A Green Strategic Activity Scheduling for UAV Networks: A Sub-Modular Game Perspective

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The authors focus on the scheduling of beaconing periods as an efficient means of energy consumption optimization. The conducted study provides sub-modular game perspective of the problem and investigates its structural properties. They also provide a learning algorithm that ensures convergence of the considered UAV network to its unique Nash Equilibrium operating point.

ABSTRACT

Unmanned aerial vehicles (UAVs) were initially developed for military monitoring and surveillance tasks but found several interesting applications in the civilian domain. A promising application/technology is to use drone small cells (DSCs) to expand wireless communication coverage on demand. Rapid deployment along with limited operating costs are key factors that boost the development of DSCs for both military and civilian utilizations. DSCs are rapidly deployable to provide connectivity for temporary users (e.g. attendees of festivals, sporting events, or seminars), or over disaster areas to replace damaged communication infrastructure. UAVs are battery-powered, which makes energy consumption optimization a critical issue for acceptable performance, high availability, and an economically viable DCS deployment. In this article we focus on the scheduling of beaconing periods as an efficient means of energy consumption optimization. The conducted study provides a sub-modular game perspective of the problem and investigates its structural properties. We also provide a learning algorithm that ensures convergence of the considered UAV network with its unique Nash equilibrium operating point. Finally, we conduct extensive numerical investigations to assist our claims about the energy efficiency of the strategic beaconing policy (at Nash equilibrium).

INTRODUCTION

Unmanned aerial vehicles (UAVs) have been commonly associated with military technology suited for tactical offensive/defensive missions. However, there has been a growing interest in broadening their usage range to cover civil applications such as monitoring traffic congestion, network coverage extension, and disaster management. Drone small cells (DSCs) are envisioned to provide temporary communication coverage in areas with no or limited network capacity through deployment of UAV fleets.

Rapidly deployed, UAVs at low altitude will act as aerial base stations for providing coverage for mobile users on the ground. Thus, they will likely form a communication backbone during temporary mass events such as sports competitions, festivals, conferences, and seminars. Besides, drone small cells could substitute damaged communication infrastructure in the aftermath of disasters (e.g. earthquakes or tsunamis). Thus, different public law enforcement and safety agencies will have a reliable communication infrastructure to coordinate rescue operations and provide timely guidance to the population.

Fast deployment and effective relocation in response to demand is one major asset of UAVs without being hampered by geographical constraints inherent to on the ground deployed communication networks. This ability to relocate allows great responsiveness to mass mobility and copes with communication disruption in the wake of disasters. Self-organizing UAV networks are highly effective in providing timely communications cover for on the ground users when a spurt in communication demand occurs. Figure 1 illustrates two UAVs deployed over a geographic area to provide network coverage in areas with different mobile user densities.

The Google Loon project [1] is based on balloon deployment to provide ubiquitous networking. The balloon will be deployed in high altitude in the stratosphere to provide Internet access, especially in rural and poorly covered areas. Internet coverage will be provided for LTE-enabled devices by balloons relying on wind to relocate. The balloons form one large communications network. Facebook has the Drone project [2], its own vision for providing Internet access. The proposed architecture is a mixture of low earth orbit, geosynchronous earth orbit, and stationary drones, depending on the density of the target population. This could potentially lead content providers such as Google and Facebook to become independent Internet service providers (ISP) and circumvent existing ISPs to distribute their content.

In order to optimize the energy consumption of mobile users and the drones acting as airborne access points, we propose the use of passive scanning for the mobiles and periodic beaconing for UAVs. The problem of optimal beaconing scheduling of relocating UAVs is a constrained optimization problem. In order for UAVs to be highly responsive to user mobility, self-organization is a key feature. The latter is hampered by the centralized nature of constrained optimization solutions. Indeed, a central authority needs to

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allocate UAVs to their optimal locations, which increases the communication overhead and slows down the responsiveness to environment changes. Besides, UAVs acting as DSCs could be owned by different operators competing to provide effective coverage for mobile users and those not reporting to a central authority. UAVs are engaged in a competition to maximize their individual coverage probability of mobile users within a geographic area of interest (festival, football field, etc.). This setup can be naturally addressed using non-cooperative game theory where rational agents compete to maximize their own individual payoff. However, in a disaster relief scenario, drones must have incentive to cooperate to provide an alternative access network for damaged communication infrastructure. Hence, cooperative game theory tools will be the most suitable.

