Drone Swarm as Mobile Relaying System: A Hybrid Optimization Approach

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***Abstract*—Drones are increasingly employed in several application domains thanks to their inherent versatility. This work envisions a scenario in which a swarm of Unmanned Aerial Vehicles (UAVs) enables the communication between a set of Sensor Nodes (SNs) and a control center. Considering a general fading channel model, a Mixed-Integer Non-Linear Programming (MINLP) problem is formulated to maximize the overall amount of relayed data by jointly optimizing trajectory and scheduling plan of each drone. Combining convex optimization and Ant Colony Optimization (ACO) algorithm, a quasi-optimal solution is obtained. Finally, numerical results demonstrate the effectiveness of the proposed solution in different parameter configurations and with respect to a benchmark algorithm.**

***Index Terms*—Internet of Drones, Optimization.**

I. Introduction

Internet of Drones (IoD) is a network architecture which enables drone-to-drone and drone-to-ground communications. The huge potential of Unmanned Aerial Vehicles (UAVs) has been demonstrated in several applications [1], [2] such as monitoring and surveying activities, moving payloads, and acting as flying Base Stations (BSs). The possibility to organize UAVs in swarms further eases the accomplishment of complex tasks. Therefore, cooperative Device-to-Device (D2D) communications play a central role in swarm management. In such a context, the allocation of network resources becomes a challenging, yet fundamental, aspect. For instance, [3] studies a scenario in which cellular networks and relays improve communications among devices. A network coding aided cooperative diversity scheme is designed from which the system data rate expression is derived considering interference among nodes. A distributed low-complexity algorithm is developed to solve a coalition formation game, thus jointly optimizing the allocation of spectrum resources and the relay selection.

Drone swarms are also employed for service provisioning, thus demanding specific solutions to optimize data processing and dissemination. To this aim, [4] proposes a holistic middleware, which employs reinforcement learning to dynamically balance the broadcast rate and knowledge loss rate. Moreover, a cooperative dissemination method is designed to fine-tune storage and energy allocation among drones.

Besides their great potential, drones are constrained devices which require sophisticated optimization strategies to finely tune on-board resources (e.g., energy and memory). From this point of view, several contributions jointly analyze different aspects such as energy-efficiency, trajectory design, achievable data rates, memory occupancy, and scheduling planning. In this regard, in [5] multiple sources and destinations communicate through a UAV-enabled relaying system. The contribution aims at maximizing the minimum throughput of all links and, at the same time, optimizing the UAVs' trajectories and transmission power levels. However, the considered channel model only accounts for Line of Sight (LoS) link. Moreover, it is assumed that for each source-destination couple a dedicated drone is deployed, which cannot always be realized.

[6] studies a scenario in which pairs of transceivers need the support of drones to communicate, thus acting as relays. The aim is to minimize the total service time, consisting of communication time and flight duration. Although interesting, the article assumes that for each pair of nodes the communication is enabled by only one drone in the whole service time. Besides, the time spent flying between two consecutive locations is not employed to serve more nodes.

This letter overtakes limitations highlighted above by envisioning a scenario consisting of a variable number of UAVs and Sensor Nodes (SNs), deployed in a reference area. Throughout the mission, the same SN can be served by different drones that continuously relay signals to a control center, through a BS. Each SN is equipped with a wake-up receiver which allows (i) to recover from sleep state, thus saving energy, and (ii) to identify the associated relaying UAV. Communications reliability has also been considered by imposing a low Out-of-Service (OoS) probability.

The present contribution aims at maximizing the total amount of relayed data, while optimizing trajectory and scheduling plan of each drone of the swarm, considering a general fading channel model. A Mixed-Integer Non-Linear Programming (MINLP) problem stems from the derived mathematical formulation, which is challenging to solve. Hence, a quasi-optimal solution is achieved by leveraging Block Coordinate Descendent (BCD) and Successive Convex Approximation (SCA) techniques combined with the Ant Colony Optimization (ACO) algorithm [7]. To the best of authors' knowledge the combination of these techniques has never been employed before. Simulation results demonstrate the validity of the proposed solution in different parameter configurations and with respect to a benchmark scheme derived from [6]. Moreover, even if convergence cannot be mathematically proved, it is numerically verified.

The rest of the work is organized as follows: Section II describes the adopted system model. Sections III and IV discuss the problem formulation and the proposed solution. Section V presents the obtained numerical results. Finally, Section VI concludes the work and draws future research perspectives.

