On the Interplay between Energy and Memory Constraints in Optimized UAV Communications

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***Abstract*—Unmanned Aerial Vehicles (UAVs) are key enablers in many emerging verticals, thanks to their versatility in fulfilling sensing, actuation, and communications tasks. At the same time, their resources are quite constrained so that sophisticated optimization approaches are required to prolong mission lifetime. Current literature mostly focuses on energy constraints, but when UAVs gather high-resolution multimedia signals, memory constraints become critical too. To this end, a lean convex optimization framework is proposed hereby to maximize the acquired/uploaded data, subject to joint energy and memory constraints. Simulation results validate the proposed approach in a realistic 5G scenario.**

***Index Terms*—5G, Mobile environments, Modeling Techniques, Internet of Drones.**

I. Introduction

Drones are key players in almost any smart domain because of their inherent capability to support sensing, actuation, and communication tasks in civil, industrial, and military fields [1]. Since drones are battery-supplied systems, on-board available energy is limited, which suggests that properly designed optimization routines are needed to maximize the lifetime of a mission. These themes have been recently investigated by the scientific community [2]–[17]. In particular, the surveyed related works aim at optimally tuning transmission power [2]–[4], [7]–[9], [13], [14], [16], energy efficiency [9], [12], achievable data-rates [2]–[11], [13]–[17], and trajectory design and mission planning [3], [7]–[17]. At the same time, it is worth remarking that energy is not the only constrained resource on board of a drone: memory availability is usually very limited and could hinder the development of services that gather high-resolution multimedia signals. For instance, considering a real drone, the onboard available memory can be quickly filled up if high-resolution video signals are acquired (e.g., 4k RAW at $\sim$1 Gbps). Unfortunately, to the best of authors' knowledge, this aspect has been neglected by the majority of the scientific literature, with the sole exceptions of [18], [19]. In particular, in [18] beamforming techniques are discussed in the context of content provisioning by multiple UAVs to users requesting specific contents of interest. This reference deals with content management, assuming that any content is simplified to a unity dimension, and envisions storage capacity as the maximum amount of contents that can be stored by each drone as a constraint for the optimization problem. In [19], instead, the problem formulation considers a drone providing video signals to a multi-hop ground infrastructure based on Visible Light Communications (VLC): an algorithm has been proposed to manage on board resources without demonstrating its optimality. However, channel modelling is neglected.

The present contribution proposes an optimization framework that accounts for both energy and memory constraints in high-resolution multimedia acquisition services. In particular, the reference scenario (described in Sec. II) involves a drone acquiring multimedia signals via onboard camera following a given trajectory. With the aim of offloading the memory, while increasing the responsiveness of the system, a low-resolution version of gathered data is uploaded leveraging air-to-ground communications (see Fig. 1). Here, uplink datastreams deserve particular attention, while downlink streams-related problems are not a major concern*.

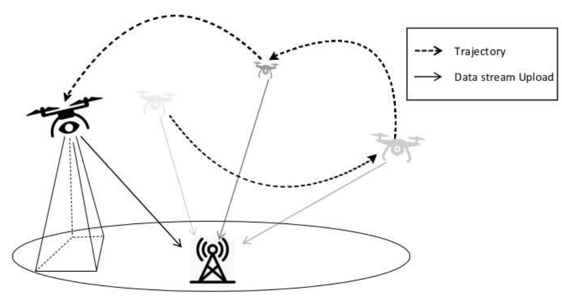

Fig. 1: Reference Scenario.

The optimization framework (proposed in Sec. III) aims at maximizing the amount of gathered and transmitted data, subject to contrasting bounds on available energy and memory. Clearly, continuous transmissions help avoid memory overflow but waste energy. Hence, finding the optimal amount of data to acquire from the camera and transmit to the ground motivates this contribution. Unfortunately, the formulation of this non-convex optimization problem makes the solution hard to be derived. To face this issue, an equivalent convex optimization formulation has been defined thanks to the introduction of a set of slack variables. Simulation results (presented in Sec. IV) demonstrate the effectiveness of the proposed approach in a realistic 5G scenario under several settings. Finally, Section V concludes the work and draws future research.