In [3] the authors investigate the optimal altitude that ensures maximal downlink ground coverage while minimizing the transmit power for a single UAV. They subsequently study the scenario of two UAVs and compute the optimal altitude for each UAV along with the separation distance to guarantee maximum coverage both in free and full interference scenarios. The authors of [4] study optimal coverage and rate performance of UAV-based wireless communication in the presence of underlaid device-to-device (D2D) communication links. Both a static and a mobile UAV scenario are considered, and the UAV altitude along with D2D user density influence the overall measured performance. For the mobile case, the optimal stopping number is computed to ensure coverage for the downlink users.

In [5] the location and movement of UAVs are optimized to improve the connectivity of a wireless network. The authors formulated deployment and movement problems for the UAV and developed adaptive algorithms to increase the network performance in terms of global message connectivity. They showed that network bisection and k-connectivity are improved by the addition of a UAV to the network. In [6] the authors proposed a novel usage model for a UAV network, where a number of UAVs are required to collect information from randomly located areas and transmit it wirelessly to a common receiver. The authors of [7] consider energy-efficiency maximization for UAV-based relay architectures. In this work a fixed-wing UAV relays data between a stationary source and destination nodes. Thus, circular maneuvering is optimized through tuning the turning radius parameter. Energy efficiency is defined as the ratio of network capacity to the power consumption of both maneuvering and communication. The authors provide a closed form for a suboptimal solution for an approximate energy efficiency formula.

The authors of [8] propose a distributed framework for UAV-based disaster sensing. The presented framework comprises a client unit hosted by the UAV on-board system and a server unit hosted by the remote computing cloud infrastructure that provides service-oriented resource support. To address the processing and storage limitations inherent in small civilian UAV, they propose in-cloud selective data offloading and processing. The selection process on the UAV filters acquired video and only offloads essential frames for power-hungry advanced processing. The work in [1] investigates UAV based relaying both for single and multiple relay UAV over testbeds. Performance bounds are derived based on stochastic geometry formulation. The proposed UAV-based relay is compared to load balancing and traffic management techniques. In [9] it has been shown that an efficient UAV system can only be improved by the use of energy efficient components. The authors propose to optimize the maximum operating range and frequency band for data-transfer to a ground station. In addition, complex tasks are distributed among multiple UAV working as a fleet. Optimal beaconing control for epidemic routing in delay tolerant networks for energy efficiency is proposed in [10]. The authors propose a continuous Markov and derive a threshold beaconing policy that maximizes the delivery ratio within an energy constraint.

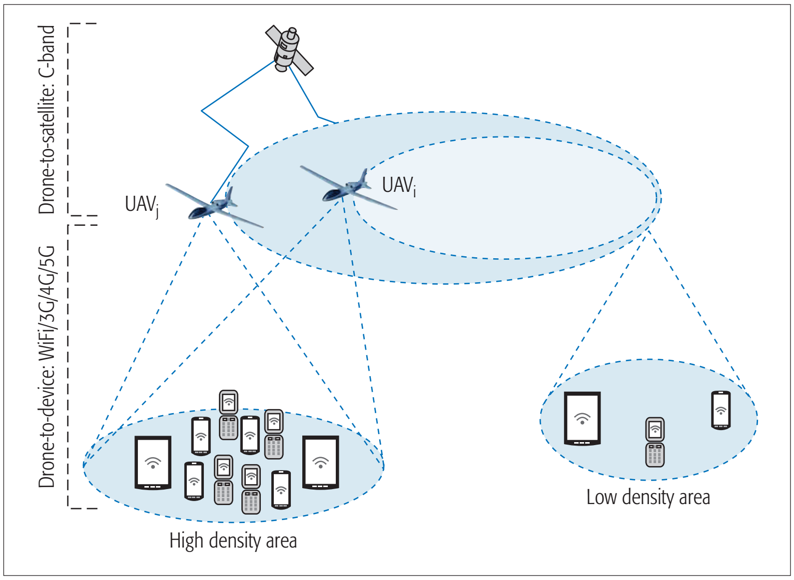

Figure 1. Drone small cells for coverage expansion.

In this work we examine the problem of optimal beaconing in drone small cells networks with two competing UAVs. To achieve the maximum system performance in terms of encounter rate and energy efficiency, we propose to carefully fix the duration of periodic beaconing periods. First, we introduce a game theory model for beaconing independent period duration choice. Second, we investigate the existence and uniqueness of Nash equilibrium based on the sub-modularity of the game. Then we provide a fully distributed learning framework allowing UAVs to discover their equilibrium beaconing period duration. Finally, we show the efficiency of our proposed beaconing strategy through extensive numerical results.