II. System Model

The total mission time T is split into N intervals with duration δ_t. The swarm is composed by D drones having the same hardware and capabilities, each one following a trajectory discretized into N points $\mathbf{q}_{k,z} \in \mathbb{R}^2, k : 1...N, z : 1...D$

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and flying at speed $\mathbf{v}_{k,z} \in \mathbb{R}^2, k: 1...N, z: 1...D$, at constant altitude H. In particular, $\mathbf{Q}_k = \{\mathbf{q}_{k,z} \forall z\}$ and $\mathbf{V}_k = \{\mathbf{v}_{k,z} \forall z\}$ refer to the position and velocity matrices of all drones in the k-th timeslot, respectively. UAVs are in charge of relaying data from S SNs placed in $\mathbf{u}_j \in \mathbb{R}^2, j: 1...S$ to a control center, through a BS located at $\mathbf{q}_\text{b}$. Without loss of generality, when the swarm flies over the area of interest, the generic j-th SN has already generated an amount of sensed data o_j. Throughout their mission, each UAV has to select which SN to serve, in each timeslot. This scheduling plan is described through a binary 3D matrix $\mathbf{X} \in \{0,1\}^{N \times D \times S}$ which is composed by vectors, i.e, $\mathbf{X} = \{\mathbf{x}_{k,j} \; \forall k, j\}$, or equivalently by 2D matrices, i.e., $\mathbf{X} = \{\mathbf{X}_j \; \forall j\}$, that can be obtained through indexes. It is assumed that each drone has two dedicated antennas for SN-UAV and UAV-BS links, while SNs have just one. As a consequence, it is necessary to guarantee that (i) each SN is served by only one drone in each timeslot k and (ii) a UAV can communicate just with one SN per time interval. Moreover, the transmission power of j-th SN and z-th UAV are defined as P^S_j and $P^\text{D}_{k,z}$, respectively. Indeed, it is assumed that drones adopt a power control mechanism such that $0 \leq P^\text{D}_{k,z} \leq P^\text{D}_\text{MAX}$, whereas SNs can only transmit with a fixed power level. Besides, the whole system employs a modulation scheme such that interference among SNs, UAVs, and BS is avoided. Let $g_{k,j}$ be the gain of the quasi-static flat-fading channel between the relaying UAV and a SN j. In each time interval k, $g_{k,j} = \sqrt{\mu_{k,j}} h_{k,j}$ where $\mu_{k,j}$ accounts for pathloss, while $h_{k,j}$ ($\mathbb{E}(|h_{k,j}|^2) = 1$) is a random variable describing a generic channel model coefficient, which remains unchanged in each k but may vary among timeslots [8]. Therefore, it results that:

$$\mu_{k,j} = \beta_0 d_{k,j}^{-\alpha}, \tag{1}$$

$$d_{k,j} = \sqrt{H^2 + \left\| \mathbf{x}_{k,j} {\mathbf{Q}_k}^\mathsf{T} - \mathbf{u}_j \right\|^2}, \tag{2}$$

where β_0 is the reference channel power gain, α is the pathloss coefficient, and $d_{k,j}$ is the euclidean distance of the UAV-SN link. Thanks to Shannon's equation, the channel capacity is defined as:

$$c_{k,j} = B_j \log_2 \left(1 + \frac{P^\text{S}_j \beta_0 |h_{k,j}|^2}{\sigma_j^2 d_{k,j}^\alpha} \right), \tag{3}$$

with $\sigma_j^2 = N_0 B_j$ as the noise power and B_j as the available SN's bandwidth. However, $c_{k,j}$ cannot be exactly know in each instant k since the instantaneous channel coefficient $|h_{k,j}|$ is stochastic. Therefore, to guarantee that the OoS probability $p_{k,j}$ remains below or equal to a threshold ζ, it is necessary to impose the following:

$$\begin{aligned} p_{k,j} &= \mathbb{P}\left(c_{k,j} < r^\text{S}_{k,j}\right) \\ &= \mathbb{P}\left(|h_{k,j}|^2 < \frac{\sigma_j^2 d_{k,j}^\alpha (2^{\frac{r^\text{S}_{k,j}}{B}} - 1)}{P^\text{S}_j \beta_0} \right) \\ &= F\left(\frac{\sigma_j^2 d_{k,j}^\alpha (2^{\frac{r^\text{S}_{k,j}}{B}} - 1)}{P^\text{S}_j \beta_0} \right) \leq \zeta, \; \forall \quad \begin{matrix} z: 1...D-1, \\ j: 1...S, \end{matrix} \end{aligned} \tag{4}$$

being $F(\cdot)$ the Cumulative Distribution Function (CDF) of $|h_{k,j}|^2$. In order to ensure a reliable transmission, the maximum tolerable OoS probability is considered i.e. $p_{k,j} = \zeta \; \forall k, s$. Therefore, the maximum achievable data rate is

$$r^\text{S}_{k,j} = B_j \log_2 \left(1 + \frac{P^\text{S}_j \beta_0 F^{-1}(\zeta)}{\sigma_j^2 d_{k,j}^\alpha} \right), \tag{5}$$

where $F^{-1}(\cdot)$ denotes the inverse CDF. With the same rationale, it is possible to define the BS-UAV channel model and, hence, the data rate as:

$$r^\text{D}_{k,z} = B_z \log_2 \left(1 + \frac{P^\text{D}_{k,z} \beta_0 F^{-1}(\zeta)}{\sigma_z^2 d_{k,z}^\alpha} \right), \tag{6}$$

with $d_{k,z} = \sqrt{H^2 + \left\| \mathbf{q}_{k,z} - \mathbf{q}_\text{b} \right\|^2}$. For the sake of notation, define the data rate vectors of sensors as $\mathbf{r}^\text{S}_j = \{r^\text{S}_{k,j} \; \forall k\}$ and $\mathbf{r}^\text{S}_k = \{r^\text{S}_{k,j} \; \forall j\}$.

