{N+1}\}. \tag{11}$$

Players will negotiate their interdependent actions to arrive to an optimal value of $U_{Network}$. The issues of convergence and efficiency arise. Convergence is whether the proposed game coverages to a steady state, a consensus between players. Moreover, what is the efficiency of the stable solution. These issues will be addressed in Sections IV-B. Thereafter, the results of Section IV-B will be used to propose a game-theoretic method in Section IV-C.

B. Stability, Optimality, and Convergence in the potential game G($\boldsymbol{N}, \boldsymbol{A}_i, U_i$)

Nash Equilibrium (NE) [15], [16] is an important concept in Game Theory that is used to define stability. NE is a stable state that occurs if players in a game act according to their Best Response (BR) correspondences. The BR correspondence of player i can be defined as:

Definition 1: action $a_i^* \in BR(a_{-i})$ *if*

$$U_i(a_i^*, a_{-i}) \geq U_i(a_i, a_{-i}); \forall a_i \in A_i. \tag{12}$$

According to the above definition, the BR correspondence of player i is its best action given other players actions. Now, define the action profile $\hat{a}$ as:

$$\hat{a} = (a_1, ..., a_{N+1}). \tag{13}$$

Here, $\hat{a}$ is a NE action profile if it satisfies the following definition:

Definition 2: $\hat{a}$ is a NE action profile if

$$a_i \in BR(a_{-i}); \forall i \in \{1, 2, ..., N\}. \tag{14}$$

The above definition implies that no player has an incentive to deviate from its action if other players do not change their actions. That is to say that the game has reached a stable state. It is worth noting that no implicit guarantee of optimal outcome is available. However, potential games, a specific kind of game, have useful properties that address achieving a NE and outcome efficiency issue. A potential game has the following properties:

- For a finite potential game, at least one pure strategy NE exists [26].
- All NEs of the potential game are either local or global maximizers of the utility function [26].
- Myopic one-sided learning based on best response or better response learning methods can be applied to the game so as to guide the game to reach the utility function maximizers [19], [26].

Lemma 1: $G(\mathbf{N}, \mathbf{A}_i, U_i)$ is a potential game.

Proof: According to [19], [26], a game is a potential game if there exists a potential function *Pot*, defined as follows:

$$Pot(a_i', a_{-i}') - Pot(a_i'', a_{-i}'') = U_i(a_i', a_{-i}') - U_i(a_i'', a_{-i}''), \tag{15}$$

where i, a', and a'' are any player and any two strategies in the game, respectively. From Eqs. (8) and (15), we can see that $G(\mathbf{N}, \mathbf{A}_i, U_i)$ satisfies the definition of a potential game, where

$$Pot = U_{Network}(\Psi); \forall i \in (1, 2, ..., N). \tag{16}$$

■

From lemma 1, we can see that $G(\mathbf{N}, \mathbf{A}_i, U_i)$ is a potential game. Based on potential games and NEs, we can guarantee that our proposed $G(\mathbf{N}, \mathbf{A}_i, U_i)$ will converge to a conscious between players, i.e., a stable state, which is a utility function maximizer. Better response and best response are two famous learning techniques that guarantee convergence to a utility maximizing NE of potential games [19], [26]. Let t be the step number. Players acting on better response learning choose their actions as follows:

$$a_i^{t+1} = \begin{cases} a_i^{rand} & \text{if } (U_i(a_i^{rand}, a_{-i}^{rand}) > U_i(a_i^t, a_{-i}^t)) \\ a_i^t & \text{otherwise.} \end{cases} \tag{17}$$

Here, each player selects a random strategy in its turn. The player keeps the random strategy whenever it results in a better utility than that of the previous strategy it had in its former turn. On the other hand, if the utility resulting from the random action results in worse utility than that of the previous action. Players acting on best response learning choose their actions as follows:

$$a_i^{t+1} = \arg_{\forall a \in \mathbf{A}_i} \max U_i(a). \tag{18}$$

Here, the player chooses the action that makes its utility maximum. Best response learning, based on Eq. (18), is characterized with fast convergence to the function maximizer. However, it incurs a higher computation cost compared with that of better response learning technique, based on Eq. (17). Yet, better response has slower convergence speed when compared with best response. That is to say that best and better response have contrasting features in terms of convergence time to the utility maximizer and computational complexity.

