An Optimal Scheme to Recharge Communication Drones

Edgar Arribas
Universidad CEU San Pablo
Madrid, Spain

Vicent Cholvi
Universitat Jaume I
Castelló, Spain

Vincenzo Mancuso
IMDEA Networks Institute
Madrid, Spain

***Abstract*—The adoption and integration of drones in communication networks is becoming reality thanks to the deployment of advanced solutions for IoT and cellular communication relay schemes. However, using drones introduces new energy constraints and scheduling issues in the dynamic management of the network topology, due to the need to call back and recharge, or substitute, drones that run out of energy. In this paper, we describe the design of a drone recharging scheme for realistically limited flight time of drones, and leverage the presence of recharging stations. Indeed, drones need to be recharged periodically, and maximizing the operational time of drones is paramount to minimize the size of the fleet of drones to be devoted to a drone mission, hence its cost. We design `Homogeneous Rotating Recharge` (`HRR`), an optimal drone recharging scheduling that extends the coverage of a cellular network. `HRR` minimizes the number of back-up drones needed to guarantee a fixed number of operational drones, so as to support the operation of an underlying cellular network. Results show that operating a network of drones with our scheme provides reliable and stable performance over time.**

I. Introduction

Unmanned aerial vehicles (UAVs), and lightweight drones in particular, are becoming attractive for service providers due to their ability to serve communication purposes and extend the capabilities of their fixed infrastructure. Drones can be useful in many situations (e.g., in case of planned communication traffic surges due to massive meetings, disaster recovery missions, military applications, etc.), and they have played an important role during the COVID-19 pandemic to deliver goods and to irrorate disinfectants [1]. There is also a strong interest for drones in the IoT community, as they can be flexibly used for generating data and for harvesting data from fixed sensors. Therefore, many recent efforts tackle the integration of UAV-carried network nodes in cellular networks, either to control drone routes effectively or to experiment with relay schemes freshly introduced with 5G [2].

With the current advances in communication technologies, the bottleneck in the adoption of drones lays in the limited energy that they can rely on. For this reason, flying several drones in a real scenario requires the accurate planning and monitoring of their energy consumption. With multiple drones and limited stations where the drones can land to get refueled, network designers need to solve new problems, and impose new constraints to their resource management algorithms. For instance, in a drone-based tactical communication network or in a patrolling mission, drones have to be recharged cyclically while guaranteeing service at all times. The problem is threefold: (i) the need to recharge a drone (or change its battery) affects the service provided by the network of drones; therefore, (ii) the fleet of drones has to account for redundancy, so that when a drone flies back to get fresh energy, the operation of the remaining drones remains consistent with the objectives of the mission; and (iii) unlike traditional swapping schemes, the time during which a drone with low energy goes offline to recharge is not negligible, since neither charging times nor the time to fly back and forth are negligible.

Related Work: Most of the work on efficient energy management of drone-based technologies focuses on the Vehicle Routing Problem [3]. Namely, the goal is to generate routes for a team of agents leaving a starting location, visiting a number of target locations, and returning back to the starting location. Among the many variants of such a problem, there is the possibility that the charging stations in which the drones will be powered be either stationary or mobile [4]. A recently considered problem is the management of a fleet of drones that are performing a persistent monitoring task. In [5], the authors consider minimizing the number of drones required when providing a persistent non-stop service. They provide two approximation algorithms: one with an approximation factor upper bound of 1.5 (when all the locations are known in advance) and the other with an average factor of 1.7 (for the online version). They were followed by [6], who consider minimizing the number of drones with multiple recharging stations. In [7], the authors show that this problem is NP-hard, even for a single *spare drone* (i.e., with just one back-up drone needed to guarantee the service), and provide two approximation algorithms for solving the problem, outperforming [6].

Our work: In this paper, we consider a fleet of drones that extend the coverage of a cellular network. We rely on existing algorithms for what concerns the dynamic optimization of drone positions in a 3D space [8]. Hence, our drones have mobile targets, which is different from what considered in the literature. In this scenario, we design `Homogeneous Rotating Recharge` (`HRR`), an optimal strategy to schedule the recharging of drones while maintaining a fixed number of operational/active drones per recharging station, so as to provide stable performance. We target the minimum possible size of the fleet, which includes back-up drones. We show that combining communication requirements with drone dynamics is not an easy task. With the help of a simulator, we study how realistic drone features impose extra costs for maintaining the level of network coverage high—with respect to the ideal case of unlimited flying time of drones—and evaluate the robustness of our proposal under realistic settings.

