Toward Fair Maximization of Energy Efficiency in Multiple UAS-aided Networks: A Game-Theoretic Methodology

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***Abstract*— Recent technological advances in electronics, sensors, and communications have accelerated the widespread deployment of Unmanned Aircraft System (UAS)-aided applications. Nevertheless, networks composed of multiple UAS and ground stations, referred to as UAS-aided communications networks, have yet to receive sufficient research attention. In this paper, we address a fundamental research challenge stunting such networks, which is how to fairly maximize the energy efficiency (throughput per energy) in networks comprising adaptive modulation-capable ground nodes. For the mobility pattern intrinsic to the UASs, we demonstrate how adaptive modulation is affected. Furthermore, we formulate the problem of maximizing fair energy efficiency as a potential game that is played between the multiple ground-nodes, and substantiate its stability, optimality, and convergence. Based on the formulated potential game, a data collection method is proposed to maximize the energy efficiency with a fairness constraint. Additionally, we analyze the Price of Anarchy (PoA) of our proposed game-theoretic data collection method. Extensive simulations exhibit the effectiveness of our proposal under varying environments.**

***Index Terms*— Unmanned Aircraft System (UAS)-aided networks, energy efficiency, throughput per energy, fairness, adaptive modulation, Game Theory, wireless network optimization.**

I. INTRODUCTION

Advances in propulsion systems, energy storage, miniaturized payloads, communications systems, and autonomous control have rendered the development of Unmanned Aircraft Systems (UASs) feasible. UASs are small unmanned airborne vehicles equipped with wireless transceivers, Global Positioning Systems (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 subject our study to the fixed-winged UASs because of their superior speed that renders the ability to complete operations in shorter periods of time. Hereafter, we refer to a fixed-winged UAS as a UAS for brevity. UASs have a great potential to create a multitude of applications in many disciplines [1]–[8]. The applications include but are not limited to polar weather monitoring [9], provisioning communications in disaster devastated areas [5], [10], and wildfire management [11]. We aim to utilize the UAS' abilities to construct an autonomous UAS-aided network, where multiple UASs fly over the sensor field to collect ambient data from sensor nodes. These sensor nodes are deployed in various kinds of terrains including dangerous areas that are difficult to reach with conventional vehicles, which include helicopters.

We consider a network where multiple UASs collect data from sensor nodes as they fly according to annular trajectories. Given that it is expensive to equip all sensor nodes with functionality to communicate directly with a UAS, special sensor nodes, Cluster Heads (CHs), which have special communication capabilities, are distributed in the area. The remaining sensor nodes entail only capabilities to communicate with the CHs. The mobility pattern of UASs causes the distance between a CH and a UAS to vary. Furthermore, the distance between a CH and a UAS affects the Signal-to-Noise Ratio (SNR), which in turn affects the modulation scheme. This is because modulation schemes that have more bits per symbol necessitate higher values of SNR for a given BER requirement [12]. Moreover, if high levels of BER are tolerable, the attainable number of bits per symbol that a modulation scheme transmits can be further improved.

Sensor nodes and CHs, which are powered only by batteries, are coveted to be able to function for prolonged durations of time without battery replenishment [13], [14]. This renders energy efficiency to be a fundamental requirement to assure the longevity of CHs without the need for battery renewal, particularly if the target applications imply hazardous environments. For the majority of data collection applications with sensor nodes it is essential to make efficient utilization of the limited battery capacities. Therefore, given a fixed budget of energy reserves, the quantity of transmitted data should be increased to the utmost. We define this metric to be energy efficiency. Adaptive modulation is a key technology that can enable transceivers to transmit more data for the same transmission power under the condition that the channel conditions are favorable, i.e., SNR level is high.

For the considered UAS-aided network, the number of bits that can be transmitted per symbol, and consequently the energy efficiency, defer according to which time slots are assigned to which CH. Since increasing the energy efficiency is of interest, the network designer is inclined to opt to give priority of transmission to CHs with higher SNR to have a higher priority to transmit. This undoubtedly will result in the unfair allocation of time slots among CHs, where the CHs that are distant from the UAS transmit less compared to CHs that are in the proximity of the UAS. Thus, our goal is to devise a method to improve the network's energy efficiency given that a determined degree of fairness among CHs holds regardless of their distance from the UAS.

Contemporary data collection methods (similar to those that are designed for mobile sinks) do not consider the challenges associated with the aforementioned energy efficiency issues in UAS-aided networks [15]–[18]. In this paper, we propose a data collection method based on game theory that improves network energy efficiency while satisfying fairness in the distribution of resource among CHs[1].

Contributions: The contributions of this paper can be summarized as follows:

- We demonstrate how adaptive modulation is affected by the UAS' annular trajectory.
- We formulate the problem of maximizing the energy efficiency with fairness among CHs using the framework provided by Game Theory, 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 substantiate the properties of stability, optimality, and convergence. These properties yield performance guarantees for the formulated game.
- Based on the formulated game, we devise a game-theoretic data collection method for enhancing the energy efficiency while considering fairness in multiple UAS-aided Networks.
- The Price of Anarchy (PoA) of our proposed game-theoretic data collection method is analyzed.

The remainder of the paper is as follows. Section II commences with a related work section. Section III details the system assumptions and definitions. Section IV gives our envisioned data collection method for multiple UAS-aided networks. In Section V, we analyze the PoA of our proposed game-theoretic method. Section VI presents the performance evaluation of our proposed data collection technique. We conclude this paper in Section VII.

