On Optimizing Drones' Communications Under Different Radio Coverage Conditions

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***Abstract*—The Internet of Drones (IoD) architecture is quickly gaining momentum thanks to its inherent ability to capitalize the pros of both Unmanned Aerial Vehicles (UAVs) and networking technologies. This work discusses a scenario involving a drone carrying out a surveying mission along a predefined path. With the aim of maximizing the gathered and transmitted high resolution video signals, a comparative study is proposed, encompassing two different radio coverage conditions. The resulting optimization problems are solved with different techniques: one of them is solved in closed-form expression, while the other one is approached using Linear Programming (LP). Simulation results are also presented to demonstrate the effectiveness of the proposed solutions.**

***Index Terms*—Unmanned systems, Optimisation, Modelling and simulation.**

I. Introduction

The IoD [1] is a network architecture specifically designed to enable interconnections among drones. Thanks to their built-in flexibility, UAVs are widely employed in several military and civil applications [2]. However, drones are resource-constrained devices, and hence dedicated optimization strategies are still necessary to fully leverage their potential. In particular, scientific literature deeply analyzed many aspects, such as energy expenditure [3], [4], [4]–[6], path and trajectory design [3], [4], [4]–[9], [9]–[11], achievable datarates [3], [6]–[9], [9]–[13] and transmission power optimization [6], [7], [9], [9]–[13].

Recently, memory budget has attracted researchers' attention [7], [14], [15] since improving this aspect may enable several multimedia applications. [7] studies a delivery content system enabled by a swarm of drones. Specifically, UAVs cooperate to dispatch requested contents to ground users, while considering the limited storage capacity of involved drones. A joint optimization problem is formulated to maximize the number of served users with minimum Quality of Service (QoS) requirements. As a consequence, it is necessary obtaining content placement, UAVs' location and other key parameters. Unfortunately, the resultant formulation yields to a Mixed-Integer Non-Linear Programming (MINLP) problem, which is hard to solve. Therefore, a framework based on difference-of-convex programming turns the original problem into a set of approximate convex problems that converge to a solution when iteratively solved. However, this reference assumes that all contents have a unity dimension, which leads to an approximation in terms of UAVs' storage capabilities. In [15], a UAV is involved in a surveying mission that aims at maximizing the overall amount of gathered and transmitted data. The proposed formulation takes into consideration energy and memory constraints, while modelling communications under general channel conditions. However, the correspondent optimization problem results to be non-convex. Therefore, thanks to a set of slack variables, it is turned into an equivalent convex form, which can be easily solved through several tools. Unfortunately, this contribution appears to be limited due to the fact that it does not consider the case in which multiple Base Stations (BSs) are deployed in the area of interest.

In [14], a UAV is in charge of acquiring, while uploading, high resolution video signals. The mission aims at maximizing the overall amount of gathered/transmitted data, while satisfying energy and memory constraints. The path followed by the drone is known in advance and is composed by Check-Points (CPs). These are not just *waypoints*, but ground infrastructures equipped with transceivers. Although interesting, some aspects of this work deserve further attention. First of all, this framework formulation mainly aimed at describing an acquisition process distributed over each segment of the mission, up to the maximum available on-board memory. This implies that offloading was not taken into account. For this reason, data acquisition process was limited by the amount of on-board memory available on the drone. Moreover, the UAV is always capable of uploading data, which leaves out the scenarios where the assumption is not verified.

This work extends the findings in [14] by proposing two main deepenings: (i) offloading operations, and (ii) two possible types of communication technologies supported by both CPs and UAV: short-range and long-range. In the first case, the drone is not able to offload memory until the CP is approached. In the second, instead, the UAV is able to continuously transmit acquired data. Therefore, it is possible to define Coverage Guaranteed (CG) and Coverage Not Guaranteed (CNG) conditions, from which two optimization problems are conceived. The CG condition problem is solved by improving Iterative Stochastic ApproAch to constrained drones' Communications (ISAAC) [14]. The CNG problem, instead, is solved employing LP, due to the lack of a closed-form expression. Finally, numerical results are discussed in several configuration settings, demonstrating the effectiveness of the improved ISAAC algorithm and the drawbacks in CNG condition.

