Energy-Efficient Mission Planning of UAVs for 5G Coverage in Rural Zones

Lavinia Amorosi,[1] Luca Chiaraviglio,[(1,2)] Fabio D'Andreagiovanni,[(3,4)] Nicola Blefari-Melazzi,[(1,2)]
1) Consorzio Nazionale Interunivesitario per le Telecomunicazioni, Italy,
2) EE Department, University of Rome Tor Vergata, Italy, email: luca.chiaraviglio@uniroma2.it
3) National Center for Scientific Research (CNRS), France,
4) Sorbonne Universités, Université de Technologie de Compiègne, CNRS, Heudiasyc
UMR 7253, CS 60319, 60203 Compiègne, France, email: d.andreagiovanni@hds.utc.fr

***Abstract*—We target the problem of providing 5G network connectivity in rural zones by means of Base Stations (BSs) carried by Unmanned Aerial Vehicles (UAVs). Our goal is to schedule the UAVs missions to: i) limit the amount of energy consumed by each UAV, ii) ensure the coverage of selected zones over the territory, ii) decide where and when each UAV has to be recharged in a ground site, iii) deal with the amount of energy provided by Solar Panels (SPs) and batteries installed in each ground site. We then formulate the RURALPLAN optimization problem, a variant of the unsplittable multicommodity flow problem defined on a multiperiod graph. After detailing the objective function and the constraints, we solve RURALPLAN in a realistic scenario. Results show that RURALPLAN is able to outperform a solution ensuring coverage but not considering the energy management of the UAVs.**

I. INTRODUCTION

According to different studies, at least two billions people are experiencing a complete lack of Internet coverage [1]. Such people are mostly living in rural zones, where the network operators are not generally keen to invest, due to the prohibitive deployment costs, as well as very low Return on Investment (RoI) rates. This includes current technologies for deploying access networks, such as 3G/4G and FTTx, and the forthcoming 5G technology. Nevertheless, the lack of Internet connectivity is one of the major impairments for the development of the United Nations (UNs) Sustainable Development Goals (SDGs) [2], [3].

Among the different solutions to reduce the Internet connectivity divide in rural and low income areas, one of the most promising is the exploitation of Unmanned Aerial Vehicles (UAVs) providing 5G coverage (see e.g., [4], [5], [6], [7]). The main idea behind most of such approches is the deployment of an opportunistic network, where the users associate to the Base Stations (BSs) carried by the flying UAVs. A radio network based on UAVs, in fact, introduces several advantages, including: i) the possibility to cover only the zones of the territory where (and when) the users are located, ii) a general decrease of the installation costs, thanks to the fact that multiple UAVs can share the same ground site to recharge themselves and to exchange data with the core of the network, and iii) the adoption of short-distance Line-of-Sight (Los) communication channels between the users and the UAV covering them.

Even though the deployment of UAV-based 5G network architectures is a promising solution, its actual evaluation in real-life scenarios is only at the early stage. In particular, when an UAV-based 5G architecture is assumed, different key questions arise, such as: i) How to cover a set of areas with a set of UAV-based BSs? ii) How to efficiently manage the energy consumed by the UAV-based BSs? iii) How to manage the energy coming from the Solar Panels (SPs) and the batteries installed at the ground sites? iv) Is it possible to define a model to take into account all the aforementioned aspects? The goal of this paper is to shed light on these issues by:

1) considering a scenario in which a set of ground sites, a set of UAVs, and a set of areas that need to be covered are given as input;
2) targeting the energy efficient management of the UAVs missions, in order to minimize the energy that is consumed by the UAVs;
3) ensuring the coverage of the areas by efficiently scheduling the UAVs missions over a set of multiple Time Slots (TSs);
4) dealing with the battery levels of each ground site to decide where and when each UAV is recharged.

More in detail, we define an optimization problem, called RURALPLAN, with the goal of minimizing the energy consumed by the UAVs during the moving operations, while ensuring coverage, energy consumption, and battery levels constraints. Results, obtained over a representative scenario, clearly show that RURALPLAN is able to outperform a solution focused solely on the problem of providing coverage over the territory.

In recent times, the optimal planning and management of networks made up of drones aimed at providing various kind of services such as surveillance, package delivery and network connectivity has received a lot of attention (see e.g., [8], [9], [10], [11]). Such optimization problems are closely related to the general problem of multi-period capacitated network design, involving flow models on a graph [12]. In line with this trend, RURALPLAN exploits a graph-based structure to model the UAVs missions.

The closest paper to our present work is [6], in which

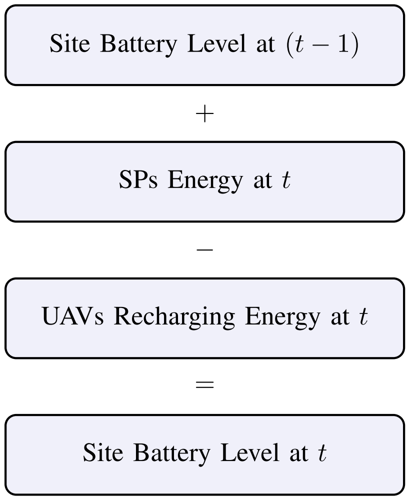


Fig. 1. Computation of the battery levels for one site at TS t

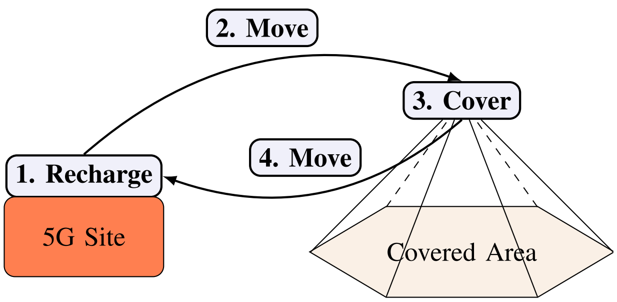


Fig. 2. An example of an UAV mission composed of recharging, moving and covering actions.

authors define an UAV-based 5G-architecture, and evaluate its feasibility in terms of economic metrics. However, the scheduling of the UAVs missions, as well as their evaluation in terms of consumed energy, is not taken into account at all. In this work, we go two steps further from [6], by: i) providing an optimization framework to schedule the UAVs missions across a set of Time Slots (TSs) and ii) targeting the minimization of the energy wasted by the UAVs during their operation.