It is worth specifying that, in this work, the exchange of signaling and control data is neglected because assumed to be less demanding than data transmission in terms of time and bandwidth [9].

III. Problem Formulation

Let be $\mathbf{Q} = \{\mathbf{Q}_k \; \forall k\}$ and $\mathbf{V} = \{\mathbf{V}_k \; \forall k\}$. The main focus of the present work is to solve the following problem, which is formulated as follows:

$$(P1): \max_{\mathbf{X},\mathbf{Q},\mathbf{V}} \sum_{j=1}^{S} \sum_{z=1}^{D} \left(\mathbf{X}_j^\mathsf{T} \mathbf{r}^\text{S}_j \right)_z \quad \textbf{s.t.}$$

$$\mathbf{x}_{k,z} {\mathbf{r}^\text{S}_k}^\mathsf{T} \leq \hat{r}^\text{D}_{k,z}, \quad \forall k: 1...N, z: 1...D, \tag{7}$$

$$\delta_t \sum_{z=1}^{D} \left(\mathbf{X}_j^\mathsf{T} \mathbf{r}^\text{S}_j \right)_z \leq o_j, \quad \forall j: 1...S, \tag{8}$$

$$\mathbf{q}_{k+1,z} = \mathbf{q}_{k,z} + \delta_t \mathbf{v}_{k,z}, \quad \forall k: 1...(N-1), \tag{9}$$

$$\mathbf{q}_{1,z} = \mathbf{q}_{N,z}, \quad \forall z: 1...D, \tag{10}$$

$$\|\mathbf{v}_{k,z}\| \leq v_\text{MAX}, \quad \forall k: 1...N, z: 1...D, \tag{11}$$

$$\frac{\|\mathbf{v}_{k+1,z} - \mathbf{v}_{k,z}\|}{\delta_t} \leq a_\text{MAX}, \quad \forall k: 1...(N-1), z: 1...D, \tag{12}$$

$$\mathbf{v}_{1,z} = \mathbf{v}_{N,z} = \mathbf{0}, \quad \forall z: 1...D, \tag{13}$$

$$\|\mathbf{x}_{k,z}\| = 1, \quad \forall k: 1...N, z: 1...D, \tag{14}$$

$$\|\mathbf{x}_{k,j}\| = 1, \quad \forall k: 1...N, j: 1...S. \tag{15}$$

Problem $(P1)$ aims at maximizing the total amount of transmitted data from SNs to BS through every drone of the swarm by jointly optimizing their scheduling plan $\mathbf{X}$, trajectory $\mathbf{Q}$ and speed $\mathbf{V}$. In particular, (7) states that SNs' data rate cannot be higher than $\hat{r}^\text{D}_{k,z}$ i.e. maximum achievable relaying UAVs' data rate. Constraint (8) implies that, for each j, transmitted sensing data must be lower than the acquired. Equations (9) and (10) describe the 2D movement of UAVs and the correspondence between start/end point of the trajectory. (13) imposes the initial/final speed of drones. Constraints (11) and (12) denote the speed and acceleration upper-bounds, respectively. Finally, (14) and (15) guarantee that a drone serves just one SN and viceversa.

IV. Proposed Solution

Problem $(P1)$ is a MINLP problem, which is hard to solve. To tackle this issue, BCD technique is applied. Therefore, $(P1)$ is divided into two sub-problems, which are more tractable, and alternately solved until convergence to a quasi-optimal solution is achieved.

A. Sub-Problem 1: Trajectory optimization

The first sub-problem aims at optimizing the trajectory-related parameters $\mathbf{Q}$ and $\mathbf{V}$. Therefore, $\mathbf{X}$ is initialized or assumed to be known. The envisioned sub-problem is:

$$(P2): \max_{\mathbf{Q},\mathbf{V}} \sum_{j=1}^{S}\sum_{z=1}^{D} \left(\mathbf{X}_j^{\mathsf{T}} \mathbf{r}_j^{\text{s}}\right)_z \quad \textbf{s.t.}$$
$$(7)-(13).$$

