

Research Article

Strategic Availability and Cost-Effective UAV-Based Flying Access Networks: S-Modular Game Analysis

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Nowadays, ubiquitous network access has become a reality, thanks to Unmanned Aerial Vehicles (UAVs) that have gained extreme popularity due to their flexible deployment and higher chance of line-of-sight links to ground users. Telecommunication service providers deploy UAVs to provide areal network access in remote rural areas, disaster-affected areas, or massive-attended events (sport venues, festivals, etc.), where full setup to provide temporary wireless coverage would be very expensive. Of course, a UAV is battery-powered with a limited energy budget for both mobility aspect and communication aspect. An efficient solution is to allow UAVs switching their radio modules to the sleep mode in order to extend the battery lifetime. This results in temporary unavailability of communication feature. Within such a situation, the ultimate deal for a UAV operator is to provide a cost-effective service with acceptable availability. This would allow meeting some target quality of service while having a good market share granting satisfactory benefits. In this article, we exhibit a new framework with many interesting insights into how to jointly define the availability and the access cost in UAV-empowered flying access networks to opportunistically cover a target geographical area. Yet, we construct a duopoly model to capture the adversarial behavior of service providers in terms of their pricing policies and their respective availability probabilities. Optimal periodic beaconing (advertising the presence of the UAV) is to be addressed, given the UAVs with limited battery capacity and their recharging constraints. A full analysis of the game, both in terms of equilibrium pricing and equilibrium availability, is derived. We show that the availability-pricing game exhibits some nice features as it is submodular with respect to the availability policy; whereas, it is supermodular with respect to the service fee. Furthermore, we implement a learning scheme using best response dynamics that allows operators to learn their joint pricing-availability strategies in a fast, accurate, and distributed fashion. Extensive simulations show convergence of the proposed scheme to the joint pricing-availability equilibrium and offer promising insights into how the game parameters should be chosen to efficiently control the duopoly game.

1. Introduction

In the recent few years, Unmanned Aerial Vehicles (UAVs), or drones, have attracted a lot of attention, since they present advantages of ubiquitous usability, high maneuverability, and low-cost deployment. UAVs, equipped with navigation systems and smart sensors, are currently being deployed for surveillance operations, rescue missions, and rapid on-demand communication. Along with the maturity of the UAVs technology and relevant regulations, they have become an important market, where a UAVs worldwide deployment is expected. For instance, the registered number of UAVs in use in the U.S. exceeds 200,000 just in the first 20 days of January 2016, after the Federal Aviation

Administration (FAA) started requiring owners to sign up [1]. Indeed, UAVs can be deployed fruitfully to support cellular communication systems when terrestrial infrastructure networks are damaged. Moreover, it supports wireless communication in exceptional scenarios such as hard to reach rural areas, festivals or sporting events, and emergency situations where the terrestrial base stations installation may be too expensive. In this context, UAVs as flying base stations have been reported as a promising approach that can boost the capacity and coverage performance of existing wireless networks. Using UAVs as aerial base stations provides several benefits such as high maneuverability and robustness, flexible deployment, and efficiency on demand telecommunication and also mobility [2].

Thanks to their high mobility and air location, UAVs are likely to have good communication channel since the UAV-ground link is more likely to have Line-of-Sight (LoS) links [3]. Furthermore, UAVs provide unlimited telecommunication applications for their advantage to efficiently sense information about the surrounding environment. They are now a key technology for intelligence, recognition, search, inspection tasks, surveillance, public services, and so on. Another key feature of UAVs is the Internet of Things (IoT) which is a technological revolution that has made the leap from conceptual to actual [4, 5]. IoT enables devices to exchange data and interoperate within the internet infrastructure, which affords ubiquitous connectivity while reducing the transmission cost and providing extended range for low-power communication. Technically, UAVs play an important role in the Internet of Things' vision. It offers flexible deployability and reprogramming in mission possibilities to deliver numerous operating solutions and services, for IoT partners.

While deploying drones as flying base stations offers numerous advantages, still a number of economic and technical challenges arise. These challenges comprise not only technical and physical issues but also effective pricing and availability of management features. Yet, for UAVs service providers to overcome these relevant challenging issues, availability or beaconing scheduling becomes a very important but largely unexplored topic. For this, comprehensive modeling and performance analysis of UAV's setups has become extremely attractive. In this article, we provide a UAV's joint pricing and availability problem, considering their limited battery capacity. We focus on the scheduling of availability periods as a key enabler that can potentially lead to better energy efficiency and then, to a better long-term availability (lifetime) as well as a satisfactory quality of service. More precisely, we are interested in the joint pricing-availability problem for the UAV-based network market. Then, we design a new scheme that jointly considers and solves the UAV's pricing and energy-efficient issue.

In order to address these issues, we examine the availability and pricing interactions between service providers as a noncooperative game. We propose a duopoly setup, where a finite network of mobile unmanned aerial vehicles is deployed according to a homogeneous Poisson Point Processes (PPP) and serving a number of ground IoT devices. The UAVs are moving according to a Random Way Point (RWP) model. As a first proposal, we derive the coverage probability expression as well as the service probability for each UAV in the current scenario. In order to achieve the maximum system performance in terms of pricing policy and energy efficiency, our proposal introduces the Nash equilibrium analysis. Furthermore, we propose a learning automaton to derive the joint price-availability equilibrium. Finally, we provide extensive numerical simulations to highlight the importance of taking price-availability as a joint decision parameter and provide thereby important insights/heuristics into how to set them.

The remainder of this article is organized as follows. In Section 2, we give an overview of the proposed UAVs duopoly system model and strategic pricing-availability. In

Section 3, we present the availability game analysis, existence, and uniqueness of NE solution and also define the game submodularity characteristics. Furthermore, the pricing game is provided in Section 4; the property of supermodularity was discussed mathematically as well analytically. Section 5 considers a joint availability-pricing approach with numerical learning implementations, and we further gave the impact on some important parameters on the learning process. Finally, Section 6 concludes the paper.