It is worth noting that $G(\mathbf{N}, \mathbf{A}_i, U_i)$ might converge to a stable solution that is a local optimum of the utility function, regardless of the existence of global optimum. In such an equilibrium the network can achieve a much more desirable outcome, i.e., that of the global optimum. Furthermore, since this suboptimal stable solution is one possible NE and according to the definition of NE in *Definition* 1, the players have no incentive to change their actions to increase their utility functions and hence will stay at the local optimum NE action profile, $\hat{a}_{LO-NE}$. To avoid players being insnared in a suboptimal NE, many researchers utilize the smoothed better response learning technique [17], [25] that introduces the factor of uncertainty to the learning process. Smoothed better response is proved to converge with a high probability to the global optimal equilibrium [27]. Thus, we use the smoothed better response learning technique in $G(\mathbf{N}, \mathbf{A}_i, U_i)$. A player acting according to the smoothed better response learning technique probabilistically chooses its actions as follows:

$$a_i^{t+1} = \begin{cases} a_i^{rand} & \text{with probability } (\omega) \\ a_i^t & \text{with probability } (\omega - 1). \end{cases} \tag{19}$$

Here, ω is a function of a_i^t and a_i^{rand} defined as:

$$\omega(a_i^{rand}, a_i^t) = \frac{e^{U_i(a_i^{rand}, a_{-i}^{rand})/\zeta}}{e^{U_i(a_i^{rand}, a_{-i}^{rand})/\zeta} + e^{U_i(a_i^t, a_{-i}^t)/\zeta}}. \tag{20}$$

As can be seen from Eq. (19), smoothed better response incorporates randomness to the learning process. The player chooses to act upon a_i^{rand} with a probability proportional to the difference between $e^{U_i(a_i^{rand}, a_{-i}^{rand})/\zeta}$ and $e^{U_i(a_i^t, a_{-i}^t)/\zeta}$. In case the difference is adequately high, the player will choose the new random action with a high probability. Inversely, if the difference is low, the player will retain its previous action with a high probability. However, if the difference is small, then $\omega \cong 0.5$, and the player will choose either a_i^{rand} or a_i^t in a predominantly random fashion. By employing such randomness in the learning behavior, the players are able to escape a current local optimal stable solution to eventually reach a different stable solution.

The smoothing factor ζ is a control parameter that affects the balance between an algorithm's performance outcome and the convergence speed. A significantly large value of smoothing factor ζ results in an exhaustive action search and slower convergence. However, a small value of ζ is associated with restricted strategy exploration and improves convergence of the algorithm. It is worth noting that a zero valued smoothing factor ζ, i.e., $(\zeta = 0)$, renders players acting under smoothed better response learning to behave precisely

Algorithm 1 Game-theoretic data collection method: CH-side game.

```
begin
Receive message from the UAS that indicates the initialization of negotiation process
repeat
    a_i^rand ← random strategy
    if (ω(a_i^rand, a_i^t) > random number[0,1]) then
        a^{t+1} ← a_i^rand
    else
        a^{t+1} ← a_i^t
Transmit a^{t+1} to the UAS
Wait for time slot assignment from the UAS
until the 𝒯 time unites are finished
end
```

Algorithm 2 Game-theoretic data collection method: UAS-side game.

```
begin
Transmit message to CHs that indicates the initialization of negotiation process
repeat
    Wait for CHs strategies
    Initialize S_decided
    repeat
        S_rand ← random slot assignment
        if S_rand satisfies β then
            if U_Network(S_rand) > U_Network(S_decided) then
                S_decided ← S_rand
    until ℒ learning steps are finished
    Transmit S_decided to CHs
until the CHs do not change their strategies
end
```

in the same manner as a players acting under better response would behave, in which the players bound from one action to another. Similar to [17], [25], [28], we use the concept of temperature on simulated annealing to set the value of the smoothing factor dynamically to be equal to $\zeta = \frac{10}{t^2}$.

C. Proposed Game-Theoretic Data Collection Method based on $\mathrm{G}(\boldsymbol{N}, \boldsymbol{A}_i, U_i)$

Based on $G(\mathbf{N}, \mathbf{A}_i, U_i)$ formulated in Section IV-A, we propose our game-theoretic negotiation-based algorithm for slot assignment that converges to a global optimum NE with a high probability. We refer to it as data collection method for brevity. The data collection method is played between the UAS and N CHs. The interactions of the data collection method can be modeled as a two-stage game, and are shown in Algorithms 1 and 2. Algorithm 1 is based on the behavior of players in $G(\mathbf{N}, \mathbf{A}_i, U_i)$. It is used by the CHs in order to improve their own utilities by basing their interdependent actions on the smoothed best response learning technique. The CHs report their strategies to the UAS and in return the UAS executes Algorithm 2 and notifies the CHs of the slot assignment (S). Algorithm 2 entails the UAS to act as auctioneer acting upon the better response learning technique to create a slot assignment S that improves $U_{Network}$ such that β criterion is satisfied. Moreover, we introduce the notion of finalization criterion, $\mathcal{T}$, which indicates the termination of the negotiation process. The finalization criterion ($\mathcal{T}$) is constructed to reflect any parameter of interest, which includes the maximum number of negotiations, time limit, computation load, or utility function thresholds. Similar to the research in [25], we employ the maximum number of negotiations as the finalization criterion, $\mathcal{T}$. Also, $\mathcal{L}$ is the number of learning steps for Algorithm 2.