The rest of this article is organized as follows. We present the adopted approaches for coverage advertisement. We formulate a sub-modular game to capture the competition among UAVs for providing drone small cells (DSCs) coverage. Then we provide implementation insights gained from the proposed learning framework. We study a representative case study through extensive numerical investigations. Finally, we draw some conclusions and discuss future directions.

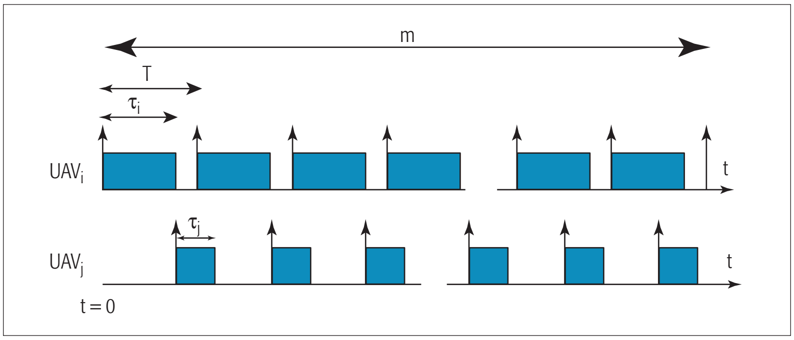

Figure 2. A snapshot of the activity schedule for two autonomous UAVs.

Drone Small Cells for Coverage Expansion: UAV Presence Advertisement

As illustrated in Fig. 1, the drones are able to carry several transceivers for different wireless access technologies. Hence, the small cells are heterogeneous and comprise WiFi and 3G/4G enabled mobile devices. The drone-satellite communications operate on the C band while the drone-to-devices communications operate on different bands (e.g. 2.4 GHz and 5 GHz for WiFi, 2 GHz for 3G, and 2.6 GHz for 4G).

The access standards support both active and passive scanning. The active scanning mode is enabled by default on mobile phones that broadcast probe-any frames. The objective of this procedure is to solicit probe responses from available access points. Thus, mobile devices actively look for reachable access points. During passive scanning, the radio listens for beacons and probe response frames. In passive mode, the radio scans are performed once per second. As reported in [11], active probing/beaconing is extremely power-hungry. For instance, WiFi probing consumes 221.4587 mW while video playback consumes 209.4283 mW, which is quite surprising.

UAVs relocate frequently in search of ground mobile users. Consequently, performing active scanning increases the mobile users' energy consumption. Besides, no guarantees for successful association with air-born access points are provided due to base station mobility (BS). Thus, passive scanning for beacons announcing the presence of BSs will be economically viable architectures for the deployment of drone small cells.

To reduce energy consumption by the mobile users, passive scanning will be used. Hence, the mobile users will avoid sending scanning packets when no drone is covering them. The drones will periodically send beacons advertising their presence to mobile users on the ground. The beaconing period duration for UAV i is $\tau_i \in [0, T]$. Hence, this UAV will send beacon packets for every slot in $[k \times T, k \times T + \tau_i]$ where $k \in \{0, 1, 2, \ldots, K\}$ is the beaconing period ID number. If a number of beacon responses exceeding a predefined threshold is received during the UAV beaconing period, a successful encounter with mobile users on the ground has been achieved. Hence, the mobile becomes the center of the small cell covering the encountered users. Otherwise, the beaconing response failed and therefore the UAV relocates according to its mobility pattern and starts beaconing in the period with ID $k + 1$. The drone remains idle during the period $[k \times T + \tau_i, (k + 1) \times T]$ to reduce its energy consumption.

The System Model

We consider two flying drones acting as aerial base stations belonging to different operators. The two drones will move randomly to cover an interest area, as depicted in Fig. 1. Each UAV will probe for mobile users on the ground during a fixed period of duration τ. Because mobile users are moving randomly, UAVs have to strategically choose their beaconing period to maximize their encounter rate. However, they should avoid battery depletion resulting from maintaining useless beaconing in the absence of contact on the ground. The probability density function of the first encounter rate follows an exponential distribution with parameter λ [12]. Figure 2 describes the beaconing schedule for two competing UAVs, i and j. Let us denote by m the activity schedule duration formed by an ordered sequence of beaconing and idle periods. m stands for the encounter deadline above which the temporary DSC establishment is no longer required. The beaconing/idle cycle is periodically repeated every T slots for a number of $l = m/T$ cycles.