2. Related Work

A significant existing literature investigates interesting features on UAVs technological performance and reducing cost. For instance, the authors in [6] study energy-efficient UAV communication via optimizing the UAV's trajectory; for this, they consider a UAV trajectory with general constraints, under which the UAV's flight radius and speed are jointly optimized. An important study of the UAV's obstacle avoidance plan is conducted in [7], where the writers propose algorithm based on Iterative Regional Inflation by Semidefinite in order to improve the fighting efficiency. A useful derivative-free one, Sliding Mode Control (SMC) theory-based learning algorithm, for the control and guidance of a UAV is proposed in [8]. Robustness, in real-time applications and finite-time convergence, was proven through intensive simulations. Another learning approach is treated in [9], where the authors provide a thorough review on deep learning methods for UAVs, including the most relevant developments as well as their performances and limitation. An important issue which is IoT applications is discussed [10]. This paper investigates the efficient deployment and mobility of multiple unmanned aerial vehicles, in order to enable reliable uplink communications for the IoT devices with a minimum total transmit power. Another IoT-related work is in [11], and it presents the features that a UAV system should implement for drone traffic management, namely, the air traffic control network, the cellular network, and the Internet. In [12], the authors introduce different classifications of Internet of Things with examples of utilizing IoT technologies. They refer to the concept of global-scaled IoT, where using unmanned aerial vehicle offers a large coverage and more flexibility, thanks to the mobility approach. The UAV-based IoT concept has been further studied in the paper [13], which provides a comprehensive survey on the UAVs and the related issues. It highlights potential for the delivery of UAV-based value-added IoT service from height.

3. Availability-Pricing Game among UAV Operators

3.1. The Flying Access Network Framework

3.1.1. Coverage Probability. Consider a circular geographical area with a radius R within which a number N of wireless users are deployed according to a homogeneous Poisson point processes with density of u (number of users per m^2). In this

area, a set of UAVs moving randomly according to a random waypoint mobility model are used as aerial mobile base stations to provide wireless service for the ground IoT devices (Figure 1). The drones are belonging to different operators and are engaged to provide an effective coverage for mobile IoT users. In this setting, the drones have the same characteristics such as altitude h , total available bandwidth, and maximum transmit power.

The coverage probability is formally defined as follows:

$$P_u^{\text{cov}}(\gamma_u) = \mathcal{P}(\gamma_u \geq \beta), \quad (1)$$

where $\gamma_u = P_u / (N + I)$ is the SINR expression for a device user that connects to the UAV, P_u is the received signal power from the UAV including fading and path loss, N is the noise power, I is the total interference power from existing transmitters, and β refers to the SINR threshold.

According to [14], for an uplink user located at (r, ϕ) , the coverage probability is given by the following equation:

$$P_u^{\text{cov}}(r, \phi, \beta) = P_{\text{LoS}}(r, \phi) \mathbb{1}\left[r \leq \left(\frac{P_u}{\beta N}\right)\right] + P_{\text{NLoS}}(r, \phi) \mathbb{1}\left[r \leq \left(\frac{\eta P_u}{\beta N}\right)\right], \quad (2)$$

where r and ϕ are the radius and angle in a polar coordinate system, and the UAV is located at the center of the area of interest. P_{LoS} , respectively, P_{NLoS} are the line-of-sight, respectively, non-line-of-sight probabilities.

The average coverage probability is computed by taking the average of $P_u^{\text{cov}}(r, \phi, \beta)$ over the area with the radius R :

$$\begin{aligned} P_u^{\text{cov}}(r, \phi, \beta) &= [E]_{r, \phi} [P_u^{\text{cov}}(r, \phi, \beta)] \\ &= \int_0^{\min[(P_u / (\beta N))^{\frac{1}{\alpha_u}}, R]} P_{\text{LoS}}(r, \phi) \frac{2r}{R^2} dr \\ &\quad + \int_0^{\min[(\eta P_u / (\beta N))^{\frac{1}{\alpha_u}}, R]} P_{\text{NLoS}}(r, \phi) \frac{2r}{R^2} dr, \end{aligned} \quad (3)$$

where α_u is the path loss exponent over the user-UAV link, η is an additional attenuation factor due to the NLoS connection, and P_u is the UAV transmit power.

The air-to-ground signal propagation is almost affected by obstacles in the surrounding environment. Thus, a common approach for channel modeling between the UAV and down-link users is based on probabilistic direct line-of-sight (LoS) and non-line-of-sight (NLoS) links. Whereby each link may occur with a specific probability which depends on the propagation environment, the UAV and users locations, and the elevation angle (here, θ).

In this scenario, we suppose designing a UAV-based communication system in a remote rural area where full setup to provide temporary wireless coverage would be very expensive. Due to its higher altitude and the low average height of building in hard to reach rural areas, UAV has higher probability of direct line-of-sight links to ground users. The probability of the NLoS component occurrence is

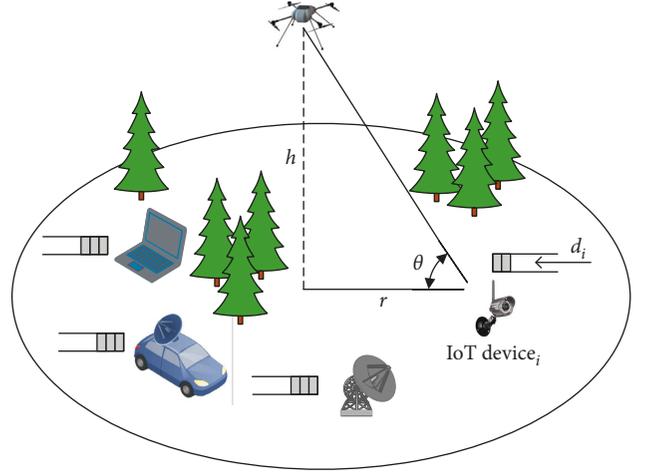


FIGURE 1: Using UAV for ubiquitous network access in IoT environments.

therefore significantly lower than that of the LoS component. For simplicity, we ignore the small scale NLoS, and as evident, the coverage probability formula would be significantly simplified as follows:

$$P_u^{\text{cov}}(r, \phi, \beta) = \int_0^{\min[(P_u / (\beta N))^{\frac{1}{\alpha_u}}, R]} P_{\text{LoS}}(r, \phi) \frac{2r}{R^2} dr. \quad (4)$$

3.1.2. Service Probability. Given the limited capacity and recharging difficulties of a UAV battery, periodic beaconing is one of the most challenging problems that need to be addressed. Each UAV i is periodically sending beacons of duration τ_i advertising this presence to mobile IoT devices. The beacon/idle cycle is periodically repeated every time slot T during a time window: $m = l * T$ (Figure 2). UAVs should define their beaconing periods strategically in order to maximize their encounter rate with the IoT ground users. However, they should avoid battery depletion resulting from maintaining useless beaconing in the absence of contact opportunities.