II. Literature Review

In this section, we investigate the works relevant to the UAS-aided networks research direction. These works include the investigations of UAS-aided networks, mobile sink-based Wireless Sensor Networks (WSNs), network segmentation know as hierarchical routing, channel adaptive modulation techniques, and wireless network optimization based on Game Theory.

UASs have been integrated into many applications across many domains that span those of civilian and military [1]–[6]. The UAS has been employed to application that include polar weather monitoring [9] and wildfire management [11]. Namuduri *et al.* [7] discussed the opportunities and challenges for using UASs in civilian applications. Daniel *et al.* [2] explored how to use multiple UASs provisioned with sensing capabilities that enable the sensing of data from hostile environments. Using the UAS' abilities for communications purposes has attracted the attention of many researchers. Bekmezci *et al.* [1] outlined communication related issues of ad hoc networks comprising multiple UASs referred to as Flying Ad-Hoc Networks (FANETs). Freitas *et al.* [3] proposed using UASs as relays to link partitioned ad hoc networks. The research in [20] explored medium access control for UASs. Varakliotis *et al.* [5] envisioned providing communications in disaster struck areas with UASs equipped with cognitive radio technology. Asadpour *et al.* [21] designed an ad hoc network composed of UASs for high traffic data application. Goddemeier *et al.* [6] proposed communication-aware steering algorithms for UAS swarms in exploration applications. The considered communication-aware positioning 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.

In comparison with the existing works on UAS-aided networks, our research aims at using the UAS' abilities to construct an autonomous UAS-aided network, where the M UAS fly 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 means like helicopters. Among all the existing works on UAS-aided networks, to the best of our knowledge, there have not been any research that taps onto the UAS' unique abilities to collect data from nodes on the ground. Indeed, we aim to devise a method on 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 of the transmissions between a UAS and a ground nodes. Since the SNR of transmissions is of varying levels, adaptive modulation [12], [22] 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 [15]–[18]. However, they do not consider the ecliptic trajectory akin to the UAS' mobility pattern and the inability of UAS to remain stationary in air. Additionally, they do not exploit favorable channel conditions by capitalizing on adaptive modulation. Most notable of which is the work of Shah *et al.* [15], where the mobile sinks go to sensor nodes to collect data of interest.

Equipping all nodes with the ability to communicate with the UAS limits the deployability of data collection applications because of hardware and energy consumption issues. Network hierarchy is a suitable solution. Many studies have been carried out that segment the network layer into smaller components, known as clusters, most notably is Low-Energy Adaptive Clustering Hierarchy (LEACH) and its many variants [13], [23]. 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 basic communication functionalities to communicate with the CHs.

Many research works have been conducted to explore adaptive M-ary Quadrature Amplitude Modulation (M-QAM) [12], [22]. Adaptive transmission techniques can harness the num-

[1]The basic idea of our game-theoretic data collection method was first presented at IEEE INFOCOM 2014 [19].

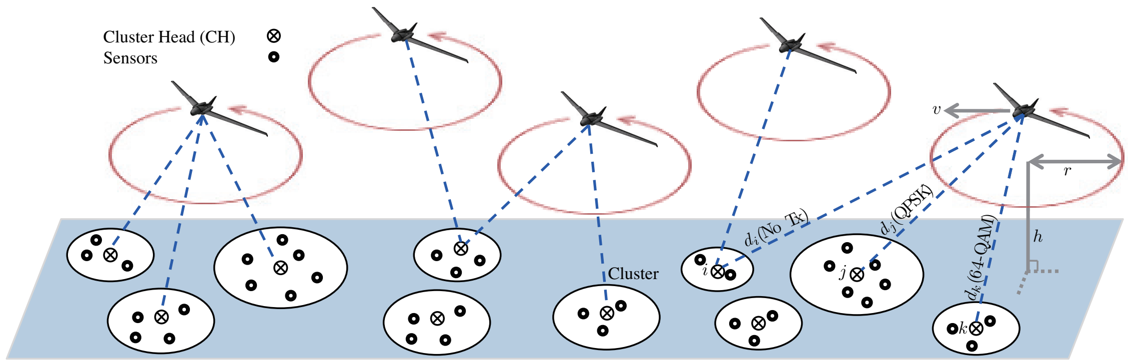


Fig. 1. Considered UAS-network topology. The M UASs travel around the sensor field according to an annular trajectory, which is characterized by altitude (h), speed (v), and radius (r). The UASs communicate with N CHs. The CHs use a low power communication standard to communicate with sensor nodes.

ber of degrees available for communications to enhance the capacity of the network by adapting the modulation scheme according to channel conditions, i.e., SNR levels. Without such a technology the transceivers on the CHs can only transmit at a constant number of bits per symbol despite the favorable SNR conditions.

Our proposal aims to maximize the energy efficiency of the UAS-aided network, where CHs located around the sensor field exist with time varying SNR levels. Thus, an optimization method is required so that the allocation of time slots of the M UASs to the CHs is done in a manner that maximizes network's energy efficiency while maintaining a predetermined 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 [24], [25]. Using the framework provided by Game Theory to solve complex issues has attracted the attention of many researchers in the last decade and their has been a plethora of applications ever since. In particular, Game Theory has been applied to many research issues in the context of wireless network communications, which include channel assignment in wireless mesh networks [26], quality of service in wireless networks [27], power control in cellular radio systems [28], and cognitive radio networks [29]. Readers unfamiliar with Game Theory concepts and its applications in wireless communications are encouraged to refer to the works in [24], [30], which contain fundamental results in wireless communications research area. In this work, we employ the framework of potential games, which have been utilized in the context of objective maximization problems such as the problem investigated in this paper.