Even though the results presented in this paper are promising, we point out that this work is an initial step towards a more complex framework. In particular, the definition of fast algorithms, able to solve the problem for scenarios more complex than the one considered here, as well as the study of the impact on the user Quality of Service, are two important aspects that are left for future work.

The rest of the paper is organized as follows. Sec. II describes the UAV-based 5G architecture and the relevance of this work. Sec. III derives the problem formulation. The scenario under investigation is described in Sec. IV. Results are discussed in Sec. V. Eventually, Sec. VI reports the conclusions and possible future work.

II. UAV-based 5G Architecture Description and Work Relevance

We concisely review the UAV-based 5G architecture defined in [6], [13], referring the reader to these papers for a more

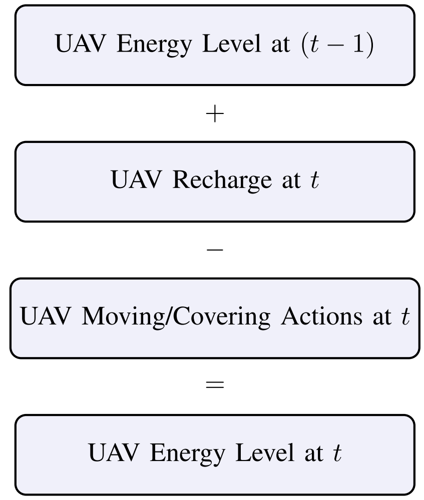


Fig. 3. Computation of the energy levels for one UAV at TS t

detailed description of the architecture. In brief, we assume that most of BS equipment, and in particular the dedicated HW one, is carried on board of the UAV. The dedicated HW includes a Remote Radio Head (RRH) and part of the Base Band Unit (BBU) in order to perform low-level operations over the received/transmitted bits between the UAV-based BS and the covered users. Clearly, each RRH is connected to a set of antennas that are also carried by the UAV. The remaining operations (e.g., the ones performed at upper layers) are performed by virtualized elements installed on the commodity HW, which is placed at a ground site. The separation between high-level and low-level functionalities allows to reduce the amount of HW carried by the UAV, and consequently the moving of the UAV over the territory in order to ensure the 5G coverage. The communication between the high-level HW functionalities hosted at the ground site and the low-level ones carried on board of the UAV is realized by means of a radio link, which has to ensure high levels of reliability.

Apart from hosting the commodity HW, each site is connected to a set of SPs and batteries, which are installed in the same site location. In particular, we assume that SPs and batteries are the only sources of energy. In this way the considered architecture is completely self-sustainable, i.e. no power is requested to the electricity grid. In the following, we assume that time horizon is discretized in TSs. In each TS, the battery level at current TS is computed as the composition of different terms, as reported in Fig. 1. In particular, the UAVs can recharge themselves in a site, and their requested energy decreases the battery level. On the other hand, the levels can be increased by the energy produced by the SPs during the current TS. The resulting battery level is then the composition of the different terms. In addition to this, the battery level is kept between a minimum level and a maximum one. Ensuring a minimum level tends to reduce the impact of battery failures [14]. On the other hand, each battery has a maximum capacity.

We then move our attention to the UAVs and their features. Fig. 2 reports an example of a typical mission performed by

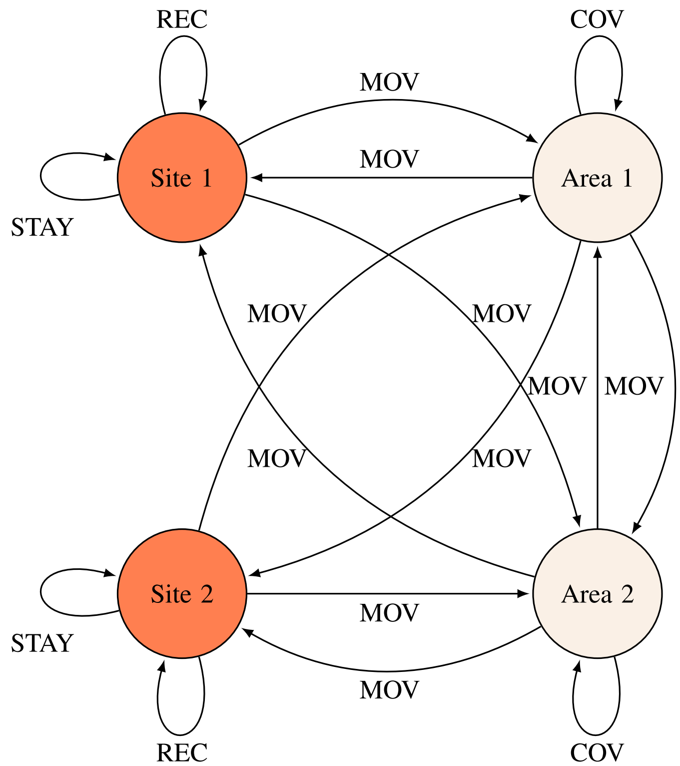


Fig. 4. Possible transitions between two sites and two areas. Each arc consumes one TS.

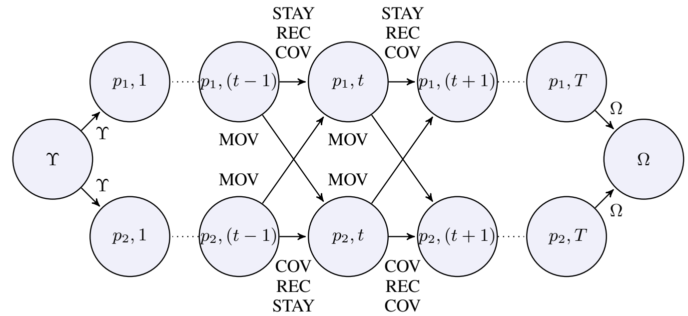


Fig. 5. General arc transitions between consecutive TSs. The source node Υ, a set of two places $\{p_1, p_2\}$, and the final sink node Ω are shown.

an UAV carrying a 5G BS. Initially, the UAV is recharged at a ground site, in order to ensure that the UAV has a sufficient energy level to complete the mission. Similarly to the ground site, each UAV stores the energy in a set of batteries. In the following, the UAV moves towards an area, and this operation consumes an amount of energy which is proportional to the distance between the site and the covered area. The UAV then remains over the area, and the 5G coverage is provided by the BS equipment carried on board of the UAV. Clearly, also this operation consumes an amount of energy, which depends on the amount of time the UAV-based BS covers the area. Eventually, the UAV moves back to the ground site, thus consuming an amount of energy which is again proportional to the distance between the area and the site. In a more general case, composed of multiple ground sites and multiple areas, the UAVs' missions can be even more complex, with multiple areas that may be covered during the same mission. Fig. 3 reports the computation of the energy levels for one UAV in one TS. In particular, starting from the previous energy level, the current energy level takes into account the contribution from recharging (if a recharge has been performed), or the consumption due to covering/moving operations. Moreover, also in this case the energy level at current TS t is kept between a minimum level and a maximum one. Eventually, a minimum energy level allows the UAV to come back to a site upon an emergency and/or bad weather condition. On the other hand, a maximum has to be imposed, since the capacity of the batteries installed on the UAV is limited.