The first encounter follows an exponential distribution with a random parameter λ . In order for a UAV i to encounter first the ground IoT destination at time τ_i , the following conditions must hold:

- (i) The UAV i has to be beaconing at τ_i .
- (ii) All potential encounters with ground destination, happening before the time instant τ_i , by the other UAVs need to be unsuccessful. In other words, the encounters need to happen while UAV i 's competitors are inactive.

Consequently, the successful contact probability is given by the following equation:

$$P_i^{\text{srv}} = [P(T_i \leq T_j) + P(T_i \geq T_j) \cdot P_j^{\text{slp}}] \cdot P_i^{\text{bcn}} \cdot P_i^{\text{cov}}. \quad (5)$$

For mathematical calculations, we focus on the case of two operators (UAV _{i} and UAV _{j}), and this minimizes

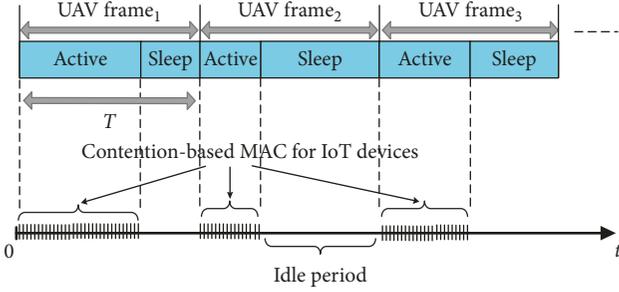


FIGURE 2: Beaconsing cycle schedule.

mathematical complication but still allows us to analyze the important features of operators strategies. We define the probability of UAV_{*i*} beaconsing while encountering for the first time the destination within $[0; m]$:

$$P_i^{\text{bcn}} = \sum_{s=0}^{l-1} \left(\int_{s*T}^{s*T+\tau_i} \lambda_i e^{-\lambda_i x} dx \right) \quad (6)$$

$$= - \frac{e^{\lambda_i T} (e^{-m\lambda_i} - e^{-\lambda_i(m+\tau_i)} - 1 + e^{-\lambda_i \tau_i})}{e^{\lambda_i T} - 1}.$$

For a UAV_{*i*}, the probability of being idle is given by the following equation:

$$P_i^{\text{slp}} = \sum_{s=0}^{l-1} \left(\int_{s*T+\tau_i}^{(s+1)*T} \lambda_i e^{-\lambda_i x} dx \right) \quad (7)$$

$$= \frac{e^{\lambda_i T} (-e^{-\lambda_i(m+\tau_i)} + e^{-\lambda_i(m+T)} + e^{-\lambda_i \tau_i} - e^{-\lambda_i T})}{e^{\lambda_i T} - 1}.$$

The probability that UAV_{*i*} encounters first the ground destination without accounting for its state (probing/idle) is expressed as follows:

$$P(T_i \leq T_j) = \frac{\lambda_j e^{-m(\lambda_i+\lambda_j)} + (-\lambda_i - \lambda_j) e^{-\lambda_j m} + \lambda_i}{\lambda_i + \lambda_j}. \quad (8)$$

And finally, we define the probability that UAV_{*i*} encounters first the ground destination without accounting for its state:

$$P(T_i \geq T_j) = \frac{\lambda_i e^{-m(\lambda_i+\lambda_j)} + (-\lambda_i - \lambda_j) e^{-\lambda_i m} + \lambda_j}{\lambda_i + \lambda_j}. \quad (9)$$

3.2. The Game Formulation

3.2.1. Customers Behavior. Most telecommunication markets are oligopolistic, this means, dominated by a certain number of service providers called oligopolists. In order to maximize benefits, the competition between service providers is becoming increasingly tough. From an oligopolist's point of view, increasing market share is the most important objective. Thus, service providers are supposed to define the optimal pricing policy, and the best QoS (represented by availability) requested in order to attract more and more customers. Because customers are rational by nature, they are likely to

register to an operator rather than the others or to stay at no subscription state according to their own satisfaction (service price, quality of service, and quality of experience).

In this paper, we assume a duopoly telecommunication market where just two service providers compete against one another to provide service for IoT ground users. Each UAV *i* belonging to SP *i* picks its availability duration τ_i represented by the periodic beaconsing time chosen within the interval $[0, T]$ and a service fee per data unit $f_i \in [0, f_{\max}]$. Formally, SPs are intelligent individuals in conflict, and this situation is involving rational decisions.

The noncooperative game theory provides the appropriate tools for determining optimal behavior in such competitive environments. It provides mathematical methodology for modeling and analyzing interactions between intelligent rational players in conflicts of interest. This branch of game theory deals largely with how intelligent individuals interact with one another in an effort to achieve their own goals. Players are selfish, and each individual player makes decisions independently without forming alliances.

We capture the pricing-availability interaction among two UAV operators as a normal form game. Each SP seeks to choose the level of service allowing a reasonable battery lifetime while maximizing its monetary profits, given the action of the competitor. The noncooperative game is formally defined as follows:

$$\mathcal{G} = \langle \mathcal{N}, \mathcal{A}, \mathcal{U} \rangle, \quad (10)$$

where

- (i) $\mathcal{N} = \{1, 2\}$ is the set of players (UAV operators)
- (ii) $\mathcal{A} = \{[0, T] \times [0, f_{\max}]\}^2$ is the strategy space of both UAV operators
- (iii) $\mathcal{U} = (U_1, U_2)$ is the vector of payoffs defined as the difference between their respective profits and costs.

Increasing the experienced market demand is the most important objective of each operator. Then, from an operator perspective, the question is to define the best beaconsing duration and the best pricing policy that attracts a high portion of subscribers. Ideally, one UAV would like to simultaneously maximize the proposed fee and minimize the total consumed energy. However, these are two conflicting objectives, since ground users are likely to be rational. Inspired by the logit model [15], we model the probability π_i that a given IoT device is registering with the service provider *i* which can also be seen as the market share of a UAV_{*i*}. The demand function follows an exponential distribution with the parameter μ . This last parameter is called the constant hazard or temperature, which defines the users' rationality, so that, the higher is μ , the less users are rational:

$$\pi_i = \frac{\exp(-(f_i/\mu))}{\sum_{j=1}^2 \exp(-(f_j/\mu))}. \quad (11)$$

The average number of customers that are registering to UAV *i* is $N \cdot \pi_i$. Because UAVs compete in quality of service and price, it seems to be obvious that the experienced demand depends on these parameters. However, it depends also on the environment variables.

3.2.2. Service Providers' Strategic Decision. We are interested in the problem of optimal pricing-beaconing in the fixed-wing UAVs that should avoid battery depletion resulting from maintaining useless activity duration in the absence of contact with the ground. We propose a new design paradigm that considers both the UAV's pricing and energy-efficient problems.