III. Preliminaries and System Model

Fig. 1 shows the envisioned UAS-aided network. CHs are provisioned with superior hardware that enable communication with the M UASs. On the other hand, a normal sensor node is equipped with basic communication facilities, and has to transmit the data that it collects to the closest CH to it. This configuration lowers the deployment cost of the UAS-aided network because only CHs need to be equipped with expensive hardware.

Sensor field: Similar to many data collection applications of sensor nodes [31]–[33], the sensor nodes sense their surroundings to collect data and report the data that they have sensed to the CH in their proximity by using a low energy consuming communications standard, which include ZigBee or Bluetooth Low Energy [34], [35]. A CH communicates with the UAS by using specific time slots assigned to it by our proposed method.

Mobility model: The UASs are used to collect data from the sensor field. They glide around the sensor field in a circular trajectory innate to UASs [36]. The UAS have varying degrees of mobility, which enable the UASs to achieve its objective of data collection. The UAS' degrees of mobility (comprising altitude (h), speed (v), and radius (r)) are flexible [1], [37]. The degree of mobility changes to accommodate mission objectives, which are influenced by time limitation of mission completion, or the terrain that the sensors are deployed in and so on.

Adaptive modulation: The CHs in the UAS-aided network are provisioned with transceivers that are capable of adaptive modulation. 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 possible K-modes ($n = 0, 1, ..., K-1$), the modulation scheme is able to transmit a different number of bits per symbol, b_n, and have M_n possible constellations.

A. System Model

The network is composed of a set of sensor nodes, N CHs, and M UAS. According to [38], [39], 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 displacement between CH i and a given UAS. φ is the path-loss exponent (it takes values between 2 and 4), and ξ is a constant dependent on the factors that are mainly determined by receiver gain, transmitter gain, and wavelength. The received signal is distorted by Additive White Gaussian Noise (AWGN) with a normalized one-sided power spectral density N_0. We assume that transmission devices

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

onboard the CHs transmit with a constant symbol-wise average transmission power P. Moreover, CHs are not able to control the transmission power, which is constant. Also, the network has a limited bandwidth B, which is measured in Hertz. Hence, the network SNR can be defined according to the following equation [38], [39]:

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

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. Adaptive Modulation Switching Levels Model

Similar to [12], [22], we adopt the fixed switching scheme that determines the switching criterion based on fixed SNR levels. In the so-called fixed switching scheme, the assignment of the SNR boundaries is performed in a fashion that renders the SNR level at the boundary to satisfy the BER requirement with the modulation scheme used in an AWGN channel. According to [12], [22] the criteria used to find the SNR switching levels are shown in Table I. The switching levels, γ_n, can be derived from the formulas devised by Alouini and Goldsmith [22]:

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

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

IV. DATA COLLECTION CHALLENGES AND PROPOSED SOLUTION

The sensor nodes and the CHs in the UAS-aided network power their operation by finite battery reserves. Energy efficiency (throughput per energy) is a critical issue since it is a measure of how much data can be transmitted with the limited battery capacities of CHs. Energy efficiency of a transmission is influenced by the UAS' mobility. The influence arises from the change of distances between the CHs and the UASs as the UAS traverses the sensor field according to its circular trajectory. Consequently, the SNR levels of the transmissions between the CHs and the UASs 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 decrease the number of bits transmitted per symbol. Such adaptation of the number of bits per symbol (b_n) controls the BER level such that it is within the BER requirement (BER_0) of the wireless system. The UAS' time slots should be assigned in a manner that allows for improved energy efficiency of the UAS-aided network. Assigning time slots for the maximization of energy efficiency results in the unfairness of the distribution of time slots among CHs. The fairness criterion (β), the extent of equality of distribution of a resource, should reflect on the fairness in both energy efficiency and throughput among the CHs in the UAS-aided network. Fairness among CHs can be expressed by using the fairness index, which is proposed by Jain *et al.* [40]:

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

where m indicates either throughput or energy efficiency. Eq. (5) has been designed by Jain *et al.* [40] to increase as the difference between m values of CHs decreases. The maximum value of Eq. (5) is 1, which occurs when all CHs have the same value of m. The minimum value of Eq. (5) is $1/N$, which occurs when one CH has a nonzero m and the remaining CHs have a zero value m. The problem of allocating the M UAS' time slots among N CHs to maximize the networks energy efficiency such that the fairness criteria is satisfied cannot be solved in real time due to the inherent number of computations entailed in solving this problem. To illustrate this issue, consider a hypothetical UAS-aided network that consists of 20 CHs, where 1000 time slots need to be assigned. For such a slot assignment, finding a slot assignment for the aforementioned problem involves computations of enormous proportions (20^{1000}). Game Theory can be used to solve this optimization problem without the associated computational burden [41]. Thus, we aim to formulate this problem as a game, as shown in Section IV-A. Additionally, we substantiate the performance characteristics of our formulated game in Section IV-B. The results found in Section IV-B are utilized to formulate a game-theoretic method in Section IV-C.