*Signalling and control data exchanges between the drone and the ground Base Station (BS) are neglected because herein assumed to be less demanding than the bandwidth needed to transfer multimedia signals.

II. Problem Formulation

The total duration of the mission T is split into N time intervals with duration δ_t, each. Before the mission starts, the available memory and energy on-board are M_0 and E_0, respectively. The amount of transmission power spent by the drone during the k-th time-slot for uploading operations is defined as P_k. Therefore, when the drone is offloading data, the channel capacity can be calculated according to the Shannon's equation:

$$R_k = B\log_2\left(1+\frac{P_k h_k}{\sigma^2}\right), \tag{1}$$

where $\sigma^2 = N_0 B$ is the noise power at the receiver's side, B is the available bandwidth, and h_k is the channel power gain.

The energy spent in the acquisition operations can be expressed as $E_c = \delta_t N P_c$, where P_c is the constant power consumed by the camera. To guarantee a uniform quality of gathered multimedia signals, the amount of acquired data over each time step is i_0. The amount of uploaded data, instead, is equal to $o_k = \delta_t R_k$, during the k-th time step. When the UAV has completed its mission, the remaining amount of energy E_F can be expressed as:

$$E_F = E_0 - E_m - \delta_t\sum_{k=1}^{N} P_k - E_c. \tag{2}$$

being E_m is the total mechanical energy spent throughout the mission. As discussed in [19], during the mission the drone has to continuously control its operations based on surrounding physical conditions, so that the energy spent cannot be exactly known in advance: therefore, a random variable has to be considered to model E_m. Without loss of generality, it is assumed that E_m's distribution is non-normal Gaussian where μ_m and σ_m are its mean and standard deviation, respectively. Nevertheless, the following considerations can be easily referred to other cases. Hence, it is possible to state that the probability that the leftover energy E_F is less than zero must be at most ε, i.e. Out-of-Service probability: $P_r(E_F < 0) \leq \varepsilon$ which is equivalent to

$$P_r(E_m > E_0 - \delta_t\sum_{k=1}^{N} P_k - E_c) \leq \varepsilon.$$

Symbol	Description
N	Time intervals the mission is composed by [#].
δ_t	Duration of a time interval [s].
P_k	Transmission power at time interval k [W].
R_k	Datarate [Bps].
E_m	Overall mechanical energy consumption [J].
E_0/E_F	Initial/Final onboard available energies [J].
i_0	Acquired data at any time interval [B].
o_k	Uploaded data at time interval k [B].
M_0	Initial onboard available memory [B].
$\mathcal{P}$	Set of Transmission Power values [W]
$\mathcal{W}$	Set of slack variables.
γ	Mechanical energy required to accomplish the mission [J].
E_c	Onboard camera energy consumption [J].
ε	Out-of-Service probability.

TABLE I: Summary of notation.

With a simple change of notation, the function that models the tail of E_m is $Q_1(x) = Q(\frac{x-\mu_m}{\sigma_m})$, from which it results $Q_1^{-1}(\varepsilon) = \gamma$. Therefore, it is possible to write:

$$E_c + \gamma + \delta_t\sum_{k=1}^{N} P_k \leq E_0. \tag{3}$$

The main focus of the present work is to solve $(P1)$, that is formulated as follows:

$$(P1): \max_{i_0,\mathcal{P}} N i_0 + \delta_t\sum_{k=1}^{N} R_k \quad \textbf{s.t.}$$