The UAV is periodically sending beacons advertising the presence to mobile users on the ground. From the UAV perspective, there are trade-offs between the strategic parameters τ and energy consumption. On one hand, as the beacon duration increases, the coverage chance P_{cov} as well as the service probability increase. On the other hand, total energy consumption is mainly proportional to the activity period duration. The same applies for the service price, where increasing the pricing policy value may increase revenues, but in the same time, it negatively affects the experienced market demand. Here, the strategy space and the reward are common knowledge; however, the chosen beaconing period and taxed fee are not since decisions are taken simultaneously. The utility of each UAV SP is a function of its own strategy as well as the decisions of the other:

$$U_i(\tau_i, \tau_j, f_i, f_j) = \pi_i \sum_{\text{IoT}_i \in \mathcal{R}_i} P_i^{\text{srv}}(\tau_i, \tau_j) \cdot f_i - E_i, \quad (12)$$

where E_i is the dissipated energy for a UAV $_i$:

$$E_i = \left[\left(1 - \prod_{i \in \mathcal{R}_i} (1 - p_u) \right) \cdot \varepsilon_r + \sum_{u \in \mathcal{R}_i} \theta_{u,i} \varepsilon_{\text{Ack}} \right] \cdot P_i^{\text{srv}} + \varepsilon_b \cdot \pi_i(\tau) + \varepsilon_s, \quad (13)$$

where $\theta_{u,i} = p_u \prod_{k \neq u} (1 - p_k)$ is the normalized throughput of the user u served by a UAV $_i$, ε_b is the energy cost per slot for sending beacons, ε_r is the reception energy, ε_{Ack} is the transmission energy cost, ε_s is the unit energy for remaining switching the transceiver status, and $\mathcal{R}_i = (\text{User}_u, d(\text{User}_u, \text{UAV}_i) \leq r)$ is the set of ground IoT devices served by the given drone i .

4. Availability Game with Fixed Fee

In literature, the pricing scheduling is almost the key parameter that affects straightly operators' revenues. However, the realism of this assumption is sometimes questioned [16]. Indeed, similar market price may affect the customers' perceptions about the UAVs' availability and then their loyalty. Due to a rough competition, availability has started to become an important strategic tool for operators to expand their market share. We examine energy-efficient-pricing trade-offs within a noncooperative game framework. This incites operators to make efforts in providing better QoS while fixing optimal periodic advertising beacons. The proposed approach is realistic enough to analyze the interplay of availability on service providers' revenues. The problem is then, to determine for each UAV, the optimal availability (beaconing period) while rival behaves optimally, and this represents exactly the Nash equilibrium status.

Recall that the Nash equilibrium strategy is the best response of each UAV to the expected best response behavior of the other.

Proposition 1. *The availability game admits at least one Nash equilibrium.*

Proof 1. To show the existence of an equilibrium, the sufficient condition is the quasiconcavity of the utility function. We notice that the strategy set $[0; T]$ is a convex, close, and compact interval. Furthermore, the utility function is continued with respect to τ_i . In addition, we show that the second derivative with τ_i is negative. After calculation, the second derivative is expressed as follows:

$$\frac{\partial^2 U_i(\tau_i, \tau_j)}{\partial \tau_i^2} = \frac{\partial^2 P_i^{\text{srv}}(\tau_i, \tau_j)}{\partial^2 \tau_i} (N f_i \pi_i - \psi_i), \quad (14)$$

where

$$\psi_i = \left[\left(1 - \prod_{i \in \mathcal{R}_i} (1 - p_u) \right) \cdot \varepsilon_r + \sum_{u \in \mathcal{R}_i} \theta_{u,i} \varepsilon_{\text{Ack}} \right]. \quad (15)$$

It has been easily proven that the second derivative of the service probability with respect to τ_i is of negative sign, and therefore, for the second derivative to be negative, it could be sufficient to make sure that the following condition fulfills:

$$N f_i \pi_i - \psi_i \geq 0. \quad (16)$$

This condition seems logical since the demand is positive, and each operator requires a certain demand threshold as an incentive to deploy a drone resource; this means that for a UAV operator to be motivated to coverage a certain area, the minimum required demand equals at least the cost of energy that is going to waste. From this, the utility function of a UAV i belonging to an operator i is quasiconcave, and then admits a local optimum point at τ_i^* which is its best response against strategies of other operators. \square

Proposition 2 (*uniqueness of availability-termed Nash equilibrium*). *The availability game is dominance solvable [17] and consequently satisfies Rosen's diagonal strict concavity condition. Henceforth, it has a unique Nash equilibrium.*

Proof 2. The dominance solvability condition is given by the following equation:

$$-\frac{\partial^2 U_i(\tau_i, \tau_j)}{\partial \tau_i^2} - \left| \frac{\partial^2 U_i(\tau_i, \tau_j)}{\partial \tau_j \partial \tau_i} \right| \geq 0, \quad (17)$$

where

$$\frac{\partial^2 U_i(\tau_i, \tau_j)}{\partial \tau_i^2} = \frac{\partial^2 P_i^{\text{srv}}(\tau_i, \tau_j)}{\partial^2 \tau_i} (N f_i \pi_i - \psi_i), \quad (18)$$

$$\frac{\partial^2 U_i(\tau_i, \tau_j)}{\partial \tau_i \partial \tau_j} = \frac{\partial^2 P_i^{\text{srv}}(\tau_i, \tau_j)}{\partial \tau_i \partial \tau_j} (N f_i \pi_i - \psi_i). \quad (19)$$

The dominance solvability conditions are verified and consequently the concave game \mathcal{G} satisfies Rosen's diagonal strict concavity condition for the uniqueness of the Nash equilibrium.

Interactions among UAVs in this noncooperative game have a very attractive property, if one UAV reduces its availability (beaconing period) and the other UAV also has an interest in decreasing its own. Informally, this type of games led us to conclude that it is about submodular games. \square

Lemma 1. *The game \mathcal{G} with N mobile devices and two UAVs service providers is submodular.*

Proof 3. To prove the submodularity of the game, we compute the second-order mixed derivative of $U_i(\cdot)$ with respect to two beaconing durations τ_i and τ_j . With the mixed derivative expression given in (19), it is straightforward to conclude that it is effectively about a submodular game.