This contribution is organized as follows: Section II describes the adopted system model and the problem formulation. Section III discusses the proposed solutions. Section IV presents the obtained numerical results. Finally, Section V concludes the work and draws future research perspectives.

II. System Model and Problem formulation

The mission involves a drone that takes-off from the starting point, follows a path composed by N CPs and, finally, reverts back to the base. The UAV has a limited energy and memory budget, hereby referred to as E_0 and M_0. During the survey of each segment $j : 1...N$, delimited by two consecutive CP, the UAV acquires and offloads a certain amount i_j and o_j of video data, which are inherently linked by a proportional relation through the $0 \leq \alpha \leq 1$ parameter. Once a CP is approached, the energy spent by the drone in the segment j is defined by E_{D_j}, while energy and memory availabilities are E_j and M_j. It is worth specifying that the energy consumption for the last segment, i.e., the one delimited by N-th CP and starting point, is described by E_T. Since the energy expenditure cannot be know in advance, $E_{D_j} \sim \mathcal{N}(\mu_j, \sigma_j^2)$ $\forall j$ and $E_T \sim \mathcal{N}(\mu_T, \sigma_T^2)$, as in [14], [15]. Moreover, it is necessary to guarantee mission feasibility, i.e. the amount of energy is sufficient to accomplish the entire mission. According to [15], γ_j is defined as the amount of mechanical energy, in each segment j, required to complete the mission with a maximum outage probability ε. Furthermore, it is assumed that the energy spent for uploading/acquiring operations is proportional to the amount of transmitted/gathered data through the constants k_1 and k_2.

This formulation leads to three possible approaches [14]:

- *iterative*, which refines the amount of acquired/uploaded data every time a CP is approached.
- *a priori*, a more conservative algorithm, which computes the amount of gathered/transmitted data at each CP once, at the beginning of the mission.
- *a posteriori*, a benchmark algorithm that uses the actual values of energy expenditure, as they are known in advance.

The conceived optimization problems in CG and CNG conditions are hereby discussed.

A. Continuous Coverage condition

In this scenario the drone communicates under the assumption of continuous radio coverage condition, i.e. without experiencing discontinuity. Such an assumption relies on real-world deployments of radio network technologies. In particular, in order to ensure a bidirectional data-flow, for each segment $j : 1...N$, the UAV acquires data while managing their upload.

In a nutshell, the reference optimization problem to be solved is:

$$\max_{\mathcal{I},\mathcal{O}} \sum_{k=j}^{N} i_k + \sum_{k=j}^{N} o_k \quad \textbf{s.t.} \tag{1}$$

$$\sum_{k=j}^{N} (k_1 o_k + k_2 i_k) \leq E_{j-1} - \gamma_{j-1}, \tag{2}$$

$$0 \leq \sum_{k=j}^{z} i_k - \sum_{k=j}^{z} o_k \leq M_{j-1}, \quad \forall z : j...N \tag{3}$$

$$i_k = \frac{\mu_k}{\sum_{l=j}^{N} \mu_l} \sum_{l=j}^{N} i_l, \quad \forall k : j...N \tag{4}$$

$$o_k = \alpha i_k, \quad \forall k : j...N \tag{5}$$

$$i_k \geq 0, o_k \geq 0, \quad \forall k : j...N \tag{6}$$

where $M_{j-1} = M_0 - \sum_{l=1}^{j-1} i_l + \sum_{l=1}^{j-1} o_l$. In particular, in both *a priori* and *a posteriori*, j is equal to 1. In the iterative approach proposed by ISAAC, instead, the value of j will vary at each segment.

The aim of this formulation is to maximize the amount of acquired and offloaded data, throughout the whole mission. For the sake of clarity, it is hereby summarized the equation set involved in the referenced scenario. The first constraint to be taken into account is related to energy. In particular, the energy constraint must not be violated, which can be expressed as:

$$\sum_{k=j}^{N} (k_1 o_k + k_2 i_k) \leq E_{j-1} - \gamma_{j-1}. \tag{7}$$

As for memory, it is necessary to ensure that at each BS the amount of available on-board memory is never exceeded. This can be expressed through the following set of constraints:

$$\sum_{k=j}^{z} i_k - \sum_{k=j}^{z} o_k \leq M_{j-1}, \quad \forall z : j...N, \tag{8}$$

which means that $\forall j$ the drone has a storage capacity equal to the difference between the amount of acquired and offloaded data in between the j-th and the z-th segments. Since the memory available on-board is never exceeded, these quantities must always be greater than zero:

$$\sum_{k=j}^{z} i_k - \sum_{k=j}^{z} o_k \geq 0, \quad \forall z : j...N. \tag{9}$$