In this scenario, reducing the amount of energy consumed by the UAVs during the moving operations introduces several advantages, including: i) the reduction of the energy consumed to recharge the UAVs at the ground sites, ii) the possibility to exploit part of the saved energy to increase the amount of time dedicated to cover the territory, and/or iii) the possibility to proper fulfil the energy requests during emergency situations (e.g., as a consequence of an UAV failure and/or unexpected bad weather conditions). In the next section, we report the problem formulation of the considered problem.

III. Problem Formulation

We model the problem through Mixed Integer Linear Programming (MILP), tracing it back to a variant of the unsplittable multicommodity flow problem defined on a multiperiod graph (see [15] for the video surveillance case). More formally, we denote: i) by A the set of areas to be covered; ii) by S the set of available ground sites; iii) by D the set of UAVs; iv) by $T = \{0, 1, 2, \ldots, |T|\}$ the set of Time Slots (TSs). We also define the set of places P, obtained as the union of the set of areas and sites (i.e., $P = A \cup S$). In each TS each UAV can perform one among the following actions:

- REC: the UAV is recharged on a given site;
- STAY: the UAV is kept idle at a given site, and it does not consume any energy;
- MOV: the UAV is moved from one area to one site, or from one area to another area, or from an area to a site;
- COV: the UAV covers a given area.

Fig. 4 reports a representative example in which the arcs represent the set of actions that can be performed by an UAV in a scenario composed by two sites and two areas. In order to cover Area 1 for an UAV starting from Site 1, the following actions need to be performed: REC in Site 1, MOV from Site 1 to Area 1, COV from Area 1 to Area 1, MOV from Area 1 to Site 1. Each of the aforementioned actions requires one TS to be executed.

In order to model the actions performed by the UAVs over the considered set of TSs, we adopt a multiperiod directed graph $G(N, L)$. The set of nodes N includes one node (p, t) for each place $p \in P$ and for each TS $t \in T$. We denote a generic arc $l \in L$ by $[(p_1, t_1), (p_2, t_2)]$, where $t(l) = (p_1, t_1)$ and $h(l) = (p_2, t_2)$ are the tail and the head of the arc, respectively. We then introduce the set of arcs L^{REC}, L^{STAY}, L^{MOV} and L^{COV} to denote the admissible transitions between each place p_1 at TS t_1 and each other place p_2 at TS t_2 for the recharging, staying, moving and coverage actions, respectively.

Fig. 5 shows the admissible arcs for a toy case example composed of two places. Apart from the nodes defined for each pair (p, t) the graph also includes the fictitious nodes Υ and Ω, which are used to keep track of the missions performed by the UAVs across the set of TSs. Our idea is in fact to associate a binary flow variable for each arc and each UAV, and to impose a flow conservation constraint starting in Υ and ending in Ω. The advantage of using the source node Υ is that the problem is able to automatically choose the optimal placement of the UAVs already during the first TS, without the need of manually specifying it. In other words, we place a number of tokens in Υ equal to the number of UAVs. In principle, each token corresponds to an UAV. The problem then automatically selects which flow variables are activated in order to preserve the token continuity until the Ω node. In particular, the Ω node allows to check that all the tokens are correctly received, i.e., the problem has considered all the UAVs until the final TS. The connections between the node Υ and the node Ω are realized through the set or arcs L^{Υ} and L^{Ω}. The union of sets $L^{REC} \cup L^{STAY} \cup L^{MOV} \cup L^{COV} \cup L^{\Upsilon} \cup L^{\Omega}$ defines the entire set of links L.

In the following, we associate an energy weight for each arc in L. Fig. 6 reports the admissible arcs and the energy values for each pair of places and consecutive TSs. More in detail, two arcs are defined when the UAV is kept on the same site between TS $(t-1)$ and TS t, as reported in Fig. 6(a). In the first case, there is one link $l \in L^{REC}$, whose weight is equal to the energy consumed for recharging an UAV, denoted with E^{REC}. Alternatively, there is the possibility to keep the UAV on the site without any energy consumption through the link $l \in L^{STAY}$. In addition, when the UAV is moved from a site $s \in S$ to an area $a \in A$ (Fig. 6(b)), an arc $l \in L^{MOV}$ is defined.[1] In this case, the weight of the arc is equal to $-E^{MOV}_{s,a}$, where $E^{MOV}_{s,a}$ denotes the amount of energy consumed for moving the UAV from site s to area a. Similarly, when the UAV is moved from an area a to a site s, another arc $l \in L^{MOV}$ is introduced, whose weight is equal $-E^{MOV}_{a,s}$ (Fig. 6(c)). On the other hand, when the area is not changed, a coverage action is performed (Fig. 6(d)). In this case, the corresponding arc $l \in L^{COV}$ has a weight of $-E^{COV}$, where E^{COV} denotes the amount of energy spent to cover an area in one TS. Eventually, when the UAV passes from area $a_1 \in A$ to a different area $a_2 \in A$ (Fig. 6(e)), an arc $l \in L^{MOV}$ with weight $-E^{MOV}_{a_1,a_2}$ is introduced. Finally, the arcs connecting Υ and Ω to the other nodes are defined in Fig. 6(f)-6(i). Clearly, such arcs do not consume any amount of energy since both Υ and Ω are fictitious nodes.

[1]The set L^{MOV} may not include all the possible links between each pair of places. This occurs, e.g., when a maximum distance between an UAV and the ground site has to be ensured.