Specifically, the contributions of this paper are: (i) we identify an optimal rotatory recharging schedule for the fleet of drones, which allows to fly all available drones while guaranteeing the participation of all but one drone in the operation of the communication network at any point in time; (ii) we prove the optimality of our scheduling algorithm; (iii) we evaluate the impact of recharging schemes on the communication performance of the underlying cellular network.

II. Reference Scenario

We consider a set of M drones that extend the coverage of a cellular network. Hence, we interchangeably use terms drone and aerial Base Station (*aBS*). The position of *aBS*s is re-optimized every T time units with a mechanism that considers as input the distribution of mobile users, the coverage provided by ground Base Stations (*gBS*s) and the number of *aBS*s. The specific mechanism that we consider in this paper is the coverage framework of [8], which optimizes the position of *aBS*s so as to maximize the number of users covered per time slot by *gBS*s and *aBS*s. Coverage is defined as the existence of a radio link between a base station and a mobile user, with signal-to-noise-plus-interference ratio (SINR) above a target threshold. What matters here is that *the target positions of aBSs change periodically because of user mobility.*

As time passes by, drones consume energy. Thus, they periodically need to meet a recharging station (RS) to recover power. While *aBS*s fly towards the RS, get recharged, or fly back to their target position, they do not operate, thus not incurring interference with the other *aBS*s.

We consider a limited operational range around an RS, and the time needed to reach RS is small but not negligible if compared to the maximum flight time. Specifically, with currently available drones, which can fly for about 30 minutes and whose cruise speed can exceed 50 km/h, we consider that drones can fly a few kilometers away from the RS. The RS has a pool of charged batteries always available. When a drone lands on the RS, an automatic mechanism can either replace its battery so that the *aBS* can be fully operational in short time [9], or recharge/refuel the drone, which takes longer time.

Homogeneous drones: For simplicity, we assume a fleet composed by homogeneous *aBS*s (which is very reasonable in our considered scenario). The maximum *flying time* of each drone (i.e., the battery life) is f. The *displacement time* from an aerial target position to the RS (or vice versa) is g. Hence, the maximum service time of an *aBS* in between "pit stops" is $s=f-2g$. The *recharging time* for the drone to be ready to fly again is c.

The Drone Recharge Scheduling Problem: With the assumptions detailed above, we aim to *find the minimum number of aBSs needed, namely M, and a recharge scheduling that guarantees that at least $N \leq M$ aBSs provide service at each time instant.* Hence, the network optimization mechanism can safely use N drones to optimize communication performance at all times. The described problem is equivalent to the following one: *Given a fleet of M drones, how many aBSs can be guaranteed to extend the communication network at all times?*

The recharge scheduling must instruct each *aBS* on when to: head to the RS, take off, and provide service.

III. Optimal Drone Recharge Scheduling: HRR

In this section, we find the optimal drone recharge schedule that minimizes the number of needed *aBS*s M to guarantee that at least N of them are always providing service.

We present the optimal drone recharge scheduling in Algorithm 1: `Homogeneous Rotating Recharge` (`HRR`); and prove its optimality in Theorem 1. Note that at each time interval of x time units (steps 3 and 4), the closest drone to run out of power goes to recharge (regardless of whether or not it is actually running out of power) and this is permanently repeated. Note that in the first round, at instant Nx, the drone instructed recharge has been flying for $f-g$ time units, and has a remaining flight time of g. Thus, it only disposes of the next g time units until it runs out of energy. This is why $x=\frac{f-2g}{N}$. Finally, note that each time a drone i_e is instructed back to RS, we send a back-up drone i_c to replace it (g time units in advance). Drone i_e, once recharged, is considered as a back-up drone.

Algorithm 1 `Homogeneous Rotating Recharge` (`HRR`)

Require: N, f, g, c.
1: Obtain $x=\frac{f-2g}{N}$.
2: Initially, N drones service in their aerial target positions.
3: After $x-g$ time units, a fully charged back-up drone i_c takes off from the RS.
4: After g time units, the closest to drain drone i_e is instructed recharge and the back-up drone i_c replaces i_e. Drone i_e will be considered as a back-up drone after $g+c$ time units, i.e., once i_e lands and gets fully charged.
5: Go back to Step 3.