Researchers have defined many metrics to quantitatively measure an algorithm's limitations due to resource constraints, which include lack of information for on-line algorithms and lack of unbounded computational resources for approximation algorithms. PoA [29] is an important concept in game theory that measures how the efficiency of a system degrades due to the greedy behavior of players in the game compared to a non-realtime centralized algorithm.

V. Price of Anarchy Analysis

As previously mentioned, $G(\mathbf{N}, \mathbf{A}_i, U_i)$ is prone to be trapped in local optimal NEs under some categories of learning techniques. The term Price of Anarchy was first used by Koutsoupias and Papadimitriou [29]. In the context of utility maximization, it quantifies the efficiency of a game-theoretic algorithm compared to a non-realtime centralized algorithm. Thus, it can be used to indicate the ratio between the utility of the worst possible NE to that of the non-realtime brute force method. It is important to note that such a brute force solution is computationally intensive and cannot be determined in real time.

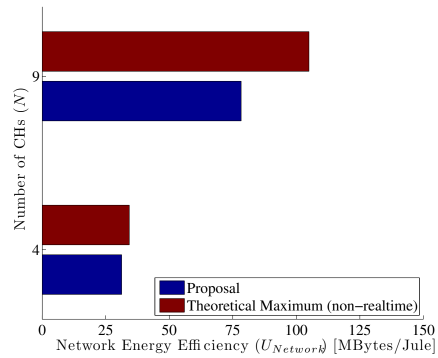
Definition 3: Price of Anarchy
let NE be the set of all possible NEs. Then

$$PoA = \frac{\max_{\Psi' \in \Psi} U_{Network}}{\min_{e \in NE} U_{Network}}. \quad (21)$$

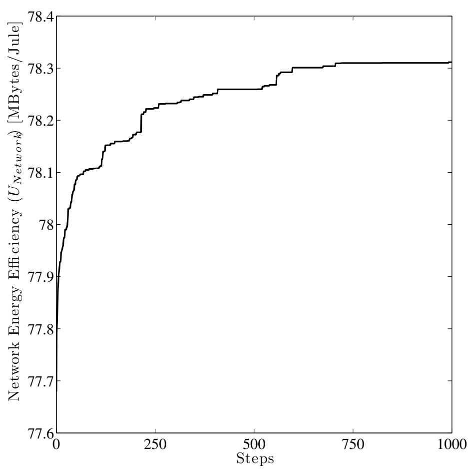
The nominator of *PoA* is $U_{Network}$ under the best possible slot assignment, $S_{\max U_{Network}}$. The denominator of the *PoA* is the $U_{Network}$ of the worst possible NE, which can be derived from the following lemmas

Lemma 2: The slot assignment that is created when all players restrict their α values to allow only for the highest SNR transmissions (S_{greedy}) is a NE.

Proof: We prove this lemma by contradiction. Assume that S_{greedy} is not a NE (contradictory to the statement of this lemma). Then, a player can increase its utility by a value (ε) through changing its strategy. Yet, such a move will allow for transmissions with less SNR, which will result in a decrease in its utility, according to Eqs. (4) and (7), or at best case make it remain constant. Hence, this player acting on the BR correspondence has no incentive to change its strategy and will remain stable. Similarly, such behavior applies to all



(a) The performance of our proposed data collection method compared with the theoretical non-realtime maximum value.



(b) The time slot assignment negotiation.

Fig. 2. Performance and negotiation of proposed method.

players in $G(\mathbf{N}, \mathbf{A}_i, U_i)$. Thus, we contradicted our preliminary assumption. ■

Lemma 3: S_{greedy} renders the lowest $U_{Network}$ in any equilibrium of $G(\mathbf{N}, \mathbf{A}_i, U_i)$.