The two drones are competing over being the first to provide coverage for the mobile users on the ground. For a given DSC, the successful encounter rate depends on its activity schedule (sequence of beaconing/idle periods) and the other drone's activity schedule. We distinguish two cases, depending on the drones' chosen beaconing durations. If drone i meets the mobile users first within one of its beaconing periods, then it succeeds. Whereas, if drone j is the first to encounter the mobile users, then in order for i to succeed, the UAV j encounter must happen during an idle period of its activity schedule. As drones belong to different operators, each UAV wants to be the first to encounter the mobile users and act as DSC. Drones need to self-organize by autonomously and independently choosing a beaconing scheduling strategy to maximize a successful encounter rate. This leads to a strategic competition with conflicting self-interests. The formulated problem fits within the framework of a non-cooperative game theory, where the drones are players that strategically choose their respective beaconing schedules, and compete to be rewarded upon first successful encounter with the mobile users on the ground. We will exhibit an equilibrium operating regime and a learning mechanism to understanding the interaction between UAVs.

Game Formulation

Game theory is a field of applied mathematics that analyzes multi-person decision situations. Its analytic tools help predict the outcome of complex interactions between independent self-interested agents in situations where rationality demands strict commitment to a strategy deducted upon perceived and measured results. Economics, political science, biology, sociology, engineering, and computer science are the main fields benefiting from game theory. There are two main branches of game theory: cooperative and non-cooperative. Non-cooperative game theory [13] deals with how individuals interact with one another, in an effort by each to achieve their own goals, and not, as it may suggest, that the theory applies only to scenarios where agents' interests conflict. In cooperative games, the competition is set among groups (coalitions) of players with the same objective. Here, the interaction among UAVs is captured using a non-cooperative game.

The beaconing scheduling game involves two UAVs (players) who independently choose the strategy maximizing their respective payoffs. UAV i fixes its beaconing period duration τ_i comprised between zero and T. A value of 0 means that the UAV will not perform on the ground user detection for the whole activity schedule duration. Whereas, with $\tau_i = T$, the UAV will perform active beaconing for mobile users all the time. The beaconing period scheduling can be modeled as a game $\mathcal{G} = \mathcal{N}, \{\mathcal{A}_{\{i\in\mathcal{N}\}}\}, \{u_{\{i\in\mathcal{N}\}}\}$. Here, $\mathcal{N}$ represents the set of UAVs, and the action set $\mathcal{A}_i = [0, T]$ for every UAV i is the beaconing period duration. If τ_i is the beaconing period duration for UAV i, then its idle period will last for $T - \tau_i$. The payoff u_i for UAV i is the difference between a reward and a cost. The reward is the probability of successful first contact with mobile users on the ground, while per slot consumed energy to send beacons and to switch the transceiver state are considered as costs. In order for the first contact to be successful, it must happen during the beaconing period. We denote by $P_s^i(\tau_i, \tau_j)$ the probability of the two drones choosing the beaconing durations τ_i and τ_j, respectively. Only the first UAV to encounter the mobile users while doing beaconing will serve as an airborne access point base station. Thus, the beaconing period duration of each UAV impacts the payoff of the other.

From a single UAV perspective, there is a trade-off between the encounter rate and energy consumption. On one hand, as the beaconing duration increases, the encounter rate P_s grows. On the other hand, energy consumption is proportional to the beaconing period duration. We denote by C_b (respectively C_s) the energy cost per slot for sending beacons (respectively remaining switching the transceiver state). The payoff of UAV i under the beaconing strategy profile (τ_i, τ_j) is

$$u_i^i(\tau_i,\tau_j) = P_s^i(\tau_i,\tau_j) - \frac{(C_b\tau_i + C_s)l}{m} \quad (1)$$

where $m = l \times T$ is the available time window for UAVs to enter in contact with mobile users on the ground. Denote by X_i (resp. X_j) the encounter time of UAV i (resp. j) with the mobile users without accounting for its state (beaconing/idle). Then, the successful encounter rate[1] is given by

$$P_s^i(\tau_i,\tau_j) = \begin{bmatrix} P(X_i \le X_j) + (P(X_i > X_j) \\ \times P(1_{\{jidle\}}) \end{bmatrix} \times P(1_{\{ibeaconing\}}) \quad (2)$$