`HRR` assumes that there is always a back-up drone ready to replace that drone that at some instant is instructed recharge. In the following lemma we prove that the minimum number of back-up drones so that `HRR` is feasible is $\left\lceil\frac{c+2g}{f-2g}N\right\rceil$.

Lemma 1. *Assume a fleet of homogeneous drones characterized by a common f, c and g. The minimum and sufficient number of drones necessary by `HRR` to guarantee that N of them will be always providing service is $M=N+\left\lceil\frac{c+2g}{f-2g}N\right\rceil$.*

Proof. According to Algorithm 1, at some time instant kx, for some $k\in\mathbb{N}$, one drone i_e is instructed recharge and heads the RS while a back-up drone i_c takes off at $kx-g$ to replace it at instant kx. While i_e gets ready, other n drones are instructed recharge. The time needed by drone i_e to be able to replace another drone is $c+2g$. Hence, there must be a number of n back-up drones ready to replace the n drones that are arriving during this period such that $nx \geq c+2g$. The minimum n that accomplishes this is $n=\lceil\frac{c+2g}{x}\rceil$, where $x=\frac{f-2g}{N}$.

Hence, with the scheduling of HRR, $M = N + \lceil \frac{c+2g}{x} \rceil$ is the minimum number of drones needed to guarantee that N of them are always providing service. ☐

Observation 1. *HRR ensures that, if $x > 2g+c$, only one back-up drone is needed: the instructed drone i_e is substituted by the back-up drone i_c, and once i_e is recharged, it becomes the back-up drone, and the process repeats with the rest of drones. This is possible since the new back-up drone will be ready before the next drone is instructed recharge.*

In the following theorem we prove that HRR is optimal as it requires the minimum number of available drones in the system. I.e., there is no alternative drone recharge scheduling that requires a lower number of available drones.

Theorem 1. *Assume a fleet of homogeneous drones characterized by a common f, c and g. The minimum and sufficient number of drones necessary to guarantee that N of them will be always providing service is $M = N + \left\lceil \frac{c+2g}{f-2g} N \right\rceil$.*

Proof. Consider any feasible scheduling in which there are at least N drones providing service at all time instant. Drone i_L that is instructed last to recharge for the first time must be instructed before all its energy drains, i.e., before $f-2g$ time units. Let A be the minimum number of back-up drones to accomplish the given feasible schedule before i_L is re-called for the first time. As A back-up drones are needed, there exists one drone i_0 that satisfies the following: there is a time instant at which i_0 is instructed recharge and there are $A-1$ more drones that are instructed recharge before i_0 is ready.

Let $\mathcal{A}$ be the set of such $A-1$ drones jointly with i_0. According to the given scheduling, each drone $i \in \mathcal{A}$ is instructed recharge every x_i time units (x_i represents the time difference between the instant at which an active drone i is instructed and the previous instructed drone). Drone i_0 exists but might not be unique. Hence, we take i_0 such that $\sum_{i \in \mathcal{A}} x_i$ is minimum among the possible sets $\mathcal{A}$ built in this way.

Drones in $\mathcal{A}$ are instructed before i_0 gets ready, hence:

$$c + 2g \leq \sum_{i \in \mathcal{A}} x_i, \tag{1}$$

since i_0 needs $c + 2g$ time units to be ready to replace an active drone. In particular,

$$\frac{c + 2g}{A} \leq \operatorname*{Avg}_{i \in \mathcal{A}}(x_i), \tag{2}$$

where Avg$(\cdot)$ represents the average value.

Moreover, the sum of all x_j of each of the drones that were initially active cannot exceed $f-2g$, in order to avoid that drone i_L runs out of energy:

$$\sum_{j \in \mathcal{N}} x_j \leq f - 2g, \tag{3}$$

where $\mathcal{N}$ is the set of all initially active drones.

Let $\mathcal{P}_{\mathcal{N}} = \{\mathcal{A}_1, \ldots, \mathcal{A}_K\}$ be the sorted partition of $\mathcal{N}$ such that all the drones of any set $\mathcal{A}_k$ have been simultaneously inactive at some instant (hence, $A_k = |\mathcal{A}_k| \leq A$, $\forall 1 \leq k \leq K$) while no back-up drone was instructed to do a replacement (hence, $\mathcal{A} \in \mathcal{P}_{\mathcal{N}}$). Note that if $A_k = A$ for some k, then $\operatorname*{Avg}_{i \in \mathcal{A}}(x_i) \leq \operatorname*{Avg}_{i \in \mathcal{A}_k}(x_i)$ due to the election of $\mathcal{A}$. Also, if $A_k < A$, note that while drones in $\mathcal{A}_k$ where active, there were needed only A_k back-up drones and hence, $\operatorname*{Avg}_{i \in \mathcal{A}}(x_i) \leq \operatorname*{Avg}_{i \in \mathcal{A}_k}(x_i)$. Otherwise, drones in $\mathcal{A}_k$ would be on average less spaced in time than drones in $\mathcal{A}$ with only A_k back-up drones. Then, additional back-up drones would be needed (as for those more spaced drones from $\mathcal{A}$ there were needed more back-up drones, A, under this *reductio ad absurdum* assumption).