A. Game-based Interactions

We model the CHs as players in oder to optimize the slot assignment using the framework provided by Game Theory. Each CH is defined to be an intelligent decision maker of the game $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$. Here, $\mathbf{N}, \mathbf{A}, \mathbf{U}$ refer to the main components of $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$, which are the $\mathbf{N}$ 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 represents the CH with index i. U_i is the utility function of CH i, which reflects the energy efficiency that can be formulated as:

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

where δ_i is the amount of data that CH i has transmitted and η_i is the amount of energy CH i consumed for the δ_i consumed energy. U_i reflects the energy efficiency of CH i, defined as throughput per energy. The utility of the UAS-aided network is formulated as follows:

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

Each CH in $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$ controls a threshold, α_i, which is the farthest distance that the CH is willing to transmit to the UAS at. Hence, α_i indicates the lowest SNR that CH i is willing to transmit at. Thus, the actions of CH i, A_i, can be defined as:

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

The game profile of $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$, Ψ, is derived from the Cartesian product of the players' actions, i.e.,

$$\begin{aligned} \Psi &= \times_{\forall i \in (1,2,....,N)} A_i \\ &= A_1 \times A_2 \times A_3 \times ... \times A_N. \end{aligned} \tag{10}$$

Let $a_i \in A_i$. Then, define a_{-i} as the set of actions chosen by all other players excluding player i. Thus, a_{-i} is defined as:

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

It is desired that players negotiate their interdependent actions to arrive to an optimized slot assignment (S) such that the value of $U_{Network}$ is maximized and the fairness constraint is satisfied. The issues of convergence and efficiency surface. Convergence is whether the proposed game can converge to a steady state solution, a consensus between players that implies stability. Moreover, what is the efficiency of the stable solution in terms of $U_{Network}$. These issues will be addressed in Section IV-B. Thereafter, the results of Section IV-B will be used to formulate a game-theoretic method in Section IV-C.

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

Nash Equilibrium (NE) [24], [25] is a central principle in Game Theory that is used to define stability between negotiating players. NE is a stable state that can occur when players in a game act according to their Best Response (BR) correspondences. The BR correspondence of player i is defined as:

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

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

As the above definition indicates, the BR correspondence of player i is its best response given other players actions, i.e., a_{-i}. Now, let $\hat{a}$ be defined as the action profile:

$$\hat{a} = (a_1, ..., a_N). \tag{13}$$

$\hat{a}$ is said to be 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 aforementioned definition indicates that no player has a motive to deviate from its action if other players do not deviate their actions. That is to say that the game has attained a stable state. However, this stable solution does not entail an implicit guarantee of optimal outcome. Nevertheless, potential games, which are a specific kind of game, have useful properties that address the convergence to a NE and the NE's efficiency issue. A potential game possesses the following useful properties:

- For any finite potential game, at least one pure action profile NE exists [42].
- All the NEs associated with the potential game are either local or global maximizers of the utility function [42].
- Myopic one-sided learning based on either the best response or the better response learning methods can be applied to the game so as to guide the game to reach the utility function maximizers, i.e., the NEs [30], [42].

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

Proof: According to [30], [42], a game is a potential game if a potential function *Pot*, exists, 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), $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$ can satisfy the definition of a potential game, where

$$Pot = U_{Network}(\Psi); \forall i. \tag{16}$$

■

From lemma 1, we can see that $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$ is a potential game. Based on the properties of potential games and NEs, we can guarantee that the formulated game, $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$, 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 notable learning techniques that guarantee convergence to a utility maximizing NE of potential games [30], [42]. Denote the negotiation step to be t, then players acting as per the better response learning choose their actions as follows:

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

According to the better response learning technique each player selects a random strategy in its turn. The player keeps the random strategy if it results in a better utility than that of the previous strategy it had in its previous turn, and vice versa if the utility resulting from the random action results in less utility than that of the former action. Players acting on the best response learning technique choose their actions as follows:

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

Here, the player chooses the action that makes its utility maximum. Best response learning, based on Eq. (18), is fast to converge to the utility function maximizer. However, it

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

begin
Receive message from the UASs that initializes of negotiation process
repeat
  $a_i^{rand} \leftarrow$ random strategy
  if $(\omega(a_i^{rand}, a_i^t) >$ random number$[0,1])$ **then**
    $a^{t+1} \leftarrow a_i^{rand}$
  else
    $a^{t+1} \leftarrow a_i^t$
Transmit a^{t+1} to the M UASs
Wait for time slot assignment of the M UASs
until the $\mathcal{T}$ time units are finished
end

exhibits a higher computation cost compared to that of the 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 in some cases $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$ might converge to a stable solution that is a local optimum of the utility function, even though the global optimum exists. In such a situation the network can achieve a better outcome, i.e., that of the global optimum. Furthermore, since this suboptimal stable solution is one instance of NE and according to the definition of NE in *Definition* 1, the players have no motive to change their actions, since they cannot increase their utility functions and hence will remain at the local optimum NE action profile, $\hat{a}_{LO-NE}$. To avoid players being insnared in a suboptimal NE, many researchers have employed the smoothed better response learning technique [26], [41] that introduces the factor of randomness to the learning process. Smoothed better response has been proved to converge with a high probability to the global optimal equilibrium [43]. Thus, we use the smoothed better response learning technique in $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$. A player acting according to the smoothed better response learning technique probabilistically chooses its actions according to the following function:

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

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

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

As can be seen from Eq. (19), smoothed better response integrates randomness to the learning process. The player chooses to act upon the new action 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 adequate to a certain level, the player will choose the new random action a_i^{rand} with a high probability. Inversely, if the difference is low, the player will keep its former 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 random manner. By employing such randomness in the learning behavior, the players are able to evade a current local optimal stable solution to eventually reach a different stable solution.