Proof: For the situation with the best value of $\max_{\Psi' \in \Psi} U_{Network}$, if a player restricts its α value to the allow only for high SNR transmissions, $U_{Network}$ will have a value less than or equal to $\max_{\Psi' \in \Psi} U_{Network}$. Furthermore, if all players apply the same α restriction, $U_{Network}$ will have the lowest possible value from an NE, $U_{Network-min}$, which occurs from S_{greedy} ■

Lemma 4: $\min_{e \in NE} U_{Network}$ occurs at S_{greedy}

Proof: Consider that $NE \subset \Psi$, and apply lemmas 2 and 3. ■

The PoA of our proposed method is further evaluated in the forthcoming section.

VI. Performance Evaluation

In this section, we evaluate our proposed game-theoretic algorithm that improves the energy efficiency of the UAS-aided network. We construct our simulation to exemplify the UAS-aided network reaching the NE through negotiations among players. The simulation scenario was configured using

TABLE II
SIMULATION SETTINGS.

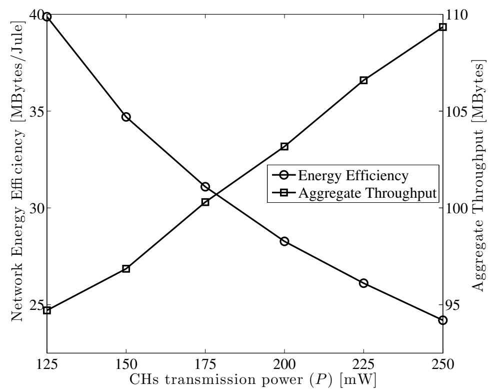
Parameter	Value
Number of CHs (N)	50-175
Sensor field dimensions	15000 × 15000 m^2
Altitude (h)	150 m
Trajectory radius (r)	5300 m
Velocity (v)	90 km/h
Symbol duration	4 μs
Time slot duration	50 ms
Target BER requirement (BER_0)	10^{-3}
Frequency	2 GHz
Bandwidth (B)	30 KHz
Transmit power (P)	125-250 mWatts

TABLE III
POA VALUES FOR DIFFERENT N.

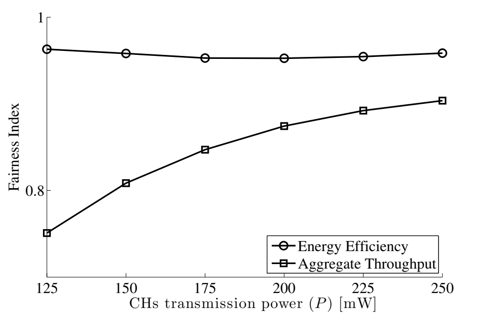
N	4	9
PoA	1.1	1.34

a customized simulator with the parameters summarized in Table II. Herein, a description of these parameters is given. The sensor field is constructed as a square field with dimensions of 15000 × 15000 m^2. The UAS travels in a circular trajectory in the center of the field, where the altitude (h), radius (r), and velocity (v) of the trajectory are set to values reported in [1], and are given in Table II. The symbol duration is set similar to the value of a common wireless interface [30]. The target BER level, BER_0, is set to ($BER_0 = 10^{-3}$), similar to the value adopted in [9]. The frequency is chosen to be in the range of most wireless technologies used in practice [16], so is the bandwidth (B). The transmission power of CHs is chosen to be in a low range, as such settings are practical for low power devices, which include CHs. The path loss exponent, φ, is set to ($\varphi = 2.5$), which is in the range of values used in common simulation settings [23], [31].

In the first part of our performance evaluation, we compare the performance of our proposed method to that of the non-realtime theoretical maximum. Towards this end, we construct two grid topologies consisting of 4 and 9 CHs, with a grid step of 800 m and 400 m, respectively. Such small topologies allow for computation of the approximate non-realtime theoretical maximum. The UAS travels with a speed of 30 km/h in a trajectory that is centered at the grids center and has a radius of 150 m. We simulate our proposed data collecting method with $\mathcal{T}$ set to 1000 and $\mathcal{L}$ is set to 30. The simulation is repeated 25 times with different seeds to calculate the average. Fig. 2(a) shows this comparison in terms of network energy efficiency with the fairness criterion ($\beta = 0.2$). This result shows that our proposed method performs at a level considerably close to that of the non-realtime theoretical maximum. Fig. 2(b) shows the negotiation process of our proposed method to reach the NE in the topology comprising 9 CH. As the graph shows, the network is converging towards the utility function maximizer. This behavior confirms the analysis derived in Section. IV-B. Furthermore, the values given in Table III show the PoA values

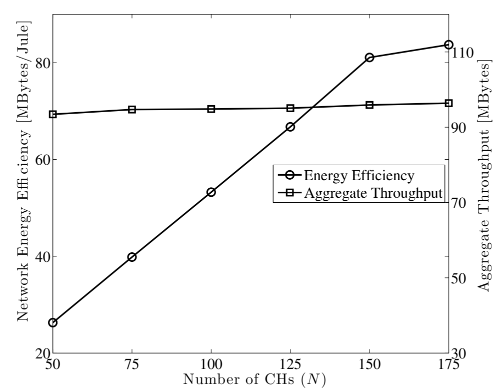


(a) The effect of CH transmission power on performance.