As a result, the fact that $\mathcal{P}_{\mathcal{N}}$ is a partition of $\mathcal{N}$ jointly with Eq. (3), it holds that:

$$\sum_{k=1}^{K} A_k \cdot \operatorname*{Avg}_{i \in \mathcal{A}_k}(x_i) = \sum_{k=1}^{K} \sum_{i \in \mathcal{A}_k} x_i = \sum_{j \in \mathcal{N}} x_j \leq f - 2g. \tag{4}$$

Moreover, as $\operatorname*{Avg}_{i \in \mathcal{A}}(x_i) \leq \operatorname*{Avg}_{i \in \mathcal{A}_k}(x_i)$, $\forall 1 \leq k \leq K$, it holds that:

$$f - 2g \geq \left(\sum_{k=1}^{K} A_k \right) \cdot \operatorname*{Avg}_{i \in \mathcal{A}}(x_i) = N \cdot \operatorname*{Avg}_{i \in \mathcal{A}}(x_i). \tag{5}$$

And particularly:

$$f - 2g \geq N \cdot \operatorname*{Avg}_{i \in \mathcal{A}}(x_i). \tag{6}$$

Finally, Eqs. (2) and (6) lead to:

$$\frac{c + 2g}{A} N \leq N \cdot \operatorname*{Avg}_{i \in \mathcal{A}}(x_i) \leq f - 2g, \tag{7}$$

which leads to the fact that

$$A \geq \frac{c + 2g}{f - 2g} N. \tag{8}$$

Hence, the number of back-up drones is $A \geq \left\lceil \frac{c+2g}{f-2g} N \right\rceil$. Since we have found in HRR a feasible schedule that needs exactly $\left\lceil \frac{c+2g}{f-2g} N \right\rceil$ back-up drones (see Lemma 1), the minimum number of total available drones needed to guarantee that at each time instant at least N of them are providing service is:

$$M = N + \left\lceil \frac{c + 2g}{f - 2g} N \right\rceil. \tag{9}$$

Hence, the theorem follows. ☐

Intuitively, by using any scheduling, if we want to guarantee that during each time interval the minimum number of drones go to recharge, we need that they go as widely spaced in time as possible, considering that if we increase the time distance between two of them, then we will decrease the time distance between two other drones. That is, one drone will go to recharge each $x = \frac{f-2g}{N}$ time units.

Lemma 2. *HRR satisfies that any drone i is instructed recharge for the k-th time at time instant:*

$$t_i^k = \left(i + (k-1)N + (k-1) \left\lceil \frac{2g+c}{x} \right\rceil \right) x, \tag{10}$$

where $x = \frac{f-2g}{N}$.

Proof. We prove the lemma by induction. Take $k = 1$. Without loss of generality, drone i is the i-th drone to be instructed in the 1st round (otherwise, drones can be resorted). Then:

$$t_i^1 = ix, \tag{11}$$

which satisfies the lemma.

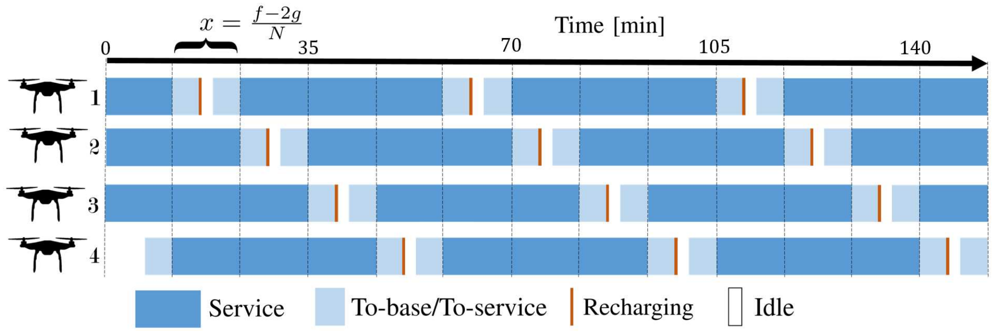

Figure 1: Optimal drone recharge scheduling with $M=4$, $N=3$, $f=45$ min, $g=5$ min, $c=15$ s.