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

begin
Transmit message to CHs that initializes of negotiation process
repeat
  Wait for CHs strategies
  Initialize $S_{decided}$
  repeat
    $S_{rand} \leftarrow$ random slot assignment
    if S_{rand} *satisfies* β **then**
      if $U_{Network}(S_{rand}) > U_{Network}(S_{decided})$ **then**
        $S_{decided} \leftarrow S_{rand}$
  until $\mathcal{L}$ learning steps are finished
  Transmit $S_{decided}$ to CHs
until the CHs do not change their strategies
end

The smoothing factor ζ is a parameter responsible for controlling the balance between an algorithm's performance outcome and the convergence speed. A significantly large value of the smoothing factor ζ results in an extensive action search and slower convergence. However, a small value of ζ is associated with a narrower strategy exploration and a shorter convergence time of the algorithm. It is worth noting that when the value of the smoothing factor ζ is zero, i.e., $(\zeta = 0)$, renders the smoothed better response learning to behave precisely in the same manner as better response, in which the players jump from one action to another. Similar to research works in [26], [41], [44], we use the principle 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 G($\boldsymbol{N}, \boldsymbol{A}, \boldsymbol{U}$)

We propose our game-theoretic algorithm based on the formulations in the Sections IV-A and IV-B as a negotiation-based algorithm for slot assignment that converges to a global optimum NE with high probability. We refer to it as data collection method for brevity. The data collection method is played between the M UAS and N CHs, and aims at increasing network energy efficiency. The interactions of the data collection method are modeled as a two-stage game, and are detailed in Algorithms 1 and 2. Algorithm 1 is played by the N CHs in order to improve their own utilities by acing as per the smoothed best response learning technique. The UAS-side algorithm, Algorithm 2, needs to be only played at one designated UAS to assign time slots of the M UASs to the N CHs. Algorithm 2 entails the designated 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 is satisfied. Furthermore, we introduce the finalization criteria, $\mathcal{T}$, which gives the negotiation a method to terminate. The finalization criteria ($\mathcal{T}$) can reflect any parameter of interest to the network designer. Its values can reflect the maximum number of negotiations, time limit, computation load, or utility function thresholds. Similar to the research work conducted in [41], we employ the maximum number of negotiations as the finalization criteria, $\mathcal{T}$. Also, we define $\mathcal{L}$ as the number of learning steps for Algorithm 2.

Researchers have defined numerous metrics to quantitatively measure an algorithm's limitations due to resource constraints, which include the lack of information for on-line algorithms or the lack of unbounded computational resources for approximation algorithms. PoA [45] is one of these metrics that is important in game theory that measures how the efficiency of a system degrades due to the greedy behavior of players in game-theoretic algorithms compared to that of a non-realtime centralized algorithm.

V. Price of Anarchy Analysis

As previously mentioned that potential games are prone to being trapped in local optimal NEs regardless of the existence of global optimal NEs under some kinds of of learning techniques. Under such a scenario, it is interesting to measure the system's performance. PoA, Price of Anarchy, was first proposed by Koutsoupias and Papadimitriou [45]. In the area of utility function maximization, it quantifies the efficiency of a game-theoretic algorithm compared to that of 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 cannot be computed in real time due to its computational burden. PoA is defined as follows.

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

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

The nominator of *PoA* is highest value of $U_{Network}$, the associated slot assignment is referred to as $S_{\max U_{Network}}$. The denominator of the *PoA* is the $U_{Network}$ of the worst possible NE, which will be derived from the following lemmas.

Lemma 2: The slot assignment that is created if 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 this lemma). Then, a player can increase its utility by an arbitrary value (ε) through changing its action. Yet, such a move will allow for transmissions with less SNR, which will result in a decrease in the player's utility, according to Eqs. (4) and (7), or at best case leave it constant. Hence, this player acting on the BR correspondence has no motive to adjust its action and will stay in the current state. Similarly, such an argument applies to all players in $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$. Thus, we have reached a contradiction of our preliminary assumption. ■

Lemma 3: S_{greedy} renders $\min_{\Psi' \in \Psi} U_{Network}$ in $G(\mathbf{N}, \mathbf{A}, \mathbf{U})$.