$$E_c + \gamma + \delta_t\sum_{k=1}^{N} P_k \leq E_0 \tag{4}$$

$$k i_0 - \delta_t\sum_{j=1}^{k} R_j \leq M_0, \quad \forall k: 1...N \tag{5}$$

$$\delta_t\sum_{j=1}^{k} R_k \leq k i_0, \quad \forall k: 1...N \tag{6}$$

$$0 \leq P_k \leq P_{MAX}, \quad \forall k: 1...N \tag{7}$$

$$i_0 \geq 0 \tag{8}$$

Problem $(P1)$ aims at maximizing the amount of acquired and offloaded data subject to several constraints on available memory and energy, where $\mathcal{P}$ is the set of $P_k\ \forall k$. In particular, in (4) it is explicitly stated that there is an upper-bound to the maximum amount of energy that the drone can use at any time during the mission. Similarly, in (5), memory limitation is presented. Respecting constraint (6) implies that the amount of data to be offloaded cannot exceed the available one, at any time during the mission. Finally, Equations (7) and (8) clarify the bounds for power consumption and acquired data, respectively.

III. Proposed solution

As clearly results from its formulation, $(P1)$ is a non-convex problem with reference to constraint (6). To tackle this issue, slack variables $\mathcal{W} = \{w_k \geq 0, \forall k\}$ can be introduced. Hence, $(P1)$ can be reformulated as:

$$(P2): \max_{i_0,\mathcal{P},\mathcal{W}} N i_0 + \delta_t\sum_{k=1}^{N} w_k \quad \textbf{s.t.}$$

$$(4), (7), (8),$$

$$k i_0 - \delta_t\sum_{j=1}^{k} w_j \leq M_0, \quad \forall k: 1...N \tag{9}$$

$$R_k \geq w_k, \quad \forall k: 1...N \tag{10}$$

$$\delta_t\sum_{j=1}^{k} w_j \leq k i_0, \quad \forall k: 1...N. \tag{11}$$

Theorem 1. *Solving problem $(P1)$ is equivalent to solving problem $(P2)$, for a sufficiently large M_0.*

Proof. The constraints in (10) can be used to reach the optimal solution of problem $(P1)$ when the equality holds. Since, R_k

represents an upper-bound for w_k, even when the equality is not respected, the condition will always be verified for increasing values of w_k, until equality holds again. Because of constrains (9) and (11), the value of w_k can be increased up to R_k if and only if M_0 is sufficiently large. ∎

IV. Performance evaluation

A simulation campaign has been carried out to evaluate, through MATLAB R2020a, (i) power consumption, (ii) achievable datarates, and (iii) memory occupation over time in a realistic 5G scenario. To this aim, two different settings were considered: the first configures an energy-bounded scenario, whereas the second is a memory-constrained one. Their main difference is the available energy E_0 before the mission starts. In the first case, the energy availability is far more than sufficient for completing the mission while offloading data with the maximum transmission power. In the second one, instead, E_0 value is restricted, thus requiring an optimized tuning of the transmission power. Therefore, the memory constraint is not dominating.

A. Parameter settings

Without loss of generality, the mean μ_m of the mechanical energy consumption E_m has been modeled as proposed in [20]. The mechanical power $P(V)$ spent by a drone, flying at a fixed quota H, is the same in every δ_t as it travels at an optimal constant cruise speed V [21]. For what concerns the channel model, instead, h_k has been defined as proposed in [14]. Starting from real, high-profile and low-profile drones, the two scenarios will envision E_0 = {213, 100} kJ, respectively. A reference area of interest is monitored by a drone flying over a specific path, described by the well-known Theodorus Spiral, which is composed of right triangles, placed edge-to-edge [22]. As a property, for each and every point $\mathbf{q}_k$, $\forall k : 1...N$ composing the spiral, the distance is constant. The latter property perfectly suites the constant velocity envisioned by the model. Once the drone takes-off from the starting point $\mathbf{q}_0$, it reaches the quota at the point $\mathbf{q}_1$ and proceeds to acquire and upload data along its spiral path. The ground BS is placed in $\mathbf{q}_b$. The mission ends when the drone reverts back to $\mathbf{q}_0$. Assuming a 16mm lens, it can be derived the equation set related to the Field of View (FoV)'s base and height as follows:

$$b = 2H \sec(\theta/2) \tan(\phi/2), \quad (12)$$

$$h = 2H \sec(\phi/2) \tan(\theta/2), \quad (13)$$

where θ and ϕ are the Angles of View (AoV) of b and h, respectively. It is worth noting that the spiral has been sized in order to obtain non-overlapping adjacent FoVs.