Unfortunately, $(P2)$ is a non-convex problem. In fact, the objective function is neither convex nor concave with respect to $\mathbf{Q}$, as well as constraints (7) and (8). However, they are convex whereas $\left\|\mathbf{q}_{k,z}-\mathbf{q}_{\text{b}}\right\|$ and $\|\mathbf{x}_{k,j}\mathbf{Q}_k\|^{\mathsf{T}}-\mathbf{u}_j$ are considered. To tackle this issue, SCA technique can be employed in order to obtain an approximate optimum solution. Indeed, reminding that first-order Taylor expansion is a global understimator for convex functions, it is possible to lower-bound $\hat{r}^{\text{D}}_{k,z}$ for each local point $\mathbf{q}^r_{k,z}$ as:

$$\hat{r}^{\text{D}}_{k,z} \geq \widetilde{r}^{\text{D}}_{k,z} = A^r_{k,z} - I^r_{k,z}\left(\left\|\mathbf{q}_{k,z}-\mathbf{q}_{\text{b}}\right\|^2 - \left\|\mathbf{q}^r_{k,z}-\mathbf{q}_{\text{b}}\right\|^2\right), \tag{16}$$

where $\Gamma = \frac{P^{\text{D}}_{\text{MAX}}\beta_0 F^{-1}(\zeta)}{\sigma_d^2}$, $I^r_{k,z} = \frac{B_z \log_2 e(\alpha/2)\Gamma}{{d^r_{k,z}}^{\alpha/2}\left({d^r_{k,z}}^{\alpha/2}+\Gamma\right)}$, and $A^r_{k,z} = B_z \log_2\left(1+\frac{\Gamma}{{d^r_{k,z}}^{\alpha/2}}\right)$. Clearly, the same rationale can be used for $r^{\text{S}}_{k,j}$:

$$r^{\text{s}}_{k,j} \geq \widetilde{r}^{\text{s}}_{k,j} = A^r_{k,j} - I^r_{k,j}\left(\|\mathbf{x}_{k,j}\mathbf{Q}_k\|^{\mathsf{T}} - \mathbf{u}_j^2 - \left\|\mathbf{x}_{k,j}{\mathbf{q}^r_k}^{\mathsf{T}} - \mathbf{u}_j\right\|^2\right). \tag{17}$$

However, it can be verified that (17) is still a concave function, raising an issue with respect to constraints (7) and (8). Therefore, introducing a set of slack variables $\mathcal{W} = \{w_{k,j} \geq 0, \forall k, j\}$, the sub-problem is reformulated as follows:

$$(P2.1): \max_{\mathbf{Q},\mathbf{V},\mathcal{W}} \sum_{j=1}^{S}\sum_{z=1}^{D} \left(\mathbf{X}_j^{\mathsf{T}} w_j\right)_z \quad \textbf{s.t.}$$
$$\widetilde{r}^{\text{s}}_{k,j} \geq w_{k,j}, \quad \forall j: 1...S, \tag{18}$$
$$\mathbf{x}_{k,z}{w_k}^{\mathsf{T}} \leq \widetilde{r}^{\text{D}}_{k,z}, \quad \forall k: 1...N, z: 1...D, \tag{19}$$
$$\sum_{z=1}^{D} \left(\mathbf{X}_j^{\mathsf{T}} w_j\right)_z \leq o_j, \quad \forall j: 1...S, \tag{20}$$
$$(9)-(13). \tag{21}$$

Solving problem $(P2.1)$ is equivalent to solve $(P2)$. In fact, $w_{k,z}$ can always be increased until equality holds in (18). Even if there exists a constraint in (19) or (20) satisfied for strict inequality in (18), there will always be $\mathbf{x}_{k,z}$ or $\mathbf{X}_j^{\mathsf{T}}$ such that (7) and (8) hold. Furthermore, $(P2.1)$ is a standard convex optimization problem, which can be solved by several tools such as CVX [10]. Since the objective function is lower-bounded by a finite value it is guaranteed to converge.

B. Sub-Problem 2: Scheduling Optimization

Given $\{\mathbf{Q},\mathbf{V}\}$, the scheduling plan $\mathbf{X}$ is hereby optimized. The related problem is stated as follows:

$$(P3): \max_{\mathbf{X}} \sum_{j=1}^{S}\sum_{z=1}^{D} \left(\mathbf{X}_j^{\mathsf{T}} \mathbf{r}_j^{\text{s}}\right)_z \quad \textbf{s.t.}$$
$$(7), (8), (14), (15).$$