Proof: For the best value of $\max_{\Psi' \in \Psi} U_{Network}$, if a player restricts its α to allow the transmissions with the highest SNRs only, $U_{Network}$ 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, $U_{Network-min}$. $U_{Network-min}$ occurs from the NE (S_{greedy}). ■

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

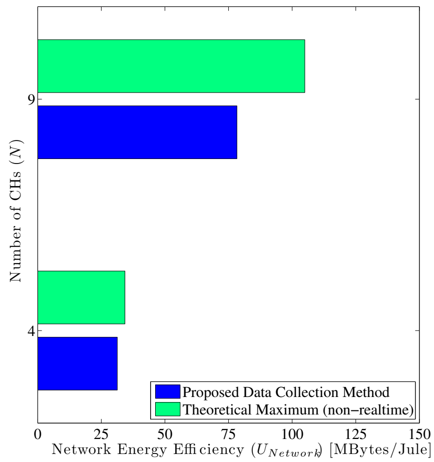
Proof: Consider that $NE \subset \Psi$, and apply lemmas 2 and 3. ■

VI. Performance Evaluation

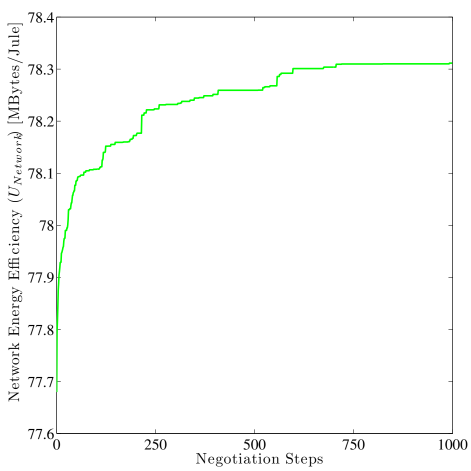
TABLE II
Parameter settings.

Parameter	Value
Number of CHs (N)	50-175
Number of UASs (M)	2-10
Sensor field dimensions	30000 × 15000 m^2
Altitude (h)	150 m
Trajectory radius (r)	5300 m
Velocity (v)	90 km/h
Symbol duration	4 μ s
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

In this section, we perform an evaluation of our proposed game-theoretic algorithm that enhances the fair energy efficiency in multiple UAS-aided networks. We configure our simulation to exemplify the UAS-aided network reaching the NE through the negotiations among CHs. The CHs use adaptive modulation as described in Sec. III. The simulation scenario was configured using a custom-built simulator with the parameters listed in Table II. The trajectory parameters, i.e., altitude (h), radius (r), and velocity (v), are set to values reported in [1], and are elaborated in Table II. The symbol duration is set to a value of a common wireless interface [46]. Herein, a description of these parameters is going to be presented. The sensor field is constructed as a rectangular field with dimensions of 30000 × 15000 m^2. Unless specified otherwise, the fairness criterion (β) is set to 0.5 in our proposal. We simulated our proposed data collecting method with $\mathcal{T}$ set to 1000 for the CHs and $\mathcal{L}$ set to 30 for the UAS. The simulation is repeated 25 times with different seeds to calculate the average. The target BER requirement, BER_0, is set to ($BER_0 = 10^{-3}$), similar to the values adopted in [12], [22]. The frequency is chosen to be in the range of most standardized wireless technologies [25], the same also applies to system bandwidth (B). The transmission power of CHs (P) is chosen to be in a low range, as such settings are practical for low power devices that need to be deployed for prolonged periods of time without battery replenishment. The path loss exponent, φ, is set to ($\varphi = 2.5$), which is in the range of values reported in numerous research works [38], [39], [47].



(a) The performance of the proposed game-theoretic data collection method compared with that of the theoretical non-realtime maximum.



(b) The time slot assignment negotiation process between N CHs for the time slots of M UASs.

Fig. 2. Performance and negotiation of proposed method.

TABLE III
PoA VALUES FOR DIFFERENT N.

N	4	9
PoA	1.1	1.34

Moreover, sensors generate data according to a random variable to simulate the effect of heterogeneous data sources. The performance evaluation is decided into two parts. The first part presents a comparison of our proposed data collection method with a theoretical non-real time optimal, the negotiation process of our proposal, and PoA analysis. In the second part, we study the effect of transmission power, number of CHs, and the number of UASs on the performance our proposal.

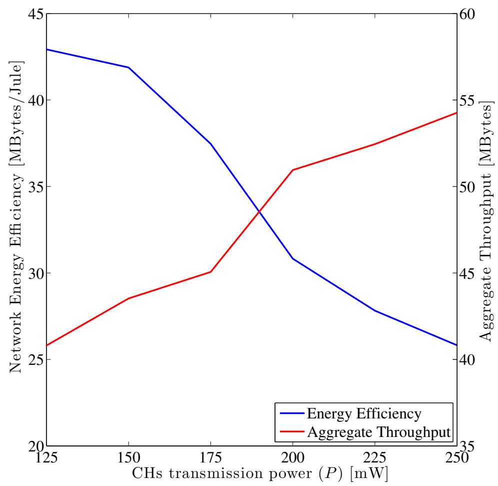
A. Comparison with a theoretical non-real time optimal, learning, and PoA analysis.

In the first part of our performance evaluation, which is reproduced from [19], we examine the performance of our proposed game-theoretic method with that of the non-realtime theoretical maximum. Towards this end, we configure two grid topologies consisting of 4 and 9 CHs, with a grid step of 800 m and 400 m, respectively. In contrast with the remaining of the simulation settings, one UAS is considered for this comparison. Such small topologies allow for computation of the approximate non-realtime theoretical maximum. The UAS travels with a velocity of 30 km/h in a trajectory that is centered at the grids center and has a radius of 150 m. Fig. 2(a) shows the results of this comparison in terms of network energy efficiency with the fairness criteria ($\beta = 0.2$). This result shows that our proposal's performance is considerably close to that of the non-realtime theoretical maximum. Fig. 2(b) shows the negotiation process of our proposal to reach the NE. As the graph shows, the network is converging towards the utility function maximizer. This behavior confirms the analysis derived in Section. IV-B. Moreover, Table III shows the PoA values for different grid topologies. The results show that the PoA of our proposed method is small, which indicates that the worst case performance of our proposed method is not far from the non-realtime theoretical maximum.