Furthermore, it is worth specifying that there is a relation between the amount of data acquired alongside the segment and the average amount of mechanical energy that will be spent until the mission ends:

$$i_k = \frac{\mu_k}{\sum_{l=j}^{N} \mu_l} \sum_{l=j}^{N} i_l, \quad \forall k : j...N. \tag{10}$$

Since o_k and i_k are directly proportional by means of α [14], the latter becomes part of the optimization problem as a constraint, thus leading to:

$$o_k = \alpha i_k, \quad \forall k : j...N. \tag{11}$$

The proposed formulation can be further simplified.

Lemma 1. *The constraint set* (3) *is equivalent to the one related to the last segment:*

$$\sum_{k=j}^{N} i_k - \sum_{k=j}^{N} o_k \leq M_{j-1}. \tag{12}$$

Proof. By contradiction, it is assumed that $\exists z : 1...(N-1) \ni' \sum_{k=j}^{z} i_k - \sum_{k=j}^{z} o_k > M_{j-1}$. Considering the problem solution that includes (12) and not (3):

$$\sum_{k=j}^{N} i_k - \sum_{k=j}^{N} o_k \leq M_{j-1} < \sum_{k=j}^{z} i_k - \sum_{k=j}^{z} o_k, \tag{13}$$

$$(1-\alpha)\sum_{k=j}^{N} i_k \leq M_{j-1} < (1-\alpha)\sum_{k=j}^{z} i_k, \tag{14}$$

$$\sum_{k=j}^{N} i_k < \sum_{k=j}^{z} i_k. \tag{15}$$

Last inequality states that the amount of acquired data, throughout the whole mission, is strictly lower than the amount of acquired data until the $z-th$ BS, which proves the Lemma.

■

B. Dis-continued Coverage condition

More in general, it is possible that the radio coverage condition might not be verified at any time. In this case, the optimization problem remains almost the same with the sole exception of (3), i.e. the constraint on the memory. In fact, it is not possible to guarantee that the drone will be able to carry out a full offload of the acquired data. Therefore, it is necessary to impose a new set of constraints for each segment:

$$(1-\alpha)\sum_{k=j}^{z-1} i_k + i_z \leq M_{j-1}, \quad \forall z : 1...N. \tag{16}$$

The above formulation clarifies that for each and every segment of the mission, a set of constraints must hold.

III. Proposed solutions

The solutions for all the aforedescribed cases will be discussed hereby. First, the CG problem can be solved taking advantage of the closed-form expression suggested by the ISAAC approach. However, some refinements on memory offload must be applied.

Requirement 1: *Once the N-th BS is reached, the energy available on-board E_N should be larger than the energy required to revert back to the starting point with probability greater than $1-\varepsilon \Leftrightarrow P_r(E_N < E_T) \leq \varepsilon$.*

Requirement 2: *Once the j-th BS is approached, the values of i_k with $k : j...N$, should be set in order to avoid a memory overflow $\sum_{k=j}^{N} i_k + \sum_{k=j}^{N} o_k \leq M_0 - \sum_{l=1}^{j-1} i_l + \sum_{l=1}^{j-1} o_l$.*

Theorem 1. *Knowing the values E_{D_l}, i_l, and o_l with $l : 1...j-1$ and assuming that E_{D_k} with $j \leq k \leq N$ and E_T are Gaussian independent random variables, Requirements 1 and 2 are satisfied if and only if*

$$i_j = \frac{\mu_{D_j}}{\sum_{k=j}^{N} \mu_{D_k}} \Omega_j, \quad \forall k : j...N \tag{17}$$

where

$$\zeta = M_0 - \sum_{l=1}^{j-1} i_l + \sum_{l=1}^{j-1} o_l, \tag{18}$$

$$\xi = \frac{E_{j-1} - \gamma_{j-1}}{k_1\alpha + k_2}, \tag{19}$$

$$\Omega_j = min\left(\zeta, \xi\right), \tag{20}$$

$$E_{j-1} = E_0 - \sum_{l=1}^{j-1} E_{D_l} - k_1 \sum_{l=1}^{j-1} o_l - k_2 \sum_{l=1}^{j-1} i_l, \tag{21}$$