Assume the lemma is true for a given k. We prove that then the lemma is also true for $k+1$.

According to the inductive hypothesis, drone i is instructed for the k-th time at:

$$t_i^k=\left(i+(k-1)N+(k-1)\left\lceil\frac{2g+c}{x}\right\rceil\right)x. \tag{12}$$

Then, drone i lands at t_i^k+g and takes off at t_i^k+g+c (i.e., after i is fully recharged). This means that i can replace a drone at t_i^k+2g+c or later.

Following the scheduling, i will replace another drone at instant jx, for some $j\in\mathbb{N}$. Concretely, at the minimum instant jx such that $jx\geq t_i^k+2g+c$. Hence, $j\geq(t_i^k+2g+c)/x$, i.e.:

$$\begin{aligned}j&=\left\lceil\frac{t_i^k+2g+c}{x}\right\rceil=\left\lceil i+(k-1)N+(k-1)\left\lceil\frac{2g+c}{x}\right\rceil+\frac{2g+c}{x}\right\rceil\\&=i+(k-1)N+(k-1)\left\lceil\frac{2g+c}{x}\right\rceil+\left\lceil\frac{2g+c}{x}\right\rceil\\&=i+(k-1)N+k\left\lceil\frac{2g+c}{x}\right\rceil.\end{aligned} \tag{13}$$

Then, Nx time units later, drone i will be instructed again for the $(k+1)$-th time at time instant:

$$\begin{aligned}t_i^{k+1}&=jx+Nx=\left(i+(k-1)N+k\left\lceil\frac{2g+c}{x}\right\rceil\right)x+Nx\\&=\left(i+kN+k\left\lceil\frac{2g+c}{x}\right\rceil\right)x.\end{aligned} \tag{14}$$

Hence, the lemma follows. □

Corollary 1. *HRR satisfies that any drone i is instructed recharge every $(N+\lceil\frac{2g+c}{x}\rceil)x$ time units.*

Proof. The difference between two consecutive times k and $k+1$ in which a drone i is instructed recharge is:

$$\begin{aligned}t_i^{k+1}-t_i^k&=\left(i+kN+k\left\lceil\frac{2g+c}{x}\right\rceil\right)x-\left(i+(k-1)N\right.\\&\left.+(k-1)\left\lceil\frac{2g+c}{x}\right\rceil\right)x=\left(N+\left\lceil\frac{2g+c}{x}\right\rceil\right)x.\end{aligned} \tag{15}$$

Hence, the corollary follows. □

In Figure 1, we show an illustrative example of how the HRR algorithm works. As it can be seen, at each time instant some drones are actively providing network service and, when needed, they are dynamically replaced by a fully charged back-up drone. Since it is assumed that the network operator disposes of $M=4$ drones, then Theorem 1 guarantees that $N=3$ drones will always be giving service (as derived from Corollary 1, each drone will give service for 35 min). Every $x=11.\overline{6}$ minutes one active drone is instructed recharge at the RS, and $g=5$ min in advance a fully charged back-up drone is also instructed take off (from the RS) and replace that drone. HRR guarantees that such replacement will be performed at the same instant when the active drone goes to be recharged, so back-up drones need to wait during an idle slot at the RS. Thus, the number of active drones remains constant.

IV. Simulation Results

In this section, we assess the performance of our proposed scheme: HRR. First, we numerically validate, by means of simulations, the obtained results in Section III (i.e., the minimum number of drones that are guaranteed to be always giving service). Furthermore, we integrate that scheme into a wireless network framework that maximizes the *coverage* of ground users by means of *aBS*s combined with *gBS*s [8]. By means of simulations over the real topology of an operational network deployed in a dense city (Madrid, Spain), we show that it is possible to guarantee a stable network service at all times.