TABLE I
SETTING OF THE $\beta^d(p,t)$ VALUES

Condition	$\beta^d(p,t)$ Value
$(p,t) = \Omega$	1
$(p,t) = \Upsilon$	-1
otherwise	0

The optimization model is based on the following families of decision variables:

1) a binary *flow variable* $f^d_l \in \{0,1\}$ $\forall\, l \in L, d \in D$ that is equal to 1 if the UAV d uses the arc l (0 otherwise);
2) a continuous variable $b^t_s \geq 0$ $\forall\, s \in S, t \in T$ representing the energy available at site s at TS t;
3) a continuous variable $e^t_d \geq 0$ $\forall\, d \in D, t \in T$ representing the energy of an UAV d at TS t.

The overall RURALPLAN problem is then formulated as follows:

$$\min \sum_{d \in D} \sum_{l \in L^{MOV}} |E_l| \cdot f^d_l \quad (1)$$

$$\sum_{\substack{l \in L: \\ h(l)=(p,t)}} f^d_l - \sum_{\substack{l \in L: \\ t(l)=(p,t)}} f^d_l = \beta^d_{(p,t)} \qquad \forall p \in P, d \in D, t \in T \quad (2)$$

$$\sum_{d \in D} \sum_{\substack{l \in L^{COV}: \\ h(l)=(p,t)}} f^d_l = 1 \quad \forall p \in A, t \in T : t \geq 1 \quad (3)$$

$$b^t_s \leq b^{t-1}_s + E^t_s \cdot N^{SP}_s - \sum_{d \in D} E_l \cdot f^d_l \quad \forall s \in S, t \in T, \quad \forall l \in L^{REC} : h(l) = (s,t) \wedge t(l) = (s, t-1) \quad (4)$$

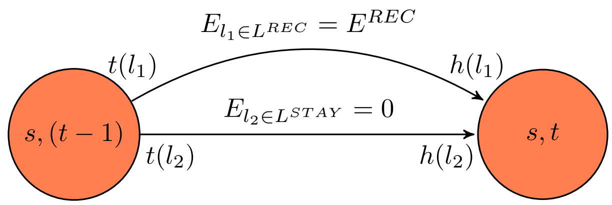
$$B^{MIN} \cdot N^B_s \leq b^t_s \leq B^{MAX} \cdot N^B_s \quad \forall s \in S, t \in T \quad (5)$$

$$e^t_d \leq e^{t-1}_d + \sum_{\substack{l \in L^{MOV} \cup L^{REC} \cup L^{COV}: \\ t(l)=(*,t-1) \\ h(l)=(*,t)}} E_l \cdot f^d_l \qquad \forall d \in D, t \in T \quad (6)$$

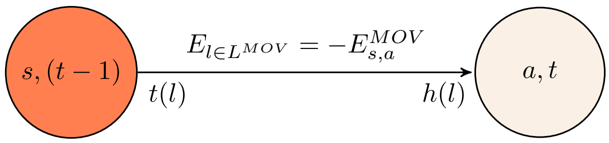
$$E^{MIN} \leq e^t_d \leq E^{MAX} \quad \forall d \in D, t \in T \quad (7)$$

$$f^d_l \in \{0,1\} \quad \forall d \in D, l \in L \quad (8)$$

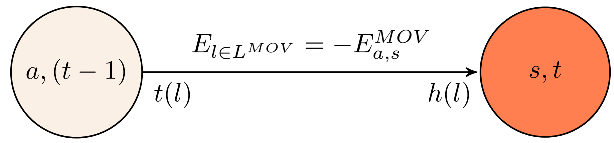
More in depth, the objective function (1) is the minimization of the energy consumed by drones to move around (expressed through the product of the flow variables and the energy values associated with the arcs of the graph belonging to L^{MOV}). Constraints (2) impose the conservation of the flow variables f^d_l, where the term $\beta^d(p,t)$ appearing in the constraint is defined in Tab. I. The coverage of each area is imposed by constraints (3), by considering only the L^{COV} arcs incoming



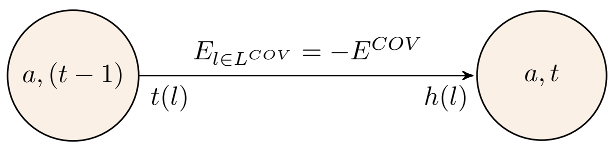
(a) Same Site: REC and STAY



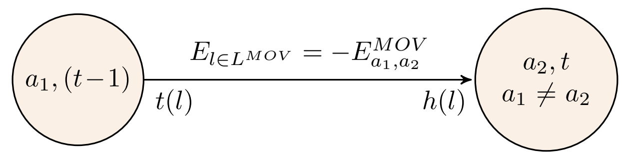
(b) Site to area: MOV



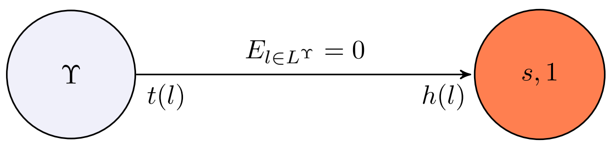
(c) Area to site: MOV



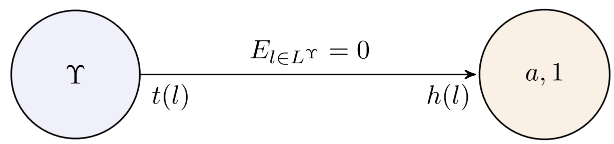
(d) Same Area: COV



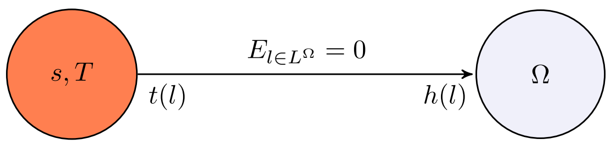
(e) Different Areas: MOV



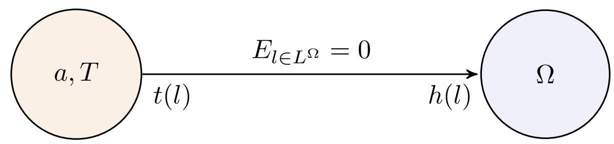
(f) Source Node to Site: Υ



(g) Source Node to Area: Υ



(h) Site to Sink Node: Ω



(i) Area to Sink Node: Ω

Fig. 6. Admissible arcs and energy values for each pair of places and consecutive TSs.

to each area. Constraints (4) impose the battery balance for each TS t and for each site s. The balance is computed by adding to the battery level at previous TS the energy produced by the SPs minus the energy requested to recharge the UAVs at current TS. The minimum and the maximum battery levels are imposed by constraints (5). The UAV energy is then set through constraints (6) by considering: i) the contributions of the $L^{MOV} \cup L^{REC} \cup L^{COV}$ energy arcs used by the UAV at the current TS, ii) the UAV energy at previous TS. The minimum and the maximum UAV energy levels are then ensured by Eq. (7). Eventually, (8) declare the binary flow variables.