With submodularity, the best response of a UAV is a decreasing function of the other UAV availability strategy (beaconing period). Consequently, this game possesses unique equilibria that the best response dynamic learning scheme can reach with probability 1. \square

5. Pricing Game with Fixed Availability Period

Despite the several advantages of availability competition, still the price is a more common strategical decision in telecommunication business. This motivates us to investigate the pricing game with the fixed availability parameter. We argue in this section that operators set prices and let the consumers decide on their experienced demand. That is, each operator is maximizing its profit believing that its competitor is doing the same. Conceptually, this situation is a typical Bertrand–Nash equilibrium (see papers in [18, 19]). We turn first to mathematically analyze the equilibrium existence.

Proposition 3. *The pricing game admits at least one Nash equilibrium.*

Proof 4. The strategy set represented in $[0; f_{\max}]$ is a convex, closed, and compact interval. In addition, the utility function is continuous with f_i . Furthermore, we show that the second derivative with respect to f_i has a negative sign. After calculation,

$$\begin{aligned} \frac{\partial \pi_i(f_i, f_j)}{\partial f_i} &= -\frac{(1/\mu)\exp(-f_i/\mu)\exp(-f_i/\mu)}{[\exp(-f_i/\mu) + \exp(-f_i/\mu)]^2} \\ \frac{\partial^2 \pi_i(f_i, f_j)}{\partial f_i^2} &= \frac{\exp(-f_i/\mu)\exp(-f_i/\mu)[\exp(-2f_i/\mu) - \exp(-2f_i/\mu)]}{\mu^2 [\exp(-f_i/\mu) + \exp(-f_i/\mu)]^4}. \end{aligned} \quad (20)$$

The second-order derivative is expressed as follows:

$$\begin{aligned} \frac{\partial^2 U_i(f_i, f_j)}{\partial f_i^2} &= N \cdot P_i^{\text{srv}}(\tau_i, \tau_j) \cdot \left[2 \frac{\partial \pi_i}{\partial f_i} + f_i \frac{\partial^2 \pi_i}{\partial f_i^2} \right] \\ &= \frac{N \cdot P_i^{\text{srv}} \exp(-f_i/\mu)\exp(-f_i/\mu)}{\mu (\exp(-f_i/\mu) + \exp(-f_i/\mu))^2} \\ &\quad \cdot \left[\frac{f_i (\exp(-2(f_i/\mu)) - \exp(-2(f_i/\mu)))}{\mu (\exp(-f_i/\mu) + \exp(-f_i/\mu))^2} - 2 \right], \end{aligned} \quad (21)$$

which is clearly negative. Hence, the profit function of each UAV is quasiconcave with respect to its own fee and then the NE existence. \square

Proposition 4 (uniqueness of price-based Nash equilibrium). *The pricing game has a unique Nash equilibrium.*

Proof 5. The utility function satisfies the dominance solvability conditions and consequently satisfies Rosen's conditions, which is defined as follows:

$$\begin{aligned} -\frac{\partial^2 U_i(f_i, f_j)}{\partial f_i^2} - \left| \frac{\partial^2 U_i(f_i, f_j)}{\partial f_j \partial f_i} \right| \\ = \frac{N \cdot P_i^{\text{srv}} \exp(-f_i/\mu)\exp(-f_i/\mu)}{[\exp(-f_i/\mu) + \exp(-f_i/\mu)]^2} \geq 0. \end{aligned} \quad (22)$$

A remarkable property of this game is that when one player picks a higher action, the others have incentive to follow and do the same. Roughly, this introduces the notion of a supermodular game characterized by strategic complementarities. \square

Lemma 2. *The game \mathcal{G} with N mobile devices and two UAVs service providers is supermodular.*

Proof 6. To prove the supermodularity of the game, we compute the second-order mixed derivative of U_i with respect to its proposed fee and that of its competitors (f_i and f_j). With the following mixed derivative expression, which is clearly of a positive sign, we argue that it is a supermodular game:

$$\frac{\partial^2 U_i(f_i, f_j)}{\partial f_j \partial f_i} = \frac{N \cdot P_i^{\text{srv}} \exp(-f_i/\mu) \exp(-f_j/\mu)}{\mu [\exp(-f_i/\mu) + \exp(-f_j/\mu)]^2} \cdot \left(1 - \frac{f_i [\exp(-2(f_j/\mu)) + \exp(-2(f_i/\mu))]}{\mu [\exp(-f_i/\mu) + \exp(-f_j/\mu)]^2} \right). \quad (23)$$

Supermodularity tends to be analytically appealing. An interesting property is that it behaves well under various learning rules. Furthermore, convergence towards the Nash equilibrium point is guaranteed under best response dynamics. \square

6. Joint Pricing-Availability Game

6.1. Insights into Real-World Implementation: Fully Distributed Learning. Learning is a fundamental component of intelligence and cognition; it is defined as the ability of synthesizing the acquired knowledge through practice, training, or experience in order to improve the future behavior of the learning agent. In this section, we introduce a learning scheme [20, 21] aiming to understand the behavior of users during the interactions and to reach the eventual convergence towards Nash Equilibrium. The goal is that UAV's service providers learn their own payoffs and determine the NE joint availability-pricing strategy. To accomplish this, the best response algorithm is a suitable class; it leads to a Nash equilibrium status by exploiting fast monotony of best response functions. In fact, the NE concept is implicitly based on the assumption that players follow best response dynamics until they reach a state from which no player can improve his utility by changing unilaterally his strategy [22].

Algorithm 1 summarizes the best response dynamics that each service provider performs in order to converge to the game Nash equilibrium. The best response strategy of a player is defined as its optimal one, given the strategies of the other players. At a time iteration t , each service provider chooses the best joint availability-pricing strategy against the opponents strategies chosen at the previous round t_{-1} . It is worth to notice that convergence of the best response dynamics is granted for s-modular games [23].

The best response algorithm exhibits enormous advantages as it offers an accurate and fast convergence to the unique Nash equilibrium point. We say UAVs learn to play an equilibrium, if after a given number of iterations, the strategy profile converges to an equilibrium status.

6.2. Numerical Investigations. The pricing-availability best response learning results are provided using MATLAB software. Parameters used in the simulation are set based on typical values such as $T = 1$, $m = 100$, $f_{\min} = 0$, and $f_{\max} = 10$. Here, we will analyze the impact of the various parameters especially market temperature, coverage probability, and encounter rates on the Nash equilibrium price as

well as the provided QoS (measured by beaconing periods) for both competitors.