It is herein assumed that the reference scenario involves 5G networking technologies. In particular, B = 20 MHz bandwidth around 3 GHz in the 5G NR in Unlicensed spectrum (NR-U) is accounted for usage by the drone. According to specifications [23] and [24], such values are justified when referring to Frequency Range 1 (FR1). Further, in order to achieve a sensible throughput increment, the communication infrastructure implements Multiple-Input-Multiple-Output (MIMO) with space-division multiplexing and carrier aggregation. Since E_m is a Gaussian random variable (see Section II), two values of the confidence interval $U_m = 3\sigma_m$ have been chosen: 5% and 10%. In other words, σ_m = [0.016, 0.033]$\cdot\mu_m$.

The configuration setting also includes: M_0 = 8 GB, P_c = 10 W, δ_t = 3 s, N = 199‡‡, ε = 0.01, V = 16 m/s, θ = 70.2°, ϕ = 43.3°, H = 100 m, $\mathbf{q}_b$ = [0 0 10], α = 2, β_0 = -60 dB, P_{MAX} = 1 W, N_0 = -174 dBm/Hz and hence $\sigma^2 \approx$ -101 dBm. Simulation parameters regarding the physical characterization of the drone are summarized in [20].

B. Discussion on results

Figure 2 shows the power trend over time in the energy-bounded cases obtained by solving ($P2$). Those values are obtained from the Shannon's equation, being $w_k = R_k$ the datarate †. These results show that a lower σ_m, i.e., a lower variability on the mechanical energy spent during the mission, implies a lower γ in the constraint (4), and, as a consequence, a larger amount of available power that can be used for transmission tasks. The results in the memory-bounded cases are omitted since the available energy is more than sufficient for completing the mission and, hence, the considered values are always equal to P_{MAX}.

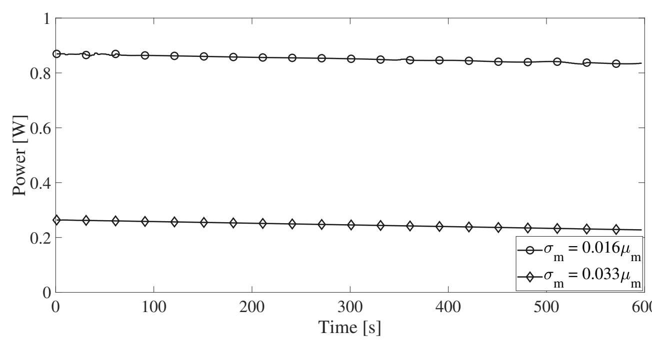

Fig. 2: Power consumption in the energy-bounded configuration.

Figure 3 shows the optimal datarates obtained from ($P2$) in all considered settings: clearly σ_m does not affect w_k (or equivalently R_k) in memory-bounded scenarios because in those scenarios the energy limitations are less severe than memory ones. On the other hand, different datarates are obtained for different values of σ_m in energy-bounded scenarios: the higher σ_m, the higher γ in (4), the smaller the amount of energy that can be allocated to communication tasks (i.e., the lower w_k). Similar results hold for i_0: being $\sigma_m = 0.033\mu_m$, in the energy-bounded configuration, 0.185 Gbps were acquired, whereas, with $\sigma_m = 0.016\mu_m$, the amount of acquired data grew up to 0.217 Gbps. In the memory-bounded ones, instead, the result was 0.221 Gbps for both values of σ_m.

‡‡ N is sized to have a 4 complete rounds trajectory over a 1.5 km^2 area.

† It is worth to note that in all simulated settings, we verified that the optimal solution of ($P2$) always provides $w_k = R_k$.