IV. Scenario Description

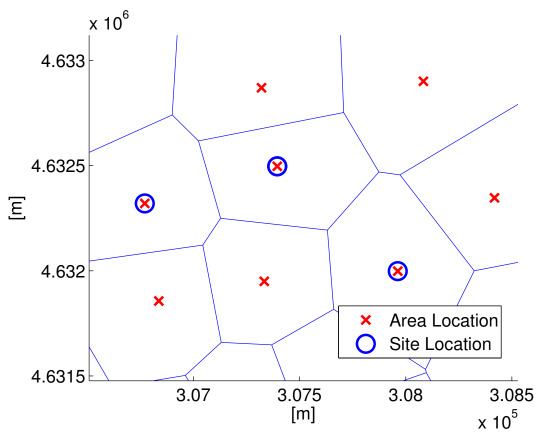
We consider a rural zone in Frascati, a town located in the countryside of central Italy. Fig. 7(a) shows the aerial view. Interestingly, the considered zone is composed of roads, fields, small houses, and buildings having at most 3-4 floors. Thanks to the fact that there are not tall obstacles, the zone can be attractive for the deployment of the UAV-based 5G architecture. Fig. 7(b) reports the locations of the places, which are spread over the considered zone. Finally, Fig. 7(c) reports the locations of the sites, as well as the centers of the areas to be covered. In particular, we consider a set S composed of 3 sites, and a set A composed of 8 areas.

Tab. II summarizes the setting of the main parameters. The selection of the sites, as well as the dimensioning of each site in terms of SPs and batteries, is done by solving the design problem of [16], in order to minimize the installation costs. In addition, we have set a number of UAVs larger than the areas to be covered. In this way, we are able to guarantee coverage over the territory in each TS, despite the fact that each UAV may be recharged, moved to an area, or moved to a site during a given TS.[2] Moreover, the B_{MIN} and B_{MAX} parameters are set in accordance to [14], in order to guarantee the recharge of the UAVs, as well as avoiding possible battery failures. Moreover, the energy produced by each SP, reported in Fig. 8, is taken from historical data from one day in June available for the location [17]. Focusing on the parameters related to the energy consumption of the UAVs, we assume that each UAV can be charged up to $E^{MAX} = 1000$ [Wh]. Moreover, we as-

[2]The investigation of the impact of varying $|D|$ is left for future work.

(a) Aerial View (Source: Google Earth)

(b) Locations of the places (Source: Google Earth)



(c) Locations of the sites and the centers of the areas

Fig. 7. The Frascati scenario.

TABLE II
PARAMETERS SETTING

Parameter	Value
A	$\{A8, A9, A10, A11, A12, A13, A15, A16\}$
$\|A\|$	8
S	$\{S9, S10, S15\}$
$\|S\|$	3
T	1 [day] divided in 24 TSs of 1 [h]
D	25 UAVs
E^{COV}	200 [Wh]
E^{REC}	1000 [Wh]
E_s^t	see Fig.8
$E_{p1,p2}^{MOV}$	see Fig.9
N_s^B	$N_{S9}^B = 21$, $N_{S10}^B = 15$ $N_{S15}^B = 15$
N_s^{SP}	$N_{S9}^{SP} = 10$, $N_{S10}^{SP} = 8$, $N_{S15}^{SP} = 7$
B^{MIN}	720 [Wh]
B^{MAX}	2400 [Wh]
E^{MIN}	100 [Wh]
E^{MAX}	1000 [Wh]

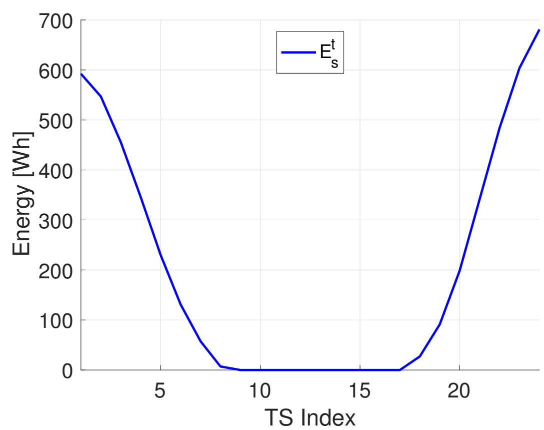


Fig. 8. SP energy E_s^t [Wh] vs. TS index.

sume that the UAV energy can be decreased up to a minimum value $E^{MIN} = 100$ [Wh]. In this way, we assume that each UAV has an amount of energy sufficiently high to safely land on a site upon an emergency and/or bad weather condition. In addition, Fig. 9 reports the energy values of the L^{MOV} arcs. Intuitively, we have set E_{p_1,p_2}^{MOV} $\forall p_1 \in P, p_2 \in P$ by considering an amount of consumed energy proportional to the distance between p_1 and p_2. However, an arc is included only if the distance between p_1 and p_2 is lower than a maximum value, which is set equal to 900 [m]. In this way, for example, the distance between a site and the UAV serving an area can guarantee an adequate Signal To Interference plus Noise Ratio (SINR) for the radio link established between the site and the UAV.[3] Consequently, the L^{MOV} graph is not a full mesh (see the yellow cells of Fig. 9, corresponding to the "NO" label in the colorbar of the figure). Moreover, there are places p_1 and p_2 with $E_{p_1,p_2}^{MOV} = 0$ [Wh], corresponding to: i) same areas or same sites pairs, or ii) area-site pairs which are co-located, and hence not consuming energy values for moving the UAVs between them (see e.g, the S10-A10 pair).

V. RESULTS

We code the RURALPLAN model by means of the IBM ILOG CPLEX Optimization Studio software (v.12.7.1) on a Cloud Azure DS13 machine equipped with 8 virtual cores

[3]A more detailed evaluation of this aspect is left for future work.