Two possible scenarios are to be considered for the computation of $P_s^i(\tau_i, \tau_j)$. Indeed, if UAV i encounters first the mobile users on the ground (i.e. $X_i \le X_j$), then i has to be in its beaconing period at X_i. However, if $X_i > X_j$, UAV i has to be sending beacons at time X_i, and j has to be idle at X_j. To this point, we have defined the UAVs involved in the beaconing periods scheduling game $\mathcal{G}$ payoffs and their strategy spaces. We let each UAV unilaterally decide how long its beaconing period will be. As mentioned previously, the payoff for each UAV is a function of that UAV's own strategy as well as the decisions of the other UAV. We are now interested in finding the outcome of this strategic interaction. Each UAV will choose the best beaconing period to maximize its payoff while taking into account that the other UAV is doing the same. The strategy space and the payoff is common knowledge of the UAVs, but the chosen period is not since decisions are taken simultaneously. Then, a rational choice for the UAVs is an operating point that is stable against individual deviation, called Nash equilibrium. At Nash Equilibrium, none of the UAVs will benefit from unilaterally deviating.

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Existence and Uniqueness of the Nash Equilibrium

The Nash equilibrium is the operating point (duty-cycling regime) from which none of the drones could unilaterally deviate while enhancing its gains. The beaconing scheduling game is sub-modular and has at least one pure Nash equilibrium. Sub-modular games have very attractive properties since they do not require concavity nor the convexity assumption to guarantee NE existence. Informally, the sub-modularity of the game $\mathcal{G}$ implies that if one UAV reduces its beaconing period, the other UAV also has an interest in decreasing its own. Stated otherwise, the best response of a UAV is a non-increasing function of another UAV beaconing duration [14].

Theorem 1–*(Debreu, Glicksberg, Fan) [13]*: Consider a strategic form game $\mathcal{G} = \{\mathcal{N}, \{\mathcal{A}_{\{i\in\mathcal{N}\}}\}, \{u_{\{i\in\mathcal{N}\}}\}\}$ such that for each $i \in \mathcal{N}$:

- $\mathcal{A}_i$ is compact and convex.
- $u_i(\tau_i, \tau_{-i})$ is continuous in τ_{-i}.
- $u_i(\tau_i, \tau_{-i})$ is continuous and quasi-concave in τ_i.

Then a pure strategy Nash equilibrium exists.

The game's structural properties such as quasi-concavity are key factors to have insight on its Nash equilibrium existence and uniqueness. Since the second order derivative

$$\frac{\partial^2 \mathcal{U}_i(\tau_i,\tau_j)}{\partial \tau_i^2}$$

is negative, $\mathcal{U}_i(\tau_i, \tau_j)$ is concave and consequently quasi-concave. Hence, according to Theorem 1, there exists at least a pure Nash equilibrium for the game $\mathcal{G}$.

For the symmetric case, the drones have the same encounter rate $\lambda_i = \lambda_j = \lambda$. The symmetric game satisfies the dominance solvability conditions stated in [15] and consequently also satisfies Rosen's conditions [15] which guarantee the uniqueness of the Nash equilibrium. We solved numerically the first order condition,

$$\frac{\partial \mathcal{U}(\tau,\tau)}{\partial \tau} = 0,$$

for several values of λ and reported the obtained results for the equilibrium beaconing period duration τ^* in Fig. 3.

[1] For details: https://sites.google.com/site/essaidsabir/publications/UAV.pdf

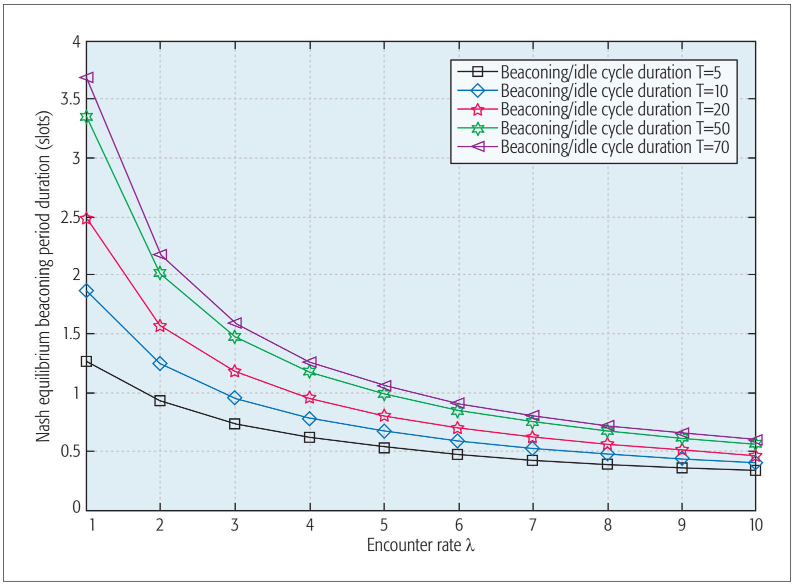

Figure 3. Beaconing period τ^* at Nash Equilibrium for different encounter rates λ values.