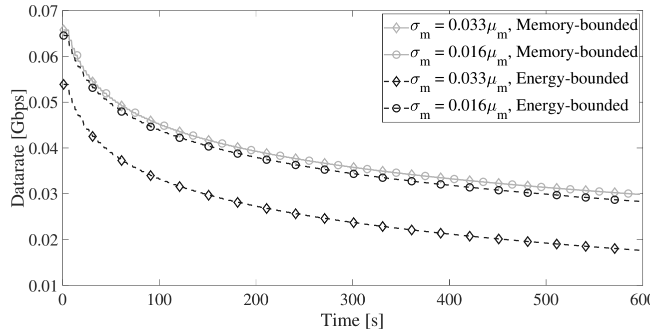

Fig. 3: Datarates in all the configurations.

Figure 4 shows the available memory over time resulting from the solution of $(P2)$. The results are identical in all configurations, since the difference between acquired and uploaded data does not change, regardless of the involved statistical fluctuations.

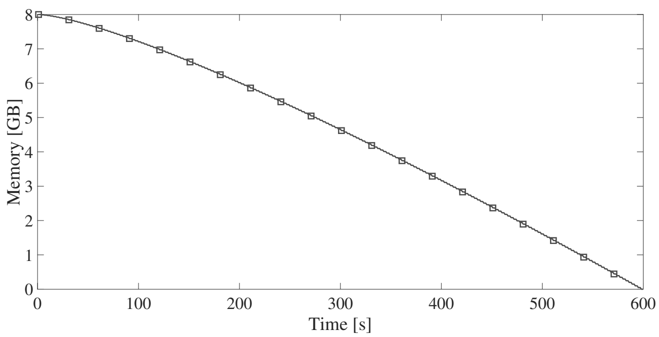

Fig. 4: Memory availability trend over the mission.

V. Conclusions

This work proposed an approach to maximize the acquired/uploaded data by a drone while satisfying contrasting transmission power and memory constraints. The optimal solution to the, initially non-convex, problem was found through an equivalent formulation involving a set of slack variables. Future research will extend the presented results to trajectory design of a swarm of cooperating drones, surveying multiple areas of interest. At the same time, more sophisticated channel and energy consumption models will be involved.

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References

[1] M. Mozaffari, W. Saad, M. Bennis, Y. Nam, and M. Debbah, "A tutorial on uavs for wireless networks: Applications, challenges, and open problems," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2334–2360, 2019.

[2] W. Feng, J. Wang, Y. Chen, X. Wang, N. Ge, and J. Lu, "UAV-Aided MIMO Communications for 5G Internet of Things," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1731–1740, 2019.

[3] H. Wang, H. Zhao, W. Wu, J. Xiong, D. Ma, and J. Wei, "Deployment Algorithms of Flying Base Stations: 5G and Beyond With UAVs," *IEEE Internet Things J.*, vol. 6, no. 6, pp. 10 009–10 027, 2019.

[4] J. Chakareski, S. Naqvi, N. Mastronarde, J. Xu, F. Afghah, and A. Razi, "An Energy Efficient Framework for UAV-Assisted Millimeter Wave 5G Heterogeneous Cellular Networks," *IEEE Trans. Green Commun. Netw.*, vol. 3, no. 1, pp. 37–44, 2019.

[5] H. Hu, C. Zhan, J. An, and Y. Wen, "Optimization for HTTP Adaptive Video Streaming in UAV-Enabled Relaying System," in *IEEE International Conference on Communications*, 2019, pp. 1–6.

[6] L. Chiaraviglio, L. Amorosi, F. Malandrino, C. F. Chiasserini, P. Dell'Olmo, and C. Casetti, "Optimal Throughput Management in UAV-based Networks during Disasters," in *IEEE Conference on Computer Communications Workshops*, 2019, pp. 307–312.

[7] Y. Sun, D. Xu, D. W. K. Ng, L. Dai, and R. Schober, "Optimal 3D-Trajectory Design and Resource Allocation for Solar-Powered UAV Communication Systems," *IEEE Trans. Wireless Commun.*, vol. 67, no. 6, pp. 4281–4298, 2019.

[8] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Mobile Unmanned Aerial Vehicles (UAVs) for Energy-Efficient Internet of Things Communications," *IEEE Trans. Wireless Commun.*, vol. 16, no. 11, pp. 7574–7589, 2017.