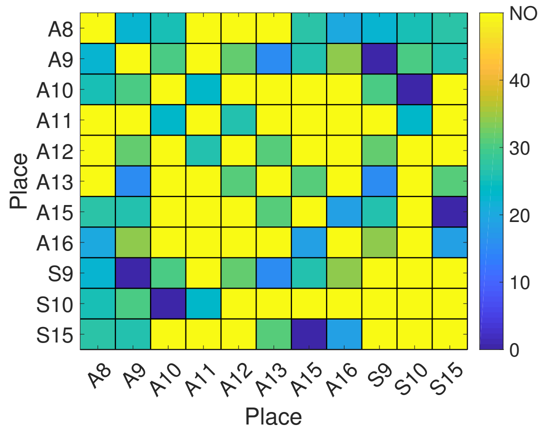


Fig. 9. $E_{p_1,p_2}^{MOV} \quad \forall p_1 \in P, p_2 \in P$ [Wh] (NOTE: cells with value "NO" denote place pairs not connected with an L^{MOV} arc).

TABLE III
RURALPLAN AND MAXCOV COMPARISON

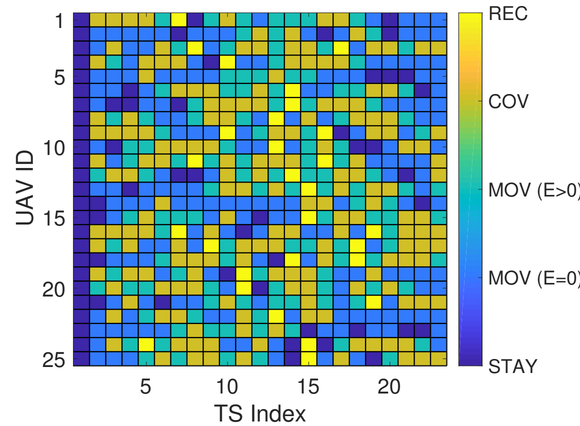
Metric	MAXCOV	RURALPLAN		
		TL=2 [h]	TL=24 [h]	TL=48 [h]
ME [Wh]	86982.4	31150.6	29115.7	23858.8
MILP Gap [%]	$< 10^{-6}$	54.6	50.2	38.1

and 56 GB of virtual Random Access Memory (RAM). We consider as a term of comparison the problem of maximizing the coverage of the territory, denoted as MAXCOV. More formally, the MAXCOV problem is defined as follows:

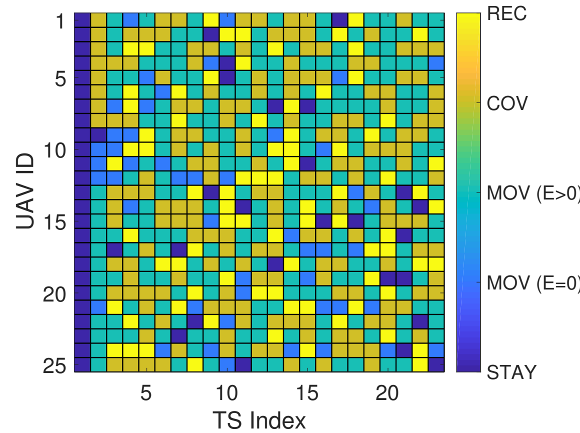
$$\max \sum_{l \in COV} f_l^{COV} \tag{9}$$

subject to: (2)-(8). More in detail, the goal of MAXCOV is to ensure that each area is covered by an UAV in each TS, under the flow conservation, the UAV energy consumption, and the battery management constraints. Differently from RURALPLAN, the MAXCOV formulation does not consider the impact of the activated L^{MOV} arcs on the total energy consumption, and, hence, it may result in a waste of UAV energy.

Tab. III reports the comparison of the RURALPLAN and the MAXCOV strategies over the Frascati scenario. Apart from the energy consumed for moving the UAVs (expressed as $ME = \sum_{d \in D} \sum_{l \in L^{MOV}} |E_l| \cdot f_l^d$) we consider also the gap obtained by setting different Time Limits (TLs) for solving RURALPLAN. Informally speaking, the MILP gap is a measure of quality of a feasible solution found by an algorithm, assessing how far the solution is from an optimal solution. In particular, when the TL is reached and the optimum has not been found, the current best solution (and the achieved MILP gap) are saved. Several considerations hold by examining in detail Tab. III. For MAXCOV it is possible to obtain an optimal solution with an energy consumption ME larger than 86 [kWh]. On the other hand, the energy is decreased to less than 32 [kWh] when RURALPLAN is solved with a strict time limit of 2 [h]. Thus, RURALPLAN is able to achieve a reduction of more than 60% of consumed energy compared to MAXCOV, even if the obtained solution is retrieved after a short amount of time. In addition, when the TL is increased, we can note that the objective function is further reduced. Clearly, the MILP gap decreases when the TL is increased (as expected).



(a) RURALPLAN Strategy



(b) MAXCOV Strategy

Fig. 10. Type of action vs. TS index for each UAV and for each strategy.

To have a better understanding of how the MAXCOV and the RURALPLAN strategies operate, Fig. 10 reports the type of actions performed by each UAV in each TS. The RURALPLAN results are the ones achieved by setting TL=2 [h]. We recall that the UAV action between one TS and the following one may be: i) staying in the same place, ii) moving between places with energy equal to zero (only for co-located sites/areas), iii) moving between places with energy larger than zero, or iv) covering an area. For the initial TS, where the UAVs are moved from the fictitious source node Υ to the areas/sites, we assume that this action is equivalent to a staying action. By observing Fig. 10, we can note that the set of UAVs covering the areas varies over time (as expected). Moreover, each UAV can be in a coverage state up to 4 consecutive TSs, in order to have enough energy to always ensure the minimum energy level of Eq.(7). By comparing the output of

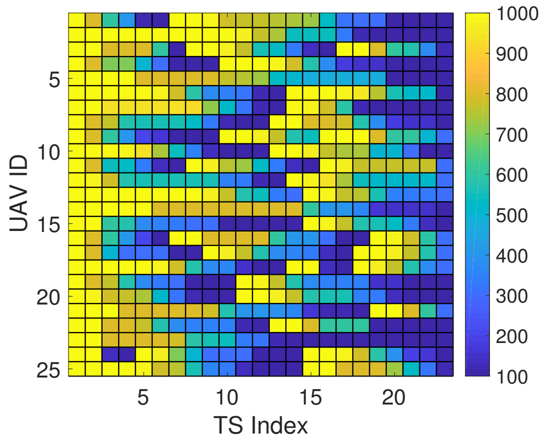


Fig. 11. Energy consumption vs. time for each UAV.