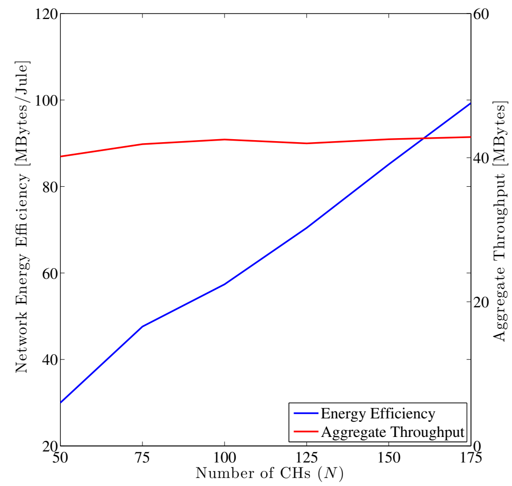
B. The effect of transmission power, number of CHs, and the number of UASs.

In this portion of the performance evaluation, we examine the effect of transmission power, number of CHs, and the number of UASs on the performance our proposal. Two UASs wheel with trajectories centered at (7500,7500) and (22500,7500), respectively. We constructed a random node topology comprising 75 CHs set according to the parameters listed in Table II and conducted the simulation for 25 different seeds.

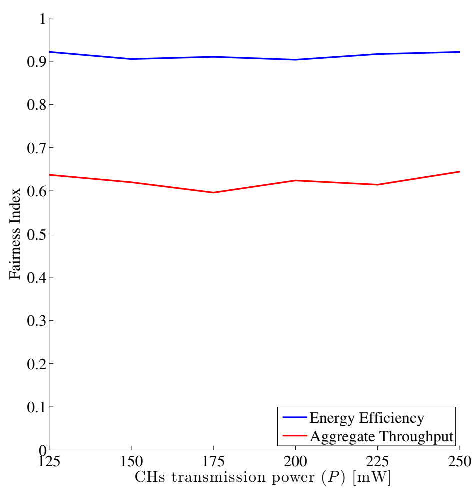
Fig. 3(a) shows performance of the proposal with respect to network energy efficiency and aggregate throughput for different values of CH transmission power. The plot aggregate throughput is the aggregate throughput for a UAS revolution. The plot shows that for the given parameters, the network energy efficiency is decreased with the increase of CH transmission power. This behavior is accounted for by the fact that a twofold increase of the transmission power equivalently increases by the denominator of the CH's utilities, Eq. (7). In comparison the increase of aggregate throughput is relatively small due to path loss, Eq. (1). Consequently, the nominator of the CH's utilities has a small increment. Also, we can see that the aggregate throughput is proportional to the CH transmission power. Intuitively, this trend can be understood from the fact that increasing transmission power allows the CHs to transmit at higher modulation levels. This undoubtedly increases the network throughput. Fig. 3(b) shows the results of the proposed method in terms of fairness of both throughput and energy efficiency with different values of CH transmission power, respectively. The plots indicate that the value of fairness in terms of energy efficiency is sustained for the simulated values of CH transmission power. It is important to point out that the value plotted is significantly larger than the threshold value specified by ($\beta = 0.5$) control parameter. Furthermore, the plot shows a similar pattern of aggregate throughput in



(a) The effect of transmission power on performance in terms on network energy efficiency ($U_{Network}$) and aggregate throughput in the proposed game-theoretic data collection method.

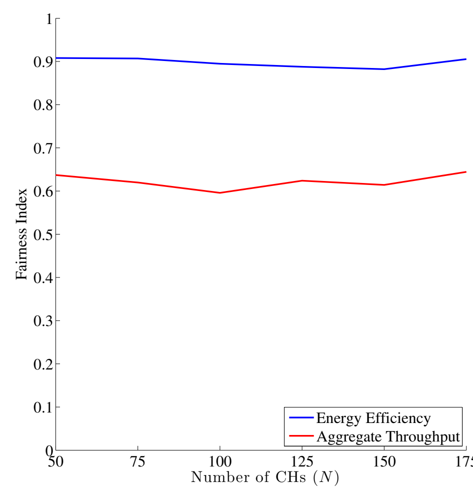


(a) The effect of the number of CHs (N) on performance in terms on network energy efficiency ($U_{Network}$) and aggregate throughput in the proposed game-theoretic data collection method.



(b) The effect of transmission power on the fairness index of energy efficiency and aggregate throughput in the proposed game-theoretic data collection method.

Fig. 3. The effect of transmission power (P) on the Performance of the proposed method.



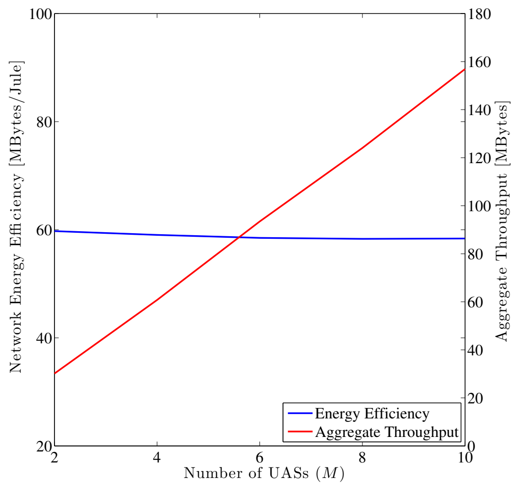
(b) The effect of the number of CHs (N) on the fairness index of energy efficiency and aggregate throughput in the proposed game-theoretic data collection method.