$$\gamma_j = Q_j^{-1}(\varepsilon), \tag{22}$$

provided that $E_j - \gamma_j \geq 0 \quad \forall j : 1...N-1$
being $\mu_{TD_j} = \mu_T + \sum_{k=j}^{N} \mu_{D_k}$, $\sigma_{TD}{}_j^2 = \sigma_T^2 + \sum_{k=j}^{N} \sigma_{D_k}^2$, and $Q_j(x) = \frac{1}{\sqrt{2\pi}} \int_{\frac{x-\mu_{TDj}}{\sigma_{TDj}}}^{+\infty} e^{-\frac{t^2}{2}} dt$.

Differently from the CG problem, the solution to the CNG one cannot be defined in a closed-form. However, it is a linear optimization problem that can be efficiently solved with different LP algorithms, such as dual-simplex [16].

IV. Simulation results

In this Section, the simulation campaign is discussed and all the obtained results are presented in details. A Monte Carlo Matlab-based simulator has been developed to compare the different scenarios and parameters involved. For each configuration, 10^5 runs have been carried out.

A. Parameter Settings

The mission involves a path composed by N = 7 CPs. The segment length is modelled as a uniform random variable with an average value of 1732 m [17] with a range of $\pm 10\%$.

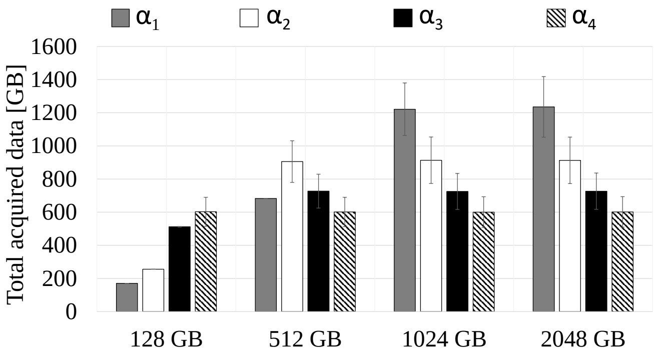
The initial amount of energy availability E_0 is set to 213.4 kJ [18]. According to the specific mission plan and requirements, it is possible to define the problem as memory-bounded (MeB) or Energy-bounded (EnB). In the former, the constrained on-board memory dominates the energy resources. In the latter, instead, the effects of energy limitations are more relevant than those on memory values. Therefore, four memory configurations are hereby considered: 128 GB and 512 GB for the MeB case, 1024 GB and 2048 GB for the EnB case.

The average mechanical energy consumption model is the same adopted in [3]. As for the confidence interval, two values U_1 and U_2 have been considered, i.e. 10% and 20% of the mean. Similarly, also two settings for ε has been used, i.e. 0.01 and 0.02. α has been made varying among four values, i.e. 0.25, 0.5, 0.75 and 1. It is assumed that in the CG configuration, both CPs and UAV communicate through a 5G infrastructure. The average energy expenditure is assumed to be 200 MBit/J [19], which leads to the definition of k_1 = 40.98 J/GB. Instead, in the CNG configuration, Visible Light Communications (VLC) technology is employed, where the mean energy consumption is assumed to be 2.3 nJ/bit [20], which leads to $k_1 \simeq$ 19.76 J/GB.