Data:
$\phi_i \in [0; 2\pi]$: perturbation phase;
$b_i > 0$: perturbation amplitude;
Ω_i : perturbation phase;
z_i: the growth rate;
Result: Equilibrium beaconing period duration τ_i
Initialization:
Assign a value for $\tau^*_{i,0}$ 2 $[0, m]$;
Learning pattern: For each iteration k
Compute $k^* \triangleq \sum_{k'+1}^{k} \frac{1}{k'+1}$;
Observe the realization $\hat{U}_{i,k}$ and estimate $\tau^*_{i,k+1}$ using
$\tau^*_{i,k+1} = \tau^*_{i,k} + k^* z_i b_i \sin(\Omega_i k^* + \phi_i) \hat{U}_{i,k}$;
Update beaconing duration τ_i using the following rule
$\tau_{i,k+1} = \tau^*_{i,k+1} + b_i \sin(\Omega_i k + \phi_i)$;

Algorithm 1. Nash seeking algorithm (NSA) for UAV i.

We notice that as the encounter rate increases, the optimal beaconing period duration τ^* decreases. Indeed, the higher are the chances to meet with the destination, the more it is logical and strategic to decrease its beaconing period duration in order to save its energy budget. This is even more accurate in the case of fully symmetric UAVs since all the other drones will have the same reasoning and have the same τ.

Insights on Real-World Implementation: Learning Automata

We now turn to investigate the learning process by which we aim to understand the behavior of the users during the interactions and the eventual convergence toward the Nash equilibrium. Best response dynamics (BRD) [14] is known to reach equilibria for S-modular (both sub-modular and super-modula) games, by exploiting the monotonicity of the best response functions. At iteration t, each UAV chooses the best strategy to the opponent strategy chosen in iteration $t - 1$. Although BRD is easy to implement and offers certain convergence to the equilibrium for S-modular games, it suffers from major shortcomings. Yet this scheme requires perfect rationality and complete information, which is not practical for real-world applications and may increase the signaling load as well. Therefore, we propose an adaptive distributed learning framework to discover equilibria for the activation game based on the "*Nash Seeking Algorithm*" [15] with stochastic state dependent payoffs for continuous actions.

The equilibrium learning framework is an iterative process. At each iteration t, the UAV i chooses its beaconing period duration $\tau_{i,t}$ and obtains from the environment the realization of its payoff. The improvement of the strategy is based on the current observation of the realized payoff and previously chosen duration. Hence, we say UAVs learn to play an equilibrium, if after a given number of iterations, the strategy profile converges to an equilibrium strategy. The proposed learning framework has the following parameters: ϕ_i is the perturbation phase, z_i is the growth rate, b_i is the perturbation amplitude, and Ω_i is the perturbation frequency.

Algorithm 1 summarizes the NSA learning steps that UAV i (resp. j) has to perform in order to discover its NE beaconing strategy. NSA exhibits enormous advantages as it is fully distributed and hence reduces the signaling overhead and does not rely on any coordination between UAVs. Besides, it does not require knowledge about the exact formula of the payoff. Indeed, the numerical value of the function at each iteration is sufficient. Also, each UAV strategy is only based on its observations. Indeed, it is not required for a UAV to acquire knowledge about strategies and payoffs of other players. These advantages are particularly suitable to the drone small cells where no central controlling entity is available to manage the different operators' UAVs. NSA is resilient to errors produced by the noisy learning environment. This learning error resilience is a result of a fine-tuning of NSA perturbation parameters.

DSCs for Temporary Events: A Case Study

The developed beaconing period learning framework is validated through numerical investigation and event-driven simulation on MATLAB®. The considered scenario comprises two UAVs moving randomly according to a random waypoint (RWP) model and a group of mobile users moving on the ground also according to a RWP mobility model. The encounter rates between the UAVs and the mobile users are, respectively, λ_1 and λ_2. For sake of comparison, we benchmark the proposed learning framework versus BRD.