Under this setup, Figure 3 illustrates the behavior of service providers under the best response algorithm and the convergence towards the Nash equilibrium price with time iterations. Here, we consider symmetric operators with randomly generated initial points. A smaller temperature μ value means that consumers are more and more rational, so that the operators' NE price tends towards lower values. Indeed with $\mu = 2$, the NE price is absolutely zero ($=f_{\min}$). However, when μ becomes greater (consumers are less rational), the NE price arises and reaches its maximal value with $\mu = 6$. The same applies to Figure 4, where we depict the convergence of Algorithm 1 towards Nash equilibrium beaconing periods with different values of μ . It is worth noting that the best response algorithm converges accurately and rapidly to the Nash equilibrium point. This feature is required in efficiently designing such a mechanism in realistic systems. With $\mu = 2$, the τ^* is zero; however, τ^* is increasing with μ . By linking that with the NE price analysis, we can say that, with an increasing availability periods, the operators propose greater prices. This shows that higher quality of service (linked to network availability) incurs additional cost.

We depict in Figures 5 and 6 the individual best response prices, respectively, beaconing periods for two asymmetric UAVs. Each UAV has a different coverage probability value (may be due to high parameter, for example). Counterintuitively, Figure 5 shows that the NE price does not depend on the coverage probability. Even with different coverage probabilities, the two competitors converge towards the same equilibrium price; this last value is increasing with UAV's coverage which is quite intuitive.

Figure 6 depicts convergence to the equilibrium beaconing time under different values of coverage probabilities and different rational levels. It is worth noticing that, the UAV with greater coverage converges to a higher beaconing NE value, thus, offers a better QoS (availability service). We exclude from this analysis the case with a small value of the parameter μ , where the two operators converge to null values. Yet, the greater is the coverage (likely UAV high), the longer is the NE beaconing availability advertising periods.

Figure 7 illustrates the impact of both μ and the encounter rate λ_i on the NE price on each UAV i in an asymmetric setup (one UAV has an encounter rate advantage over the other). We remark that, even with different encounter rates, the NE prices are the same; however, the NE with a minimum temperature is greater than that of the symmetric case.

We plot in Figure 8 the beaconing best response learning evolution for two inhomogeneous UAVs (one UAV has an encounter rate advantage over the other), and the NE beaconing periods are straightforward affected by μ as well as λ . Thus, with a greater μ and λ , the best response converge to a high value of τ^* ; however, the NE beaconing period for a UAV with smaller λ is always lower.

In order to study the evolution impact of the parameter μ on the learning results, Figures 9 and 10 illustrate the NE price and NE beaconing period versus temperature

Initialisation:
 Service Provider i initializes f_i and τ_i at random values;
Learning path:
 for $t=0, 1, 2, \dots, m$
 $(f_i^{t+1}, \tau_i^{t+1}) = \arg \max_{f_i, \tau_i} U_i^t(f_i, f_j^t, \tau_i, \tau_j^t)$
 end for

ALGORITHM 1: Best response dynamics.

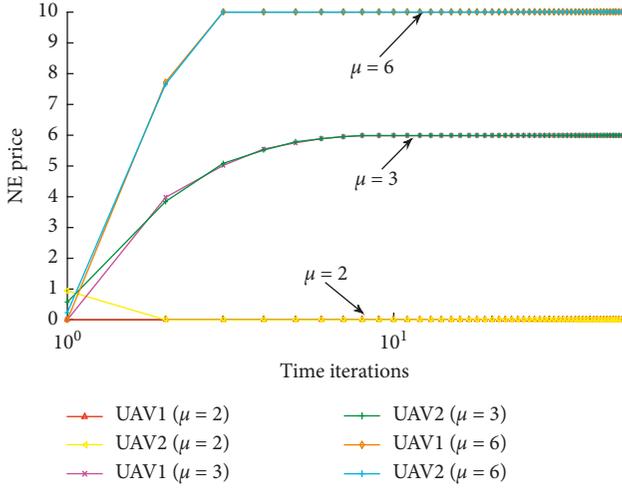


FIGURE 3: NE price with temperature parameter under best response dynamic for two homogeneous operators.

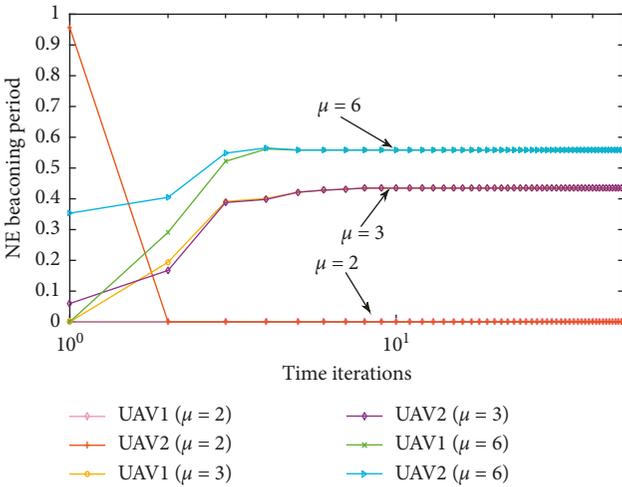


FIGURE 4: NE beaconing period with temperature parameter under best response dynamic for two homogeneous operators.

parameter for two symmetric UAVs and different IoT population sizes, respectively. The results in Figure 9 show that with temperature parameter smaller than a certain threshold (for example, $\mu = 2$ for $N = 50$), the NE price is in its minimum value, and from this point, the price is increasing until the maximum price value (f_{max}) (for example, $\mu = 6$ for $N = 50$). In this figure, we argue that, with a greater population density, the price tends to converge faster to the

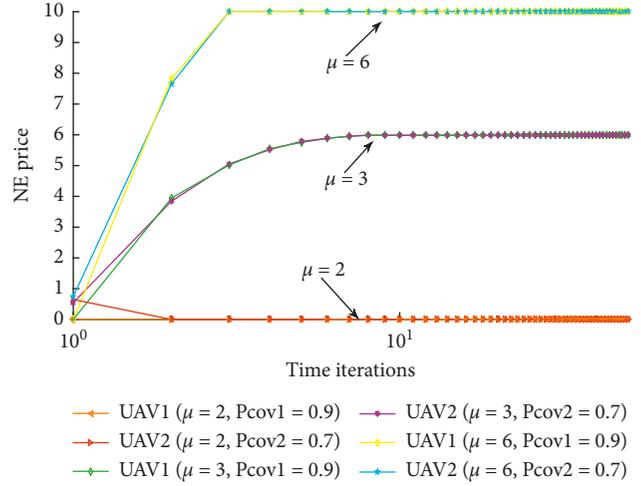


FIGURE 5: NE beaconing period under best response dynamic for inhomogeneous operators coverages.