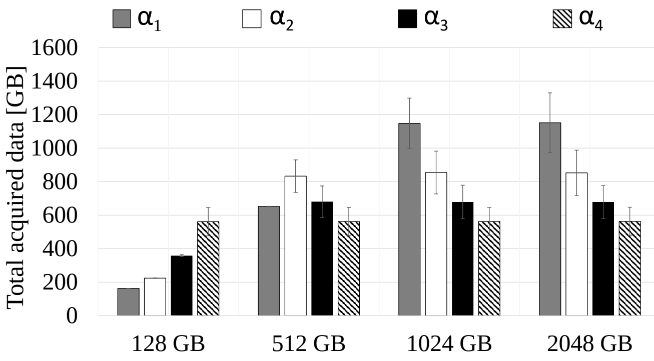
B. Discussion on Results

As reported in Figure 1, for a low amount of available memory, when α grows, the amount of acquired data grows as well and the problem is to be considered memory-bounded. Therefore, with increasing amounts of on board memory, the focus moves from the optimization of memory-constrained cases (i.e., MeB) toward available energy ones. This phenomenon is motivated by the fact that the amount of energy available on-board is fixed and, in any case, limited. Offloading implies an energy expenditure that, with increasing values of alpha, grows as well. In fact, when α reaches values that are high enough, the effect of offloading operations becomes more relevant in terms of energy requirements. Hence, the problem turns to EnB. It is remarkable that the values of acquired data in the 1024 GB and 2048 GB configurations are the same.

The graphs reported in Figure 1 only refer to U_1 and ε_1 since, with all the other combinations, the trends are pretty much the same. Similar considerations can be done on the comparison between CG and CNG conditions. To provide a deeper insight in these assessments, all the Figures that will be proposed will be related to the mission completed in CG condition. The choice is motivated by fact that the main findings properly appoint general results that do not sensibly differ from the CNG condition. Figures 2a and 2b show that increasing the ratio between the offloaded and acquired data, i.e., α. This demonstrates that the employment of the improved ISAAC algorithm provides significant results in constrained configurations. With a larger amount of on-board available memory, i.e., 1024 GB configuration, (see Figures 2c and 2d), the increase of α leads to a lower amount of acquired data compared with the previous case. Thanks to Figure 3, it is possible to observe that, with increasing values of ε and U, i.e., with larger variability, the new ISAAC approach demonstrates a slight enhancement in terms of acquiring and uploading. This is independent from configuration parameters (memory, α) and reference scenario. This is motivated by the continuous refinement that ISAAC is able to provide in data acquisition, which becomes more evident at the last segment, where acquisition will certainly be greater than in cases where there is less variability.



(a) CG condition



(b) CNG condition

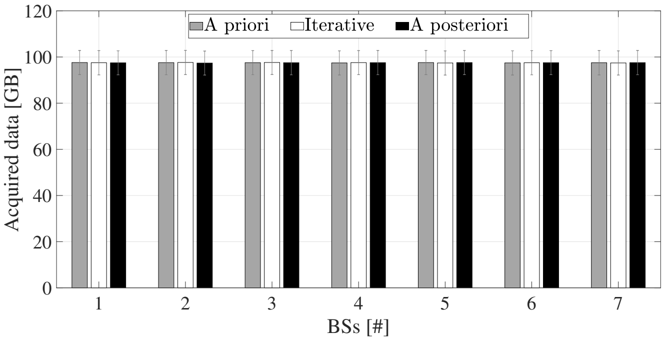
Fig. 1: Total acquired data in all on-board memory configurations with different values of α, and U_1 and ε_1 fixed.

Under discontinued radio coverage conditions, during the mission segments, offloading may be difficult, if not forbidden. Although ISAAC provide benefits during the acquisition phase, setting a constraint on each segment of the mission lowers the overall amount of acquired data (see Figure 4).

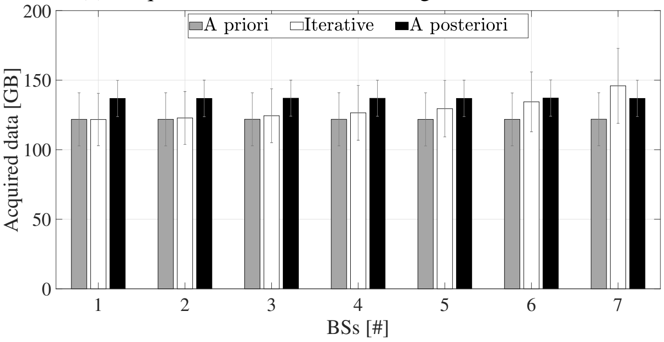
Overall, in the comparison between CG and CNG, the first is able to offer better performance in terms of acquired data and offloading activities. Such an advantage may be more or less evident depending on the configuration, as in the 128 GB configuration with α_3. Moreover, in this case, even the ISAAC's iterative approach struggles to improve the achievable performance. To sum up, the amount of acquired data that is actually downloaded in the CNG case is lower. This obviously has a non-negligible impact on uploaded data, which lowers as well.