Figure 4 depicts the behavior of the proposed learning algorithm over time and how it converges to the equilibrium beaconing duration. Here we consider two UAVs with identical encounter rates $\lambda = \{0.1, 1, 10\}$. In addition, we plot the best reply dynamics learning curve that serves as a baseline for comparison with NSA. The proposed learning approach converges within approximately 20 iterations, while the BRD approach needs five to 15 iterations to converge. The relatively small number of extra iterations required by the NSA to converge are a very acceptable price for the associated benefits, i.e. fully distributed and reduced signaling. We notice that UAVs with high encounter rates beacon less, which is quite intuitive. This behavior participates to reduce their energy consumption, which explains the result observed in Fig. 4.

Figure 5 shows the beaconing duration at equilibrium as a function of per-slot beaconing energy cost for several λ values. Increasing sensing energy cost will reduce the UAVs' incentive to beacon for potential on the ground mobile users, which results in saving energy. This decrease in the beaconing period is more visible on the behavior of UAVs with high encounter rates, as illustrated in Fig.4. Henceforth, one can efficiently define a mobility-beaconing tradeoff, i.e. one can compensate for the decrease of beaconing duration by fine-tuning mobility parameters (e.g. speed, direction, …).

We define the energy efficiency metric as the ratio of the successful probability encounter and the consumed energy. Hence, an efficient beaconing strategy will be reached by increasing the encounter rate while reducing the associated energy consumption, equivalently reducing the beaconing duration. Namely, we measure the individual energy efficiency by the following metric:

$$EE(\tau_i,\tau_j)=\frac{P_s(\tau_i,\tau_j)}{C_b\times\tau_i+C_s} \tag{3}$$

Figure 6 plots both the energy efficiency and the analytical successful encounter rate for the strategic beaconing and the always-beaconing policies. Some key observations are worth mentioning. Indeed, the equilibrium beaconing strategy exhibits high energy efficiency with a slight decrease regarding the encounter rate level compared to the continuous-beaconing policy. For instance, at encounter rate λ = 0.1, identical energy efficiency is achieved at a price of an 8 percent decrease in encounter rate. For encounter rates exceeding 1.3, the encounter rate is identical with an energy efficiency increasing from 1.59 to 5.64 folds. Thus, our strategic beaconing scheme efficiently performs as well as the continuous-beaconing scheme for moderate and high values of λ in terms of encounter rate. Regarding energy efficiency, our scheme outperforms the continuous-beaconing policy and guarantees clearly higher network lifetime. Therefore, one can efficiently define a delivery-energy tradeoff. Yet, one can achieve a high energy efficiency level while keeping the encounter rate close enough to the continuous-beaconing policy.

In order to check and evaluate the accuracy of the success probability closed-form expression we derived so far, we implemented the behaviour of UAVs in the opportunistic network environment (ONE) simulator. Namely, we implemented a scenario consisting of two UAVs competing to provide DCS access to a randomly located population of mobile users in a geographic area of interest. Both UAVs are moving according to the RWP mobility model. For each configuration of the mobility model (UAVs speed, waiting time, etc.), we run 1000 simulations and record the distribution of the inter-contact times. We then use the maximum likelihood estimation to obtain an

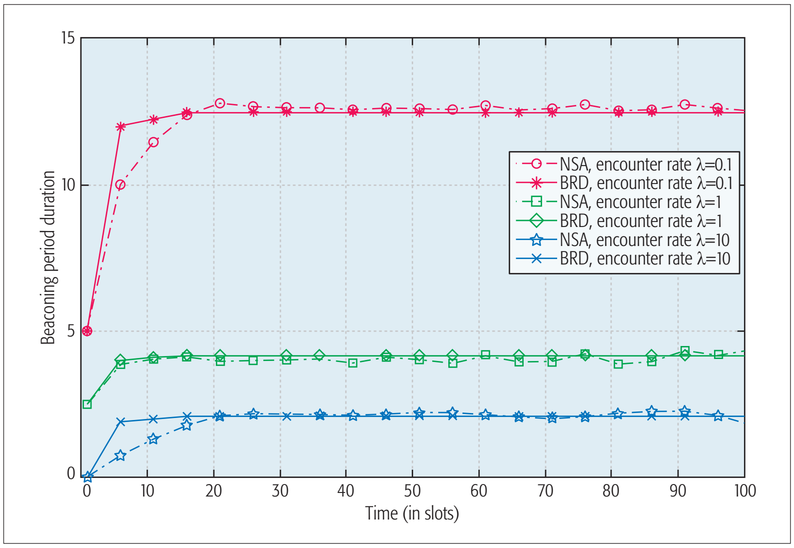

Figure 4. Seeking the equilibrium beaconing duration using NSA and BRD under different encounter rates λ.