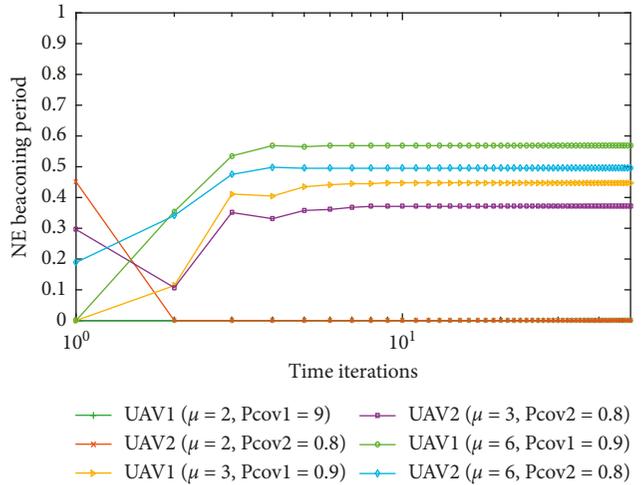


FIGURE 6: NE price under best response dynamic for asymmetric operators coverages.

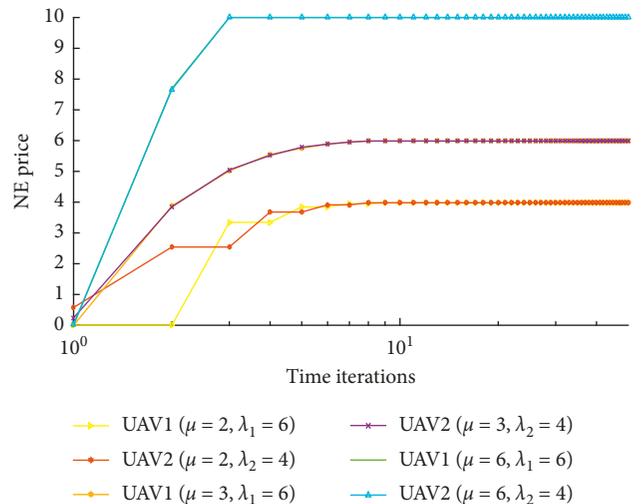


FIGURE 7: NE prices under best response dynamic for inhomogeneous operators encounter rates.

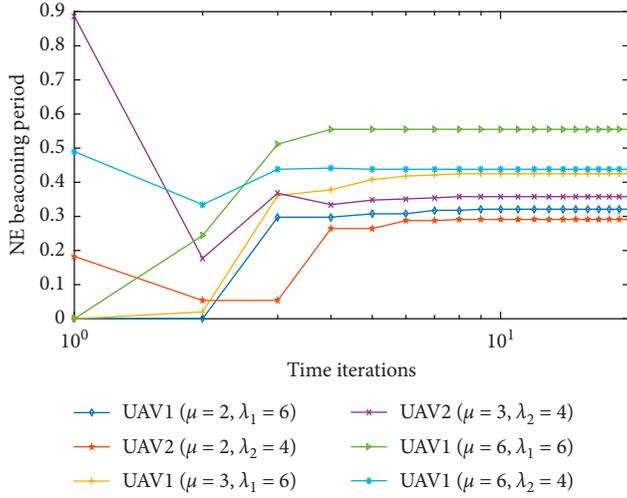


FIGURE 8: NE beaconing periods under best response dynamic for inhomogeneous operators encounter rates.

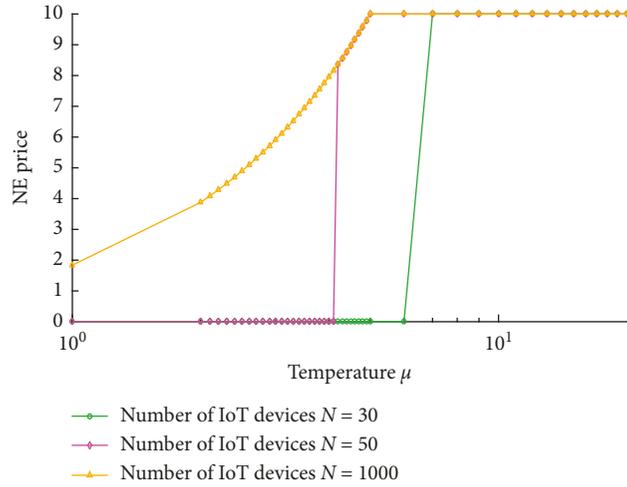


FIGURE 9: NE price evolution for operators with respect to μ in different population sizes.

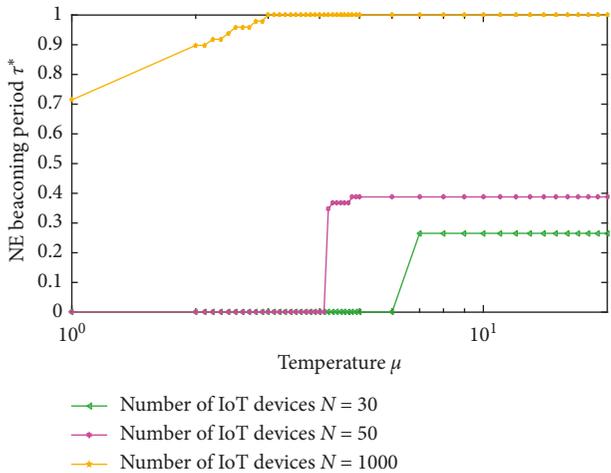


FIGURE 10: NE beaconing periods evolution for operators with respect to μ in different population sizes.

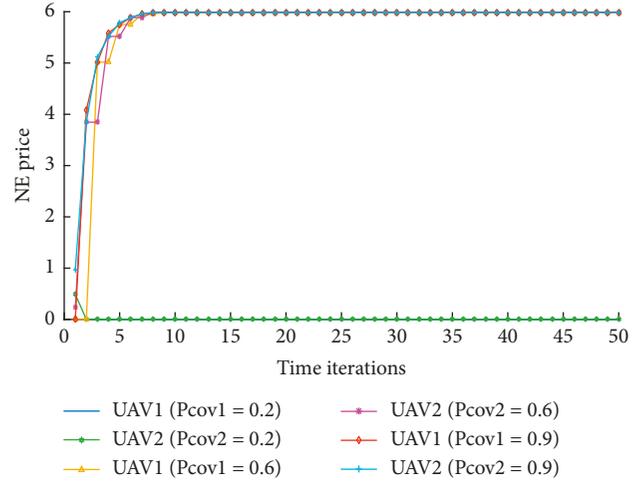


FIGURE 11: NE price with coverage probability under best response dynamic for two homogeneous operators.