$(P3)$ is a MINLP problem and due to its combinatorial nature is challenging to solve. Therefore, the well-know ACO algorithm is employed, which has been proved to converge to optimality [7], [11]. $(P3)$ is a large-scale optimization problem since the number of possible states exponentially grows with N and D, i.e., $(S+1)^{ND}$. To face this issue, problem $(P3)$ is solved for each k and z, where it is put in place a colony of L ants which can move among the possible S+1 states, described by a matrix $\mathbf{M}^{S\times(S+1)} = [\mathbf{0}\ \mathbf{I}_S]^{\mathsf{T}}$. In particular, $\mathbf{0}$ defines the No-Transmission (NT) state, while $\mathbf{I}_S$, i.e, identity matrix, expresses the communication with one of the S SNs. As a consequence, constraint (14) is inherently satisfied. The ant's transition among states happens with a probability described by $\mathbf{e}_{k,z} = \{e_{k,z,m}\ \forall m: 1...S+1\}$, defined as:

$$\mathbf{e}_{k,z} = \frac{\boldsymbol{\tau}_{k,z}(1-\sum_{i=1}^{z-1}\frac{\mathbf{e}_{k,i}}{D})^{\gamma}}{\sum_{m=1}^{S+1} e_{k,z,m}}, \quad \forall k: 1...N, z: 1...D, \tag{22}$$

being $\boldsymbol{\tau}_{k,z} = \{\tau_{k,z,m}\ \forall m\}$ the vector of S+1 pheromone trails, $1-\sum_{i=1}^{z-1}\frac{\mathbf{e}_{k,i}}{D}$ a specific coefficient which discourages adoption of states already selected by other components of the swarm, thus satisfying (15), and γ an exponential penalty coefficient. Further, fixed j, a stochastic vector $\boldsymbol{\kappa}$ is updated with the current cumulative sum of sensing transmitted data:

$$\boldsymbol{\kappa}_j = \boldsymbol{\kappa}_j + \mathbf{x}_{k,z}\mathbf{r}^{\text{s}}_k e_{k,z,j+1}, \quad \forall k: 1...N, z: 1...D. \tag{23}$$

Therefore, employing penalty function method, the resultant expression $K_{l,k,z}$, with $l: 1...L$, that characterizes each ant is:

$$K_{l,k,z} = \underbrace{1 - \frac{\mathbf{x}_{k,z}{\mathbf{r}^{\text{s}}_k}^{\mathsf{T}}}{r^{\text{s}}_{\text{MAX}}+\varepsilon}}_{Cost} + \eta_1 \underbrace{\frac{\mathbf{x}_{k,z}{\mathbf{r}^{\text{s}}_k}^{\mathsf{T}} - \hat{r}^{\text{D}}_{k,z}}{\hat{r}^{\text{D}}_{k,z}}}_{\mathcal{C}_1} + \eta_2 \underbrace{\frac{\boldsymbol{\kappa}_j - o_j}{o_j}}_{\mathcal{C}_2}.$$

Cost tends to zero when SN-UAV data rate $\mathbf{x}_{k,z}{\mathbf{r}^{\text{s}}_k}^{\mathsf{T}}$ approaches its maximum, i.e., $r^{\text{s}}_{\text{MAX}}$, that cannot be reached. Indeed, $\varepsilon > 0$ is an arbitrary small value that guarantees $K_{l,k,z} \neq 0, \forall l, k, z$. Moreover, $\mathcal{C}_1$ and $\mathcal{C}_2$ account for the violation of constraints (7) and (8), whereas η_1 and η_2 are weight penalty coefficients. Since all terms are normalized between 0 and 1, it is sufficient that η_1 and η_2 are greater, by some orders of magnitude, than $\max(Cost) + \max(\mathcal{C}_1) + \max(\mathcal{C}_2) = 3$ whereas constraints are not satisfied, zero otherwise. Finally, the pheromone trails $\tau_{k,z,m}$ are updated at each iteration as follows:

$$\tau_{k,z,m} = \tau_{k,z,m} + \frac{1}{\sum_{l=1}^{L} K_{l,k,z}}, \quad \tau_{k,z,m} = (1-\rho)\tau_{k,z,m}, \tag{24}$$

with ρ denoting the evaporation rate. The overall time complexity of the proposed algorithm is $\mathcal{O}(RNDL)$, where R denotes the number of iterations. It is worth specifying that the conceived ACO-based approach leads to a quasi-optimal solution, which theoretically does not guarantee the convergence of the BCD technique. However, it has been numerically verified that convergence to a stationary point is always achieved in considered scenarios.

V. Numerical results

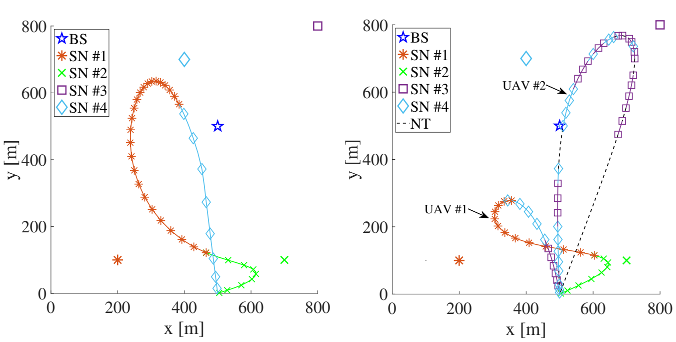
In this Section an assessment of the envisioned solution is proposed. To this end, four different scenarios are investigated:

1) The first aims at showing the relation between the trajectories and the scheduling plans obtained with different number of drones, in a simple context.
2) The second analyzes the trajectories and the total relayed data when mission time varies, in a more complex situation.
3) The third considers a larger number of UAVs and SNs with different transmission power levels.
4) The fourth demonstrates the effectiveness of the proposed hybrid approach with respect to an algorithm derived from [6].