A. Dynamic of the drones

In this section, we analyze how the system performance (as the number of servicing drones) is affected by the *displacement times* g, the *flying times* f and the *recharging times* c.

a) Displacement times: In Figure 2, we show several scenarios with different values of g. The scenario with $g=1$ min represents the case where drones (with an average speed of 25 m/s) fly close to the RS (e.g., 1.5 km). As pointed in Observation 1, only 1 back-up drone is needed (since $x>2g+c$), which explains why we observe an increasing straight line. When $g=5$ min, the condition $x>2g+c$ is still preserved provided the number of active drones is small (i.e., only 1 back-up drone is enough), but when the number of active drones needs to exceed 3, additional back-up drones need to be used. This behavior is more pronounced when we still increase g, so that several back-up drones are needed, even when the required number of active drones is small.

At this point, we are aware that, in a realistic scenario, the values of g may not be completely accurate. Thus, we have

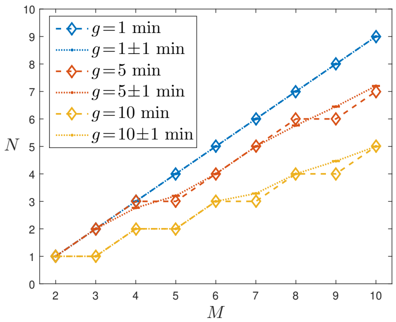

Figure 2: *Displacement times:* Number of active drones N over M available drones, for $f=$ 45 min and $c\!=\!15$ s and non constant g.

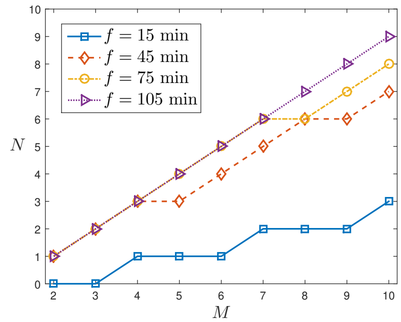

Figure 3: *Flying times:* Number of active drones N over M available drones, for $g\!=\!5$ min and $c\!=\!15$ s.

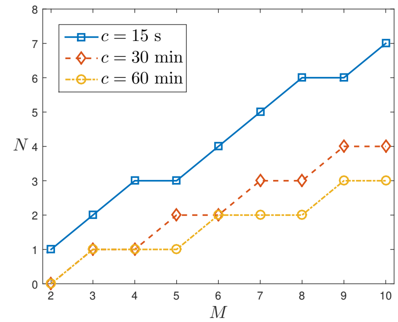

Figure 4: *Recharging times:* Number of active drones N over M available drones, for $f=$ 45 min and $g\!=\!5$ min.

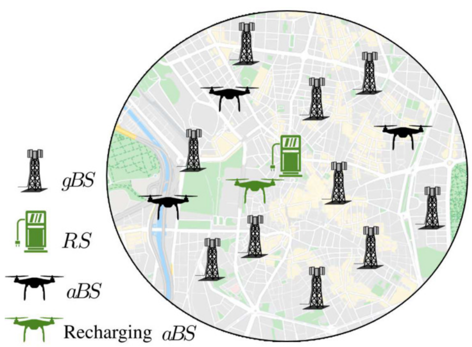

Figure 5: Drone-aided cellular network of Madrid.

also validated our proposal by varying, in a random manner, the above-mentioned values of g by ± 1 min. As observed, there are no relevant differences from our predicted behavior.

b) Flying times: In Figure 3, we analyze what happens when the maximum flying time f varies. As expected, we observe that the higher the value of f, the lower the required number of back-up drones (see Theorem 1). Observe that, in some cases, there is no scheme capable of guaranteeing a given constant number of active drones (e.g., when $M\!=\!2$ or 3).

c) Recharging times: In Figure 4, we have compared the effect of replacing the exhausted batteries (e.g., $c=15$ s, as stated in [9]) against recharging them (e.g., $c\!=\!30$ or 60 min). Clearly, the replacement of batteries provides very significant benefits over battery charging, which makes it advisable for network operators to opt for the use of battery replacement.

B. Network performance over time

We assess the communications performance in the network of Figure 5: we consider a simplified map of the center of Madrid, Spain, and consider a dense network environment on those zones of main affluence of people. The RS is located in the center of the network. Drones are able to service over periods of $f\!=\!45$ min, have flying speeds that allow to reach the RS from any position in the network in a few minutes (we consider g values that span from 1 to 10 minutes), and need to stay at the RS for either a few seconds to swap their battery ($c\!=\!15$ s) or several minutes to get their battery fully recharged ($c\!=\!30$ min). We have also tested other configurations, whose results are not shown here due to space constraints.