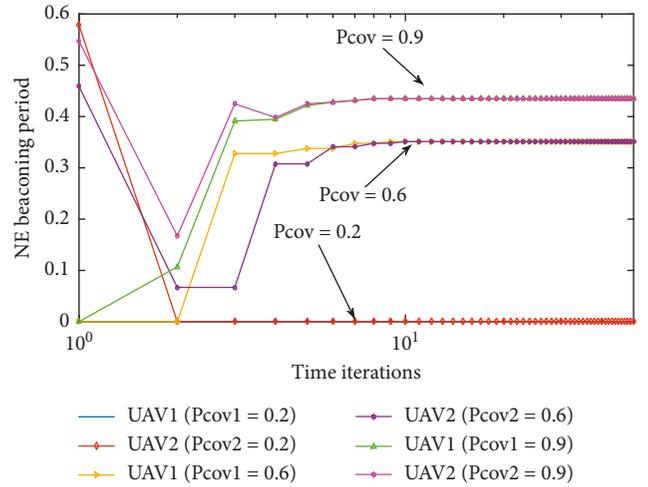


FIGURE 12: NE beaconing period with coverage probability parameter under best response dynamic for two homogeneous operators.

maximum value. These findings impact obviously the beaconing period evolution illustrated in Figure 10. With a greater population, the NE beaconing increases and reaches the equilibrium status in a smaller time window.

Pricing and beaconing learning evolution under different coverage probability values are illustrated in Figures 11 and 12, respectively. In Figure 11, the NE price is minimal with low coverage, and from a certain coverage probability value (nearly 0.6), the best strategy tends to f_{max} . However, Figure 12 shows clearly the linear impact of P_{cov} on NE beaconing strategies. This last are increasing with P_{cov} , that confirms results in Figure 5.

Figures 13 and 14 illustrate the NE price with coverage probability and NE beaconing period for two symmetric UAVs and different IoT population sizes, respectively. These two figures are provided to study the impact of coverage probability on the learning results while considering

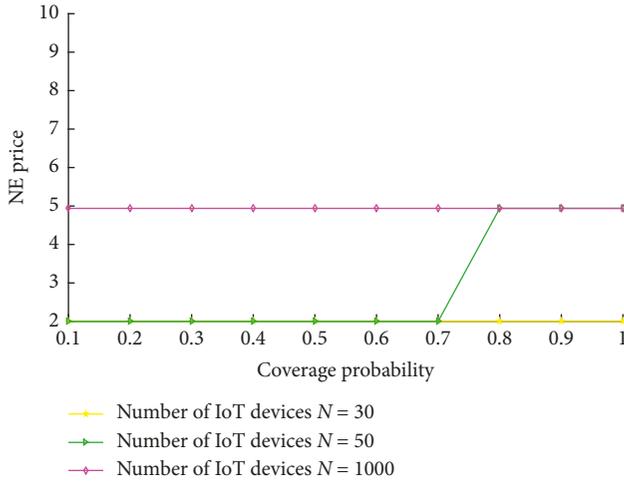


FIGURE 13: NE price evolution for operators with coverage probability and different population sizes.

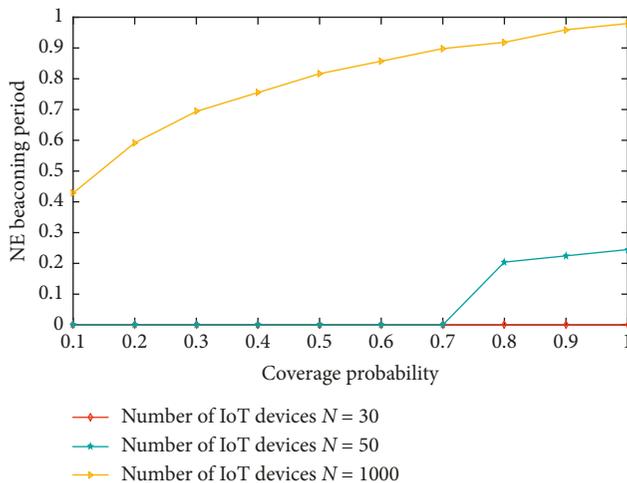


FIGURE 14: NE beaconing periods evolution for operators with coverage probability and different population sizes.

$f_{\min} = 2$. Figure 13 shows clearly the “natural” impact of population density on the service price, with a greater population that the operators can set greater prices. Furthermore, an interesting finding in Figure 14 is that, with a greater population, the NE beaconing duration is maximized, confirming thereby the results in Figure 13. It is worth mentioning how fast and accurate the proposed algorithm is for the convergence to the unique Nash equilibrium, which provides numerous insights into how to implement it and measure its effectiveness.

7. Conclusion

In this article, we deal with the pricing-availability interaction among adversarial unmanned aerial vehicles acting as flying base stations. We construct a theoretic framework based on the noncooperative game theory and characterize the equilibrium strategies for each UAV, both in terms of equilibrium fees and equilibrium availability probability.

Furthermore, a special feature is obtained as the availability game with fixed price is submodular while the pricing game is supermodular under fixed availability. Next, we check that a simple iterative best response-based algorithm allows exploring the unique Nash equilibrium of the game. Performance evaluation at equilibrium results allows UAV’s service providers to optimize their energy consumption while maximizing their monetary revenues.

As a future work, we are generalizing our proposal while considering heterogeneous mobility motions. Furthermore, some field experiments are also envisioned.

Data Availability

We hereby declare availability of all data related to our submission.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

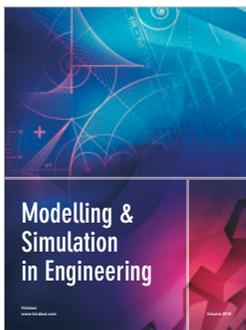
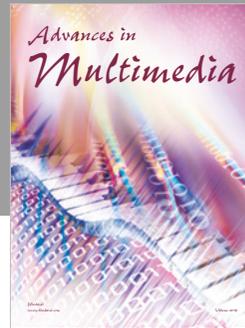
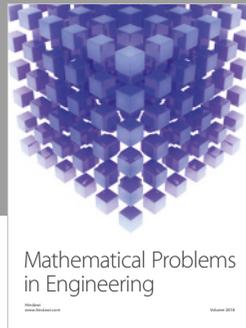
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