Parameter	Value	Parameter	Value
η_1,η_2	10^3 [#]	β_0	-60 [dB]
R	500 [#]	α	2 [#]
L	40 [#]	ρ	0.05 [#]
δ_t	1 [s]	H	50 [m]
K_c	10 [dB]	v_{MAX}	50 [m/s]
$P^{\text{D}}_{\text{MAX}}$	1 [W]	a_{MAX}	5 [m/s^2]
ζ	0.01 [#]	$\mathbf{q}_\text{b}$	$[500\ 500]^\mathsf{T}$ [m]
N_0	-174 [dBm/Hz]	γ	78.2 [#]

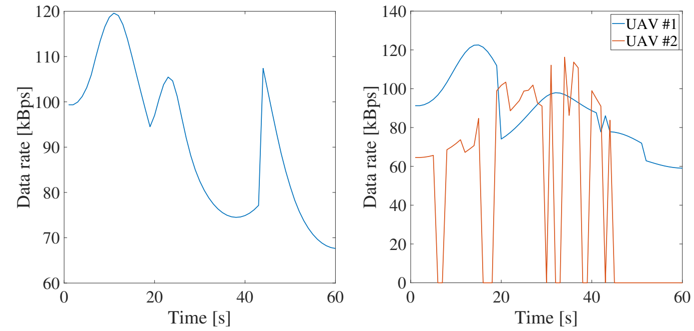
TABLE I: Parameter settings.

The adopted channel model is the Rician fading one, characterized by Rician factor K_c. The CDF $F(\cdot)$ can be modeled as $F(u) = 1 - Q_m(\sqrt{2K_\text{c}}, \sqrt{2(K_\text{c}+1)u})$, where $Q_m(\cdot,\cdot)$ is the Marcum Q-function [12]. As for the transmission, according to IEEE P802.16t, bandwidth B_j = 10 kHz $\forall j$, whereas P^s_j = 10 mW $\forall j$. Further, for each j, the generated sensed data is o_j = 2 Mbit. Drones take-off/land from/at $[500\ 0]^\mathsf{T}$. Similarly to [13], the remaining simulation parameters are summarized in Table I. All the above are common to the configurations analyzed hereafter, if not otherwise specified. The first considered scenario compares a single-drone setup with a 2-drones one. In



(a) D = 1 (b) D = 2

Fig. 1: Trajectories followed by drones and association with SNs in the first scenario.

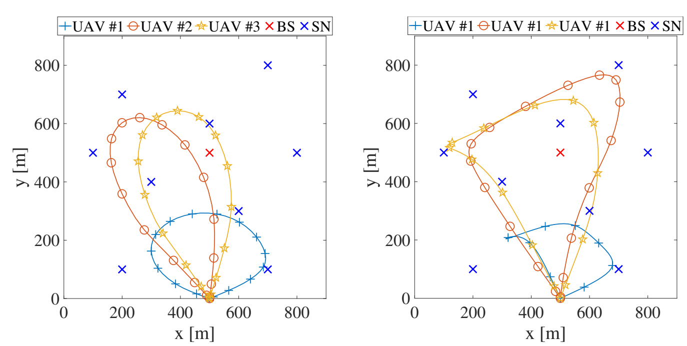


(a) D = 1 (b) D = 2

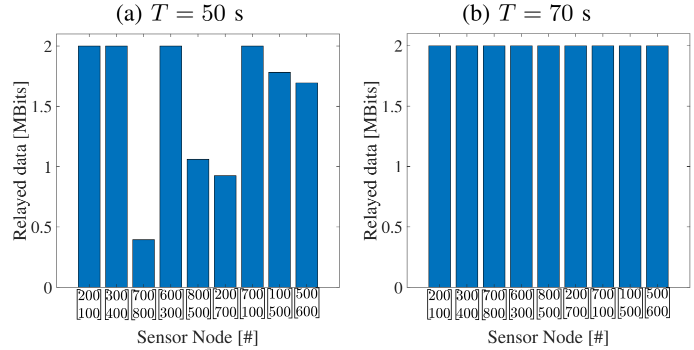
Fig. 2: Data rate in the first scenario.

particular, $S = 4$ SNs are randomly deployed as shown in Fig. 1 with a fixed mission duration time $T = 60$ s. As can be seen, in both configurations, drones approach SNs to maximize the amount of relayed data. Specifically, in the first setup the UAV starts serving SN located at $[700\ 100]^\mathsf{T}$ and then it proceeds towards the closer one, i.e., SN #1. This process repeats also for the node placed at $[400\ 700]^\mathsf{T}$. Similar considerations can be done for 2-drones configuration. In particular, in Fig. 1b it is shown that SNs #1 and #2 are exclusively associated to UAV #1, while SN #3 and SN #4 are cooperatively served by both drones.