The network is composed by 10 *gBS*s, 1000 randomly located users moving according to the random way-point model and M *aBS*s, N of which offer service. Their target position is updated every minute with the algorithm proposed in [8]. Upon each update, *aBS*s move to the new positions without interrupting the service. M is an input of the experiment, while N depends on the recharge schedule. In particular, we evaluate `HRR` and a greedy drone recharging schedule (`Greedy`) in which all M *aBS*s stay active except when they need a *pit stop* to recharge. I.e., with `Greedy`, *aBS*s head to the RS when they strictly need to, and take off as soon as they are recharged.

We use a custom simulator for the mobility of users and drones and for the evaluation of coverage, measured as the number of mobile users per time unit that receive signal from either *gBS*s or *aBS*s above a given SINR threshold, which we fix to 10.9 dB. Transmission powers and fading/shadowing coefficients are like in the experiments presented in [8]. The maximum operational height of drones is fixed to 600 m.

We simulate each scenario a thousand times to gather the average coverage results of Figure 6, which shows the number of users under aerial coverage when `HRR` is used. When $g=1$ min, the aerial coverage initially increases with the number of available drones until $M=6$, while larger fleets incur coverage decays. This behavior was observed in [8] for always active infinite-powered drones: the higher drones density, the higher interference they mutually cause, which eventually reduces user's SINR more than proximity to *aBS*s can increase. We also unveil that, in some scenarios like with displacement time g of 5 or 10 minutes, it is possible that different fleet sizes achieve equal performance with `HRR`. For instance, the aerial coverage with $M=4$ does not change when a fifth drone is added: this is because the value of N that can be guaranteed with either $M\!=\!4$ or $M\!=\!5$ is 3, as previously shown in Figure 2. This situation is more frequent when g increases (e.g., $g\!=\!10$ min).

Using `HRR`, the number of active *aBS*s is constant, yet not maximal. Instead, `Greedy` can operate all available *aBS*s. This results in a variable number of active *aBS*s over time. To assess the differences between both approaches, with the same drone positioning scheme in both cases, we re-run the above discussed simulation scenarios with `Greedy`. Due to space constraints, we only show a coverage comparison between

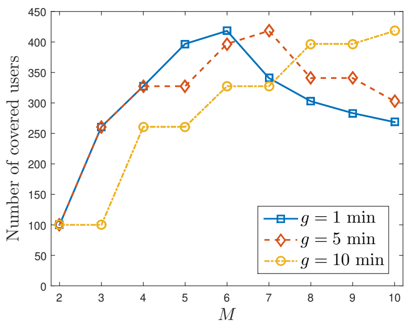

Figure 6: Average aerial coverage when M drones are available, for $f = 45$ min and $c = 15$ s.

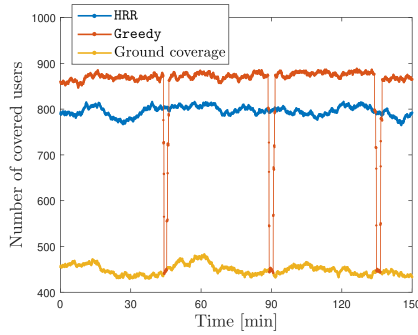

Figure 7: `HRR` vs. `Greedy`: network coverage over time (2.5 h) for $M = 5$, $f = 45$ min, $g = 1$ min, $c = 15$ s.

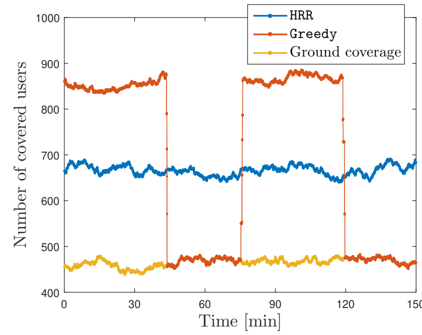

Figure 8: `HRR` vs. `Greedy`: network coverage over time (2.5 h) for $M = 5$, $f = 45$ min, $g = 1$ min, $c = 30$ min.

`HRR` and `Greedy` for a fleet of $M = 5$ aBSs, with maximum flying time of $f = 45$ min and displacement time $g = 1$ min.