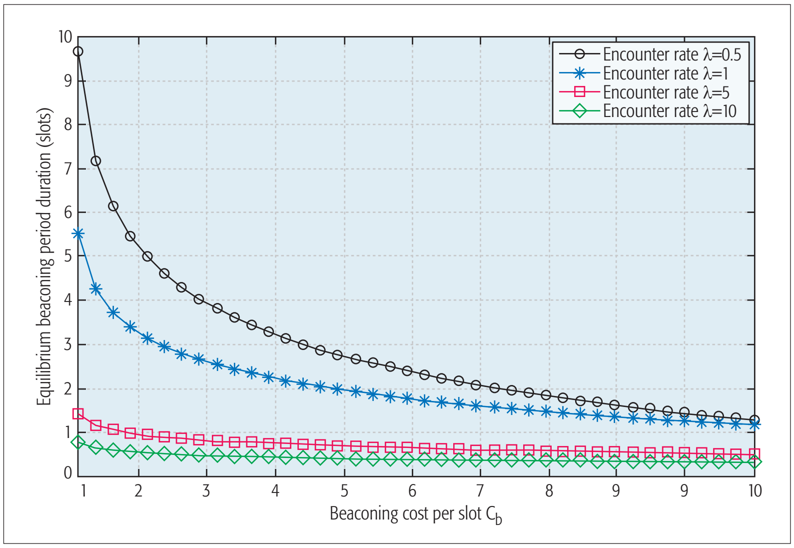

Figure 5. Equilibrium beaconing duration as a function of the beaconing cost (energy consumption) under different λ.

estimator of the exponential distribution parameter value. The latter happens to be the inverse of the sample mean and models the number of encounters within five hours of simulation. As depicted in Fig. 6, we notice that the simulation based measurement of success probability is coherent with the analytically obtained formula. Indeed, the analytically obtained result falls within the simulation confidence interval, and only a slight gap occurs between the two values.

Conclusion

In this article we dealt with the activity scheduling of competing unmanned aerial vehicles acting as drone small cells for temporary events and disaster-relief activities. We constructed the induced non-cooperative game and characterized the equilibrium beaconing period durations for the competing drones. Next we described a fully distributed mechanism that allows each drone to self-discover its equilibrium beaconing strategy without any knowledge of its opponent's sched-

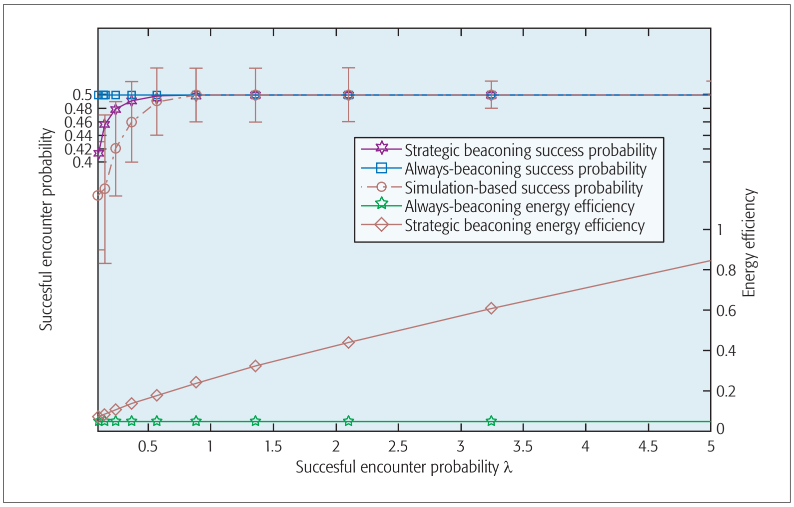

Figure 6. Encounter rate and Energy Efficiency for strategic beaconing (i.e., at Nash equilibrium) and always-awake scheme.

ule. Latter equilibrium point allows drones to efficiently optimize their energy consumption while maximizing the likelihood of getting in contact with the mobile users on the ground.

As a future work, we are working toward generalizing our scheme while considering both competing UAVs and collaborating UAVs scenarios. The case where energy harvesting is possible is also a very attractive open issue we would like to deal with. Furthermore, we also seek to implement such a distributed mechanism in a real UAV network.

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