Fig. 4. The effect of the number of CHs (N) on the Performance of the proposed method.

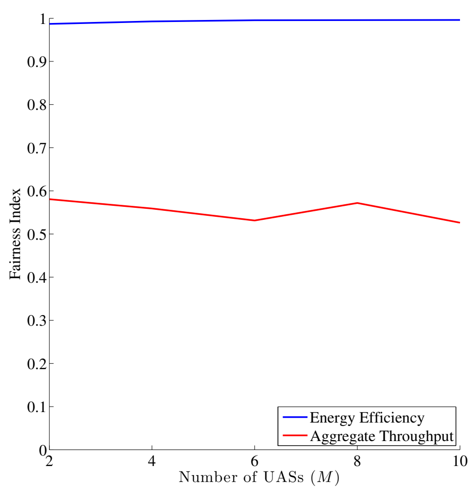
terms of the performance being significantly larger than the control parameter.

Herein, we investigate how our proposal performs under topologies with a different number of CHs. Fig. 4(a) shows the network energy efficiency and aggregate throughput for topologies of different sizes. The graph shows the increase of network energy efficiency with the growth of number of CHs. This behavior is to be expected from the definition of network energy efficiency in Eq. (8), as the increase of number of CHs increases the number of terms in the summation of Eq. (8). Also, the figure shows that the aggregate throughput is predominantly non-changing. Fig. 4(b) gives the fairness index of both energy efficiency and aggregate throughput. It can be seen that the proposal can maintain fairness for large topology sizes.

Finally, we investigate the influence of the number of UASs (M) on the performance of our proposal. For this portion of the experiment, $N = 100$, $P = 125\ mWatts$, and $r = 2500\ m$. The other parameters are set according to the values in Table II. r is chosen so that no overlap occurs between the UAS' trajectories for the UAS positions indicated by the information shown in Table IV. These positions are chosen so that a grid topology is formed by the UASs. Inter-UAS x-displacement and inter-UAS y-displacement is the distance between any two consecutive UASs with on the x and y axes, respectively. Furthermore, inter-UAS x-displacement and inter-UAS y-displacement also indicate the space between the border of the simulated sensor field and the closest UAS on the x and y axes, respectively. Fig. 5(a) shows the network energy efficiency and aggregate throughput for networks with a different number of UASs. The graph shows that proposed method can sustain network energy efficiency for different



(a) The effect of the number of UASs (M) on performance in terms on network energy efficiency ($U_{Network}$) and aggregate throughput in the proposed game-theoretic data collection method.



(b) The effect of the number of UASs (M) on the fairness index of energy efficiency and aggregate throughput in the proposed game-theoretic data collection method.

Fig. 5. The effect of the number of UASs (M) on the Performance of the proposed method.

numbers of UASs. Also, it can be seen that the throughput increases with the increase of the number of UASs. This behavior is explained by understanding that the number of slots in the network increase by increasing the number of UASs. Consequently, the aggregate throughput is increased. Fig. 5(b) gives the fairness index of both energy efficiency and aggregate throughput. It can be seen that the proposal can maintain fairness well above the fairness criterion for large topology sizes.

In conclusion, the simulation results show that our proposed game-theoretic data collection method is capable of improving the fair network energy efficiency for UAS-aided networks, comprising M UASs and N adaptive modulation capable CHs.

TABLE IV
UAS' POSITIONS.

M	**Inter-UAS x-displacment**	**Inter-UAS y-displacment**
2	10000 m	7500 m
4	10000 m	5000 m
6	7500 m	5000 m
8	6000 m	5000 m
10	5000 m	5000 m

VII. CONCLUSION

In this paper, we proposed a method to improve energy efficiency while ensuring fairness in multiple UAS-aided networks with adaptive modulation. The considered UAS-aided network comprises M UASs and N CHs. Furthermore, for the mobility pattern of UASs, we showed how adaptive modulation behaves. We formulated the problem by using the framework of potential games. Additionally, we substantiated the properties of the game that guarantee the efficiency of the obtained solution such as stability, optimality, and convergence. A game-theoretic data collection method was proposed to improve the energy efficiency while taking into consideration of the fairness in UAS-aided networks using the formulated game. Moreover, we analyzed the PoA of our proposed data collection method. Finally, extensive simulations were conducted to evaluate the performance of our proposed method. Our results could validate that the proposed game-theoretic method could provide near optimal performance in terms of network energy efficiency. In conclusion, we should that our proposed game-theoretic method can improve the network energy efficiency while taking account of fairness. For our future work, we are aiming to study more strategies for enhancing network performance in UAS-aided. These include changes of trajectory to respond to urgent needs in the network. This optimization can be undertaken by studying the effect of UAS radius and UAS position on network performance.

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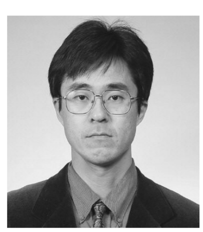

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