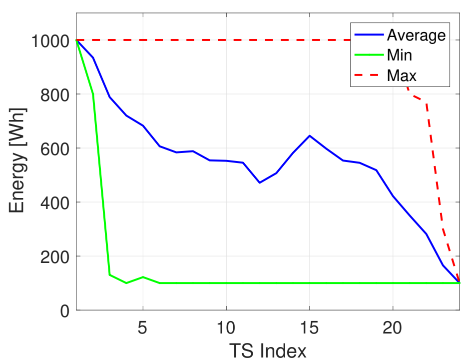


Fig. 12. Maximum, minimum and average UAV energy consumption for each TS.

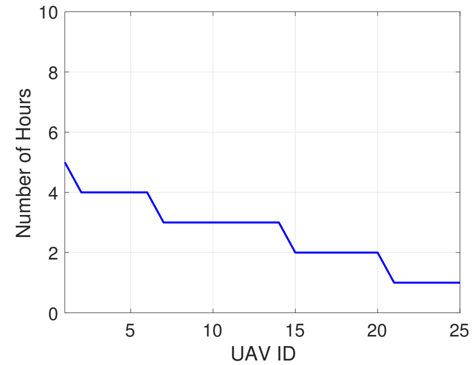


Fig. 13. Number of hours in staying state vs. the UAV ID (note: the IDs are ordered by decreasing hours in the staying state).

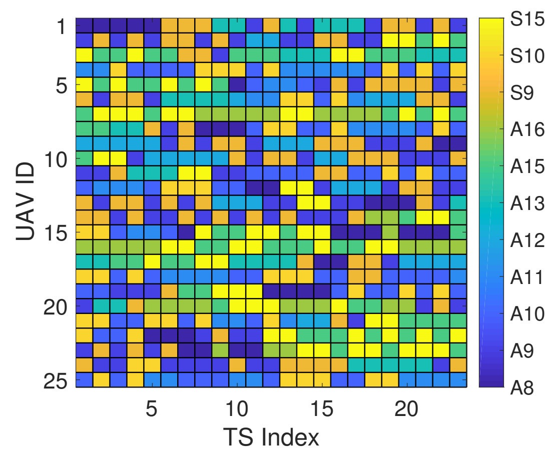


Fig. 14. Positioning vs. TS index for each UAV.

MAXCOV and RURALPLAN, we can clearly see that the latter is able to greatly reduce the energy due to moving operations. This is achieved by increasing the number of actions with a zero energy consumption, i.e. staying and moving between co-located areas/sites.

In the following, we concentrate on the RURALPLAN strategy and its impact on the UAV energy consumption. Fig. 11 shows the energy consumed by each UAV in each TS. As expected, the energy of the UAVs ranges between the $E^{MIN} = 100$ [Wh] and $E^{MAX} = 1000$ [Wh] values. In general, the energy of each UAV is decreased up to E^{MIN}, and then it is increased to E^{MAX} when the UAV is recharged. To give more insight, Fig. 12 reports the minimum, average, and maximum energy consumed by the UAVs in each TS. At the initial TS, all the UAVs start with E^{MAX}. Therefore, the minimum, average and maximum consumption are the same. Then, as soon as the UAVs start performing the missions, their average energy consumption is reduced. However, the average energy is again increased in the middle of the considered period of time, as a consequence of the recharge operations. Then, the energy is again decreased, until the E^{MIN} value is reached. Clearly, in a realistic setting, the solution of the problem in each day would require to reserve a budget of UAV energy which should be used to perform the UAV operations in the following day(s). We leave the investigation of this aspect as future work. Moreover, by observing also the trends of the maximum and the minimum energy values, we can see that there are UAVs that are completely charged or kept with E^{MIN} energy in most of TSs of the considered day.

In the following, we focus on the analysis of staying states for each UAV. To this aim, Fig. 13 reports the number of hours in the staying state for each UAV (in decreasing order). Overall, we can note that the staying state in not very frequent, i.e., less than 3 [h] for most of UAVs. This number suggests that most of the UAVs perform missions involving the coverage of the areas, which include recharge/moving/coverage states rather staying ones.

Fig. 14 shows the positioning of each UAV in each TS. As expected, the positioning in general change across time. However, there are cases where an UAV is positioned on the same site/area for different consecutive TS. For example, the UAV 7 is positioned over the area A16 for 5 consecutive TSs. This corresponds to the moving of the UAV to area A16, plus the covering of the area A16 for 4 consecutive TSs (see also Fig. 10(a)). Moreover, we can note that the moving between the area A9 and the site S9, which are co-located, often occurs (see, e.g, UAV 2).

We then extract from Fig. 14 the number of UAVs posi-

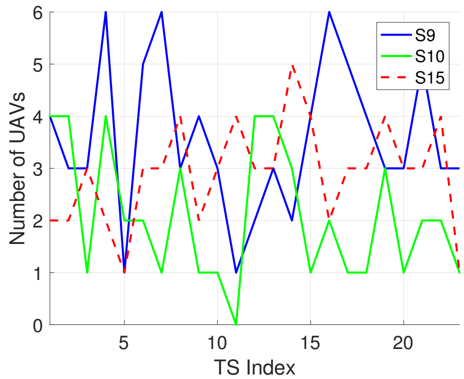


Fig. 15. Number of UAVs per site vs. TS index.