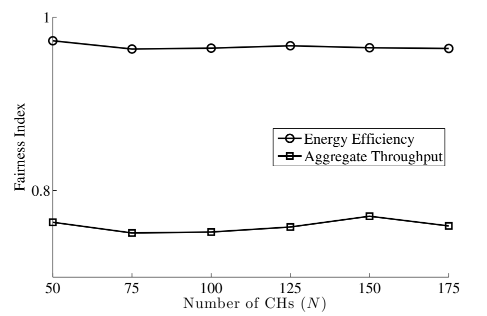


(b) The effect of CH transmission power on fairness.

Fig. 3. The effect of CH transmission power on the proposed method.



(a) The effect of the number of CHs on performance.



(b) The effect of the number of CHs on the fairness.

Fig. 4. The effect of the number of CHs on the proposed method.

for the two grid topologies. The results shows that the PoA of our proposed method is small, and indicate that the method in worst case our proposed method does not suffer much. The second part of the performance evaluation investigates the effect of CH transmission power on our proposal. We constructed a random node topology of 75 CHs according to the parameters listed in Table II and executed the simulation for 25 different seeds with the fairness criterion ($\beta = 0.2$). It is important to note that the fairness criterion is a lower bound and the actual fairness may be possibly higher. Fig. 3(a) shows the performance of the proposed data collection method in terms of network energy efficiency and aggregate throughput for different values of CH transmission power. The curve aggregate throughput shows aggregate throughput for one UAS revolution. The plot shows that for the chosen parameters, the network energy efficiency is inversely proportional to the CH transmission power. This behavior is explained by the fact that increasing the transmission power increases the denominator of the CH's utilities by, Eq. (7), twofolds while the increase of nominator of the CH's utilities, aggregate throughput, is not as much. It is worth noting that although the increase of SNR that allows for higher modulation levels is dependent on both the transmission power and the path loss, i.e., Eq. (1). This relationship is demonstrated in the plot aggregate throughput, which shows the increase of aggregate throughput with respect to CH transmission power. Fig. 3(b) shows the performance of the proposed method in terms of fairness of both throughput and energy efficiency with different values of CH transmission power, respectively. The plots shows that the fairness in terms of energy efficiency is sustained for the simulated values of CH transmission power. As previously noted, the actual fairness is more than value specified by the fairness criterion. Furthermore, the figure shows a similar behavior of aggregate throughput in terms of performance being significantly larger than the control parameter. Finally, we investigate how our proposed method performs under different numbers of CHs. Fig. 4(a) shows the network energy efficiency and aggregate throughput for different topology sizes. The graph shows the increase of network energy efficiency with the increase of number of CHs. This behavior is predictable from the definition of network energy efficiency in Eq. (8). Also, the figure shows that the aggregate throughput has a slight increase. Moreover, Fig. 4(b) shows the fairness index of both energy efficiency and aggregate throughput. It can be seen that the proposed method can sustain fairness regardless of the number of CHs.

In conclusion, the simulation results show that our proposed game-theoretic data collection method is a promising method for improving network energy efficiency while ensuring fairness for UAS-aided networks.

VII. Conclusion

In this paper, we proposed a method to improve energy efficiency while ensuring fairness for UAS-aided networks comprising adaptive modulation capable nodes. Additionally, for the mobility pattern of UASs, we showed how adaptive modulation behaves. We formulated the problem as a potential game, in addition to proving the properties of the game that guarantee the efficiency of the obtained solution, i.e., stability, optimality, and convergence. A game-theoretic data collection method was proposed based on the formulated game that improves the energy efficiency while taking into consideration the fairness in UAS-aided networks. Moreover, we analyzed the PoA of our proposed data collection method. Finally, extensive simulations were conducted to validate that the proposed game-theoretic method can provide near optimal performance in terms of network energy efficiency. In conclusion, our proposed method can significantly improve the network performance in terms of energy efficiency. For our future work we aim to explore the issues associated with multiple UAS-aided networks.

VIII. Acknowledgment

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