[9] S. Zhang, H. Zhang, B. Di, and L. Song, "Joint Trajectory and Power Optimization for UAV Sensing Over Cellular Networks," *IEEE Commun. Lett.*, vol. 22, no. 11, pp. 2382–2385, 2018.

[10] N. Zhao, X. Pang, Z. Li, Y. Chen, F. Li, Z. Ding, and M. Alouini, "Joint Trajectory and Precoding Optimization for UAV-Assisted NOMA Networks," *IEEE Trans. Commun.*, vol. 67, no. 5, pp. 3723–3735, 2019.

[11] L. Amorosi, L. Chiaraviglio, F. D'Andreagiovanni, and N. Blefari-Melazzi, "Energy-efficient mission planning of UAVs for 5G coverage in rural zones," in *IEEE International Conference on Environmental Engineering*, 2018, pp. 1–9.

[12] Y. Choi, Y. Choi, S. Briceno, and D. N. Mavris, "Energy-constrained multi-UAV coverage path planning for an aerial imagery mission using column generation," *J. Intell. Robot. Syst.*, vol. 97, no. 1, pp. 125–139, 2020.

[13] C. Zhan and R. Huang, "Energy Efficient Adaptive Video Streaming with Rotary-Wing UAV," *IEEE Trans. Veh. Technol.*, pp. 1–1, 2020.

[14] C. Zhan, H. Hu, X. Sui, Z. Liu, and D. Niyato, "Completion Time and Energy Optimization in UAV-Enabled Mobile Edge Computing System," *IEEE Internet Things J*, pp. 1–1, 2020.

[15] H. D. Tran, T. X. Vu, S. Chatzinotas, S. Shahbazpanahi, and B. OTTERSTEN, "Coarse Trajectory Design for Energy Minimization in UAV-enabled Wireless Communications with Latency Constraints," *IEEE Trans. Veh. Technol.*, pp. 1–1, 2020.

[16] C. Zhan, H. Hu, Z. Wang, R. Fan, and D. Niyato, "Unmanned Aircraft System Aided Adaptive Video Streaming: A Joint Optimization Approach," *IEEE Trans. Multimedia*, vol. 22, no. 3, pp. 795–807, 2020.

[17] C. You and R. Zhang, "3d trajectory optimization in rician fading for uav-enabled data harvesting," *IEEE Trans. Wireless Commun.*, vol. 18, no. 6, pp. 3192–3207, 2019.

[18] P. Dinh, T. M. Nguyen, S. Sharafeddine, and C. Assi, "Joint location and beamforming design for cooperative uavs with limited storage capacity," *IEEE Trans. Commun.*, vol. 67, no. 11, pp. 8112–8123, 2019.

[19] Iacovelli , G. and Boccadoro , P. and Grieco , L.A., "An iterative stochastic approach to constrained drones' communications," in *IEEE/ACM 24th International Symposium on Distributed Simulation and Real Time Applications*, Prague, Czech Republic, September 2020.

[20] Y. Zeng, J. Xu, and R. Zhang, "Energy Minimization for Wireless Communication With Rotary-Wing UAV," *IEEE Trans. Wireless Commun.*, vol. 18, no. 4, pp. 2329–2345, Apr. 2019.

[21] L. F. Zuluaga and T. Terlaky, *Modeling and optimization: theory and applications: selected contributions from the MOPTA 2012 conference*. Springer, 2013, vol. 62.

[22] H. K. Hahn and K. Schoenberger, "The ordered distribution of natural numbers on the square root spiral," 2007.

[23] 3GPP, "User Equipment (UE) radio transmission and reception; Part 2: Range 2 Standalone (R. 15)," 3rd Generation Partnership Project, Tech. Rep. 38101-2, July 2018.

[24] 3GPP, "Technical Specification Group Radio Access Network; Study on NR-based access to unlicensed spectrum (R. 16)," 3rd Generation Partnership Project, Tech. Rep. 38889, December 2018.