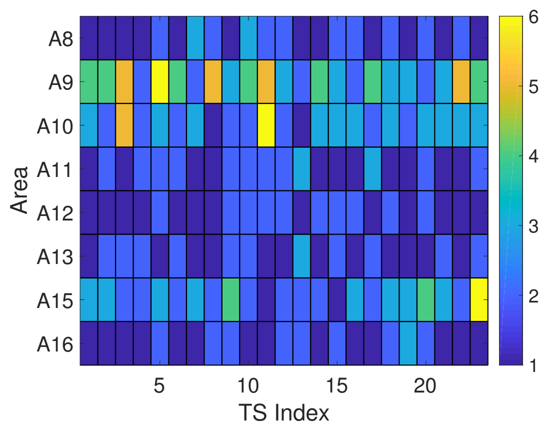


Fig. 16. Number of UAVs per area vs. TS index.

tioned in each site in each TS. Fig. 15 reports the obtained results. Interestingly, the number of UAVs per site notably varies over time. Moreover, the highest peaks are incurred by site S9. This is due to the fact that this site has a larger number of deployed SPs and batteries, and hence it is able to recharge multiple UAVs.

In the last part of our work, we extract from Fig. 14 the number of UAVs per area, as reported in Fig. V. Overall, the number of UAVs per area is pretty small, i.e., one or two. However, the areas that share their location with a site, i.e., A9, A19, A15, present a larger number of UAVs. This is due to the fact that these locations are acting as hubs for the UAVs. Moreover, the moving between an area and a co-located site consumes zero energy, and therefore, is equivalent to a staying state.

VI. Conclusions and Future Works

We have focused on the problem of minimizing the energy consumed for moving the UAVs of a 5G architecture when covering a set of rural areas. After detailing the main features of the proposed approach, we have presented the RuralPlan formulation, which is able to cover a set of areas, while minimizing the energy consumed by the UAVs. Results, obtained over a representative scenario, reveal that RuralPlan is able to reduce the energy consumption more than 60% compared to the MaxCov formulation.

As future work, we plan to put into place a number of activities. First of all, we will design fast algorithms, able to solve the problem also for larger instances considering multiple days. In addition, we will consider the impact of varying the set of available UAVs, as well as introducing a methodology to evaluate the QoS perceived by users.

Acknowledgments

This work was supported by the University of Rome Tor Vergata BRIGHT project (Mission Sustainability Call).

References

[1] M. Eriksson and J. Van de Beek, "Is Anyone Out There? 5G, Rural Coverage, and the Next One Billion," in *Comsoc Technology News*, 2015. Last Accessed: 2018-15-01.

[2] "United nations sustainable development goals." http://www.un.org/sustainabledevelopment/sustainable-development-goals/, 2015. Last Accessed: 2018-06-02.

[3] J. Wu, S. Guo, H. Huang, W. Liu, and Y. Xiang, "Information and Communications Technologies for Sustainable Development Goals: State-of-the-Art, Needs and Perspectives," *IEEE Communications Surveys and Tutorials*, vol. on press, 2018.

[4] I. Bor-Yaliniz and H. Yanikomeroglu, "The New Frontier in RAN Heterogeneity: Multi-Tier Drone-Cells," *IEEE Communications Magazine*, vol. 54, no. 11, pp. 48–55, 2016.

[5] Y. Zeng, R. Zhang, and T. J. Lim, "Wireless communications with unmanned aerial vehicles: opportunities and challenges," *IEEE Communications Magazine*, vol. 54, no. 5, pp. 36–42, 2016.

[6] L. Chiaraviglio, N. Blefari-Melazzi, W. Liu, J. A. Gutierrez, J. van de Beek, R. Birke, L. Chen, F. Idzikowski, D. Kilper, P. Monti, A. Bagula, and J. Wu, "Bringing 5G into Rural and Low-Income Areas: Is It Feasible?," *IEEE Communications Standards Magazine*, vol. 1, no. 3, pp. 50–57, 2017.

[7] V. Sharma, K. Srinivasan, H.-C. Chao, K.-L. Hua, and W.-H. Cheng, "Intelligent deployment of UAVs in 5G heterogeneous communication environment for improved coverage," *Journal of Network and Computer Applications*, vol. 85, pp. 94 – 105, 2017.

[8] J. Kim, B. D. Song, and J. R. Morrison, "On the scheduling of systems of uavs and fuel service stations for long-term mission fulfillment," *Journal of Intelligent & Robotic Systems*, vol. 70, no. 1, pp. 347–359, 2013.

[9] C. C. Murray and A. G. Chu, "The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery," *Transportation Research Part C: Emerging Technologies*, vol. 54, pp. 86 – 109, 2015.

[10] N. Nigam, S. Bieniawski, I. Kroo, and J. Vian, "Control of multiple uavs for persistent surveillance: Algorithm and flight test results," *IEEE Transactions on Control Systems Technology*, vol. 20, no. 5, pp. 1236–1251, 2012.

[11] B. D. Song, J. Kim, J. Kim, H. Park, J. R. Morrison, and D. H. Shim, "Persistent uav service: An improved scheduling formulation and prototypes of system components," *Journal of Intelligent & Robotic Systems*, vol. 74, no. 1, pp. 221–232, 2014.

[12] F. D'Andreagiovanni, J. Krolikowski, and J. Pulaj, "A fast hybrid primal heuristic for multiband robust capacitated network design with multiple time periods," *Appl. Soft Comput.*, vol. 26, pp. 497–507, 2015.

[13] L. Chiaraviglio, N. Blefari-Melazzi, W. Liu, J. A. Gutierrez, J. van de Beek, R. Birke, L. Chen, F. Idzikowski, D. Kilper, P. Monti, and J. Wu, "5G in rural and low-income areas: Are we ready?," in *Proc. of ITU Kaleidoscope: ICTs for a Sustainable World, Bangkok*, pp. 1–8, 2016.

[14] Y. Zhang, M. Meo, R. Gerboni, and M. A. Marsan, "Minimum cost solar power systems for lte macro base stations," *Computer Networks*, vol. 112, pp. 12–23, 2017.

[15] A. Trotta, F. D'Andreagiovanni, M. Di Felice, E. Natalizio, and K. R. Chowdhury, "When UAVs ride a Bus: Towards Energy-Efficient City-scale Video Surveillance," in *IEEE INFOCOM*, 2018.

[16] L. Chiaraviglio, L. Amorosi, N. Blefari-Melazzi, P. Dell'Olmo, P. Monti, and C. Natalino, "Optimal design of 5g networks in rural zones with uavs, optical rings, solar panels and batteries," in *International Conference on Transparent Optical Networks (ICTON), Bucharest*, 2018.

[17] B. Marion and M. Anderberg, "PVWATTS - an online performance calculator for grid-connected PV systems," in *Proceedings of the solar conference*, pp. 119–124, American Solar Energy Society, 2000.