A considerable difference between the two setups lies in the absence of NT state in Fig. 1a with respect to Fig. 1b. In fact, due to the lack of time, in T s, the single-drone setup is only able to partially relay data from the three served nodes,



(a) $T = 50$ s (b) $T = 70$ s

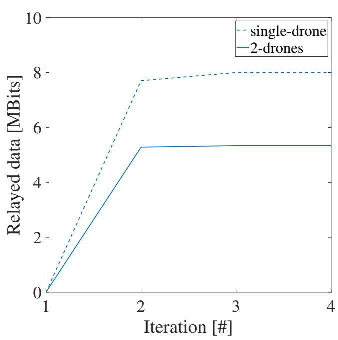


(c) $T = 50$ s (d) $T = 70$ s

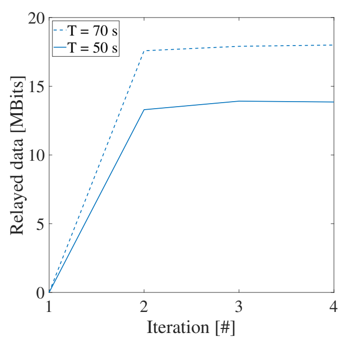
Fig. 3: Trajectories and total relayed data in the second scenario.

i.e., $\sim$ 5.33 Mbits, while ignoring the farthest one. On the opposite, two drones are more than sufficient to fulfil the mission, thus implying NT timeslots during the mission in order to satisfy (8). This is further highlighted in Fig. 2b in which valleys are present differently from Fig. 2a where a continuous transmission is depicted.

To provide further insights, a second more complex scenario is investigated hereby. In particular, $S = 9$ SNs are randomly deployed in the reference area. In this case, given a fixed number of drones $D = 3$, the mission duration is made varying. In the first setup $T = 50$ s, while in the second $T = 70$ s. In Figs. 3a and 3b, the trajectories adopted by the UAVs are shown. It clearly emerges that, in the first configuration, due to the lack of time, the swarm focuses on relaying signals from the regions closer to the starting point and with higher SNs density. This is further confirmed by Fig. 3c, where nodes located at $[700\ 800]^\mathsf{T}$, $[800\ 500]^\mathsf{T}$, and $[200\ 700]^\mathsf{T}$ result to be the most penalized. Indeed, the total amount of transmitted data is $\sim$ 13.9 Mbits. On the opposite, in the second configuration, the swarm has enough time to successfully complete the mission. Remarkably, in both scenarios, the proposed approach converges to a quasi-optimal solution (see Fig. 4) in 4 iterations. Besides, all solutions result to be feasible with respect to (15) because no overlap has been registered.



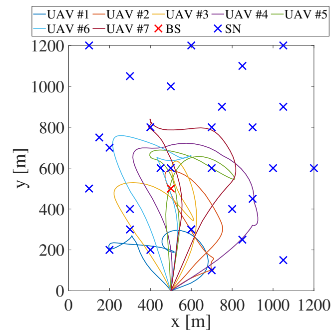
(a) Scenario 1



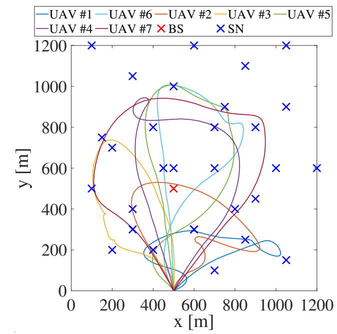
(b) Scenario 2

Fig. 4: Convergence in the first two scenarios.

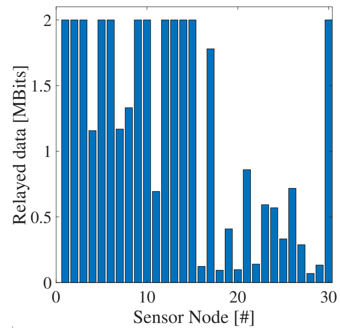
To demonstrate the applicability to larger simulations, a swarm of $D = 7$ drones and a set of $S = 30$ SNs are considered in the third scenario. Moreover, to provide parameter variability with respect to previous scenarios, two values of sensors' transmission power is probed, i.e, $P_j^{\mathrm{s}} = \{1, 10\}$ mW, in a mission of $N = 80$ time intervals. As can be seen in Figs. 5a and 5b, the area covered by the swarm is wider when a higher transmission power is granted and, viceversa, it restricts with a lower P_j^{s}. This is due to the fact that is more convenient maximizing the data rate of nodes closer to the starting point when the transmission power is limited. Moreover, the amount of relayed data, for each sensor, is less when a lower P_j^{s} is considered, as highlighted in Figs. 5c and 5d. This is further confirmed by Fig. 6a that shows the average data rate of the swarm in the two configurations. Furthermore, as depicted in Fig. 6b the overall algorithm converges, thus granting a total amount of relayed data equal to $\sim$ 34.55 Mbits, for $P_j^{\mathrm{s}} = 1$ mW, and $\sim$ 48.34 Mbits, for $P_j^{\mathrm{s}} = 10$ mW. Note that, in both