In Figure 7, we consider the case of recharging time $c = 15$ s, i.e., here the battery is swapped. In this scenario, `HRR` finds that a maximum of 4 aBSs can constantly provide coverage, so we use exactly 4 aBSs. `Greedy`, instead, uses 5 aBSs, except when one drone needs a pit stop. Both schemes permit to increase coverage by a factor 2 or more, with respect to the ground coverage shown in the figure. As all aBSs will try to pit stop at about the same time with `Greedy`, this strategy results in frequent intervals with low coverage, of the order of a few minutes. The rest of the time, `Greedy` offers a better coverage than `HRR`, with a margin of about 15% over `HRR`. In Figure 8, we instead consider the case of $c = 30$ min, i.e., here the battery is recharged. In this scenario, `HRR` can only guarantee 3 active aBSs, which reduces coverage from about 800 to about 690 users with respect to the case with $c = 15$ s. `Greedy`, with the 5 available aBSs, suffers very long-lasting coverage drops and, in practice, the coverage oscillates between peaks of about 880 users and long intervals (about 40% of the time) with only 470 users covered, which is what can be covered by the ground base stations. Different scenarios, not illustrated here due to space constraints, show similar results, except the coverage with more aBSs is not guaranteed to be better than with less aBSs, as commented above. Therefore, the limitation of a greedy approach is two-fold: (i) it can force the operation of an unnecessarily high number of aBSs, and (ii) coverage is unstable and the network incurs long periods in which the offered service is poor. The performance drops of `Greedy` are extreme and lead to periods in which no aBS is available, because all of them are either swapping/charging the battery or waiting for their turn to do so at the RS. This behavior could be certainly obviated by, e.g., using batteries with non-homogeneous charge levels or by introducing a phase shift in the operation of aBSs. However, what cannot be easily prevented is that the service level varies over time. In contrast, `HRR` offers a simple solution that enables a stable number of active aBSs, so that operators can guarantee a stable network service at all times.

V. Conclusions

We derived `HRR` to recharge drones that assist the operations of a cellular network, with the specific example of network coverage. `HRR` is optimal, as proven in the paper, in the sense that it solves the problem of finding how many back-up drones are needed to guarantee stable network performance or, equivalently, how many drones can serve as active aBSs at all times when the operators dispose of a fixed number of drones. Our result is paramount to correctly dimension a network of relay drones with realistic drone energy constraints, at minimal cost. Having an optimal strategy that guarantees a constant number of servicing drones results to be crucial to guarantee the maximum stable network service at all times, in comparison to suboptimal recharging strategies.

Acknowledgments

This work was partially supported by the Region of Madrid through the TAPIR-CM project (S2018/TCS-4496).

References

[1] V. Chamola, V. Hassija, V. Gupta, and M. Guizani, "A Comprehensive review of the COVID-19 pandemic and the Role of IoT, drones, AI, blockchain, and 5G in managing its impact," *IEEE Access*, vol. 8, pp. 90 225–90 265, 2020.

[2] I. Bor-Yaliniz, M. Salem, G. Senerath, and H. Yanikomeroglu, "Is 5G ready for drones: A look into contemporary and prospective wireless networks from a standardization perspective," *IEEE Wireless Communications*, vol. 26, no. 1, pp. 18–27, 2019.

[3] J. R. Montoya-Torres, J. López Franco, S. Nieto Isaza, H. Felizzola Jiménez, and N. Herazo-Padilla, "A literature review on the vehicle routing problem with multiple depots," *Computers & Industrial Engineering*, vol. 79, pp. 115–129, 2015.

[4] M. Shin, J. Kim, and M. Levorato, "Auction-based charging scheduling with deep learning framework for multi-drone networks," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 5, pp. 4235–4248, 2019.

[5] E. Hartuv, N. Agmon, and S. Kraus, "Scheduling spare drones for persistent task performance under energy constraints," in *Proceedings of the 17th AAMAS International Conference*, 2018, pp. 532–540.

[6] H. Park and J. R. Morrison, "System design and resource analysis for persistent robotic presence with multiple refueling stations," in *ICUAS*, 2019, pp. 622–629.

[7] E. Hartuv, N. Agmon, and S. Kraus, "Spare drone optimization for persistent task performance with multiple homes," in *ICUAS*, 2020, pp. 389–397.

[8] E. Arribas, V. Mancuso, and V. Cholvi, "Coverage optimization with a dynamic network of drone relays," *IEEE Transactions on Mobile Computing*, vol. 19, no. 10, pp. 2278–2298, 2019.

[9] B. Michini, T. Toksoz, J. Redding, M. Michini, J. How, M. Vavrina, and J. Vian, "Automated battery swap and recharge to enable persistent uav missions," in *Infotech@ Aerospace 2011*, 2011, p. 1405.