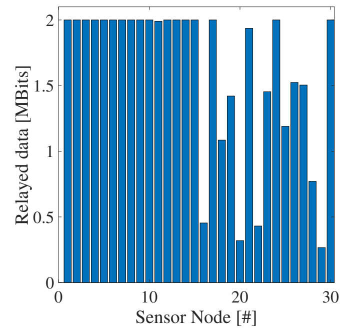
(a) $P = 1$ mW



(b) $P = 10$ mW



(c) $P = 1$ mW

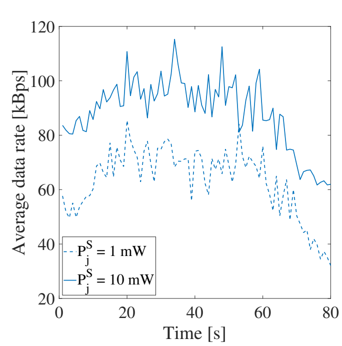


(d) $P = 10$ mW

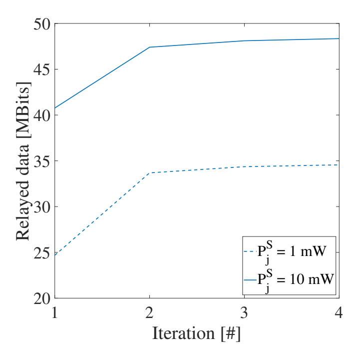
Fig. 5: Trajectories and total relayed data in the third scenario.

configurations, mission time and nodes' transmission power are not sufficient to completely relay the sensing data to the BS.

Lastly, in the fourth scenario, the proposed solution is compared with a benchmark approach derived from [6], in a mission with a set of $S = 12$ randomly deployed SNs. In particular, each drone of the swarm relays data of a SN group by hovering over multiple optimum locations, thus maximizing the data rate of each UAV-SN-BS link. The locations can be easily obtained by solving a problem similar to $(P2)$, which is omitted due to space restrictions. Nonetheless, since $B_d \gg B_s$, these spots correspond, on x-y plane, to the SNs' positions which minimize the distance, i.e., $d_{k,j} = H\ \forall k, j$. Moreover, each UAV flies at constant speed v_{MAX} among assigned locations adopting a rectilinear motion, moving from

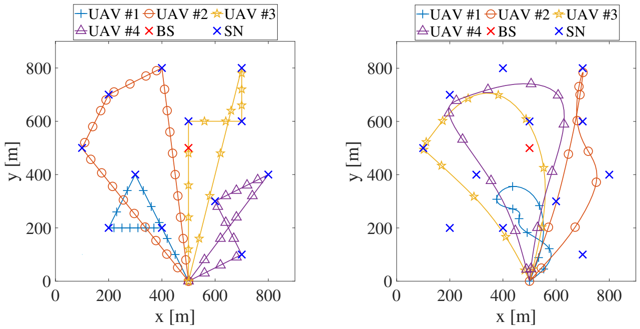


(a) Average data rate.



(b) Convergence.

Fig. 6: Average data rate of swarms and convergence in the third scenario.



(a) Benchmark (b) Proposed approach

Fig. 7: Trajectory plans comparison in the fourth scenario.

the current position to the closer one. Therefore, all nodes are equally divided among UAVs, as shown in Fig. 7a, where the related swarm path plan is depicted. Besides, trajectories obtained by the proposed hybrid approach are illustrated in Fig. 7b. It results that, the trajectory plan derived from the hybrid proposed approach allows drones to accomplish the mission by cooperatively relaying all the data in 70 s. On the contrary, when the benchmark algorithm is employed, the swarm completes the mission in 81 s. This leads to a a performance gain of $\sim 14\%$. It is worth specifying that this result is a lower-bound in terms of performance: drones in benchmark approach fly at speed v_{MAX} without taking into consideration the acceleration limitations, as in the hybrid approach.

VI. Conclusions

This work presents an optimization problem aiming at maximizing the total amount of relayed data through a swarm of UAVs, generated by SNs. The solution is conceived as a hybrid approach combining convex optimization and ACO algorithm. The simulation campaign demonstrates its validity through different parameter configurations and by comparing it with a benchmark algorithm. Future research perspectives include energy consumption and memory models. Further, a deeper study regarding the choice of penalty weights, which affect the solution quality, will be conducted. Besides, a formal mathematical convergence proof for the proposed hybrid approach will be investigated. Finally, more sophisticated criteria will be applied for scheduling plan design.

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