V. Conclusions

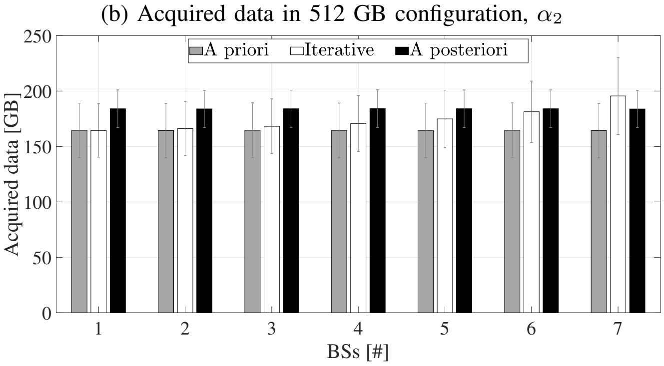
This work aimed at maximizing the overall amount of acquired and transmitted data by a drone involved in a surveying mission. Two scenarios involving different operative coverage conditions, and the correspondent problem formulations, have been analyzed. The discussion on the obtained results has shown the effectiveness of the improved version of the ISAAC algorithm under CG conditions. In the CNG cases, the obtained values are lower anyway. Future research



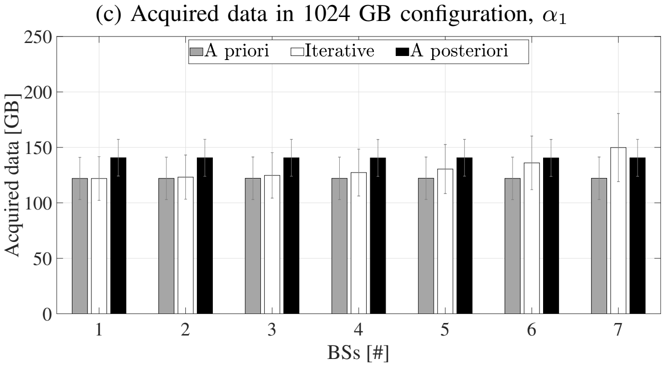
(a) Acquired data in 512 GB configuration with α_1



(b) Acquired data in 512 GB configuration, α_2

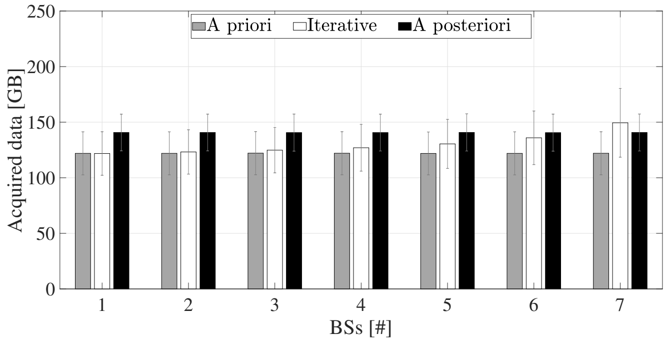


(c) Acquired data in 1024 GB configuration, α_1

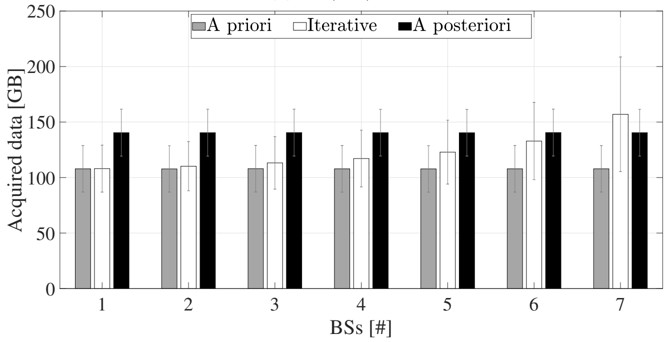


(d) Acquired data in 1024 GB configuration, α_2

Fig. 2: 512 and 1024 GB memory configurations comparison with Continuous Coverage, U_1, ε_1.



(a) $U_1, \varepsilon_1, \alpha_2$



(b) $U_2, \varepsilon_2, \alpha_2$

Fig. 3: Acquired data in the 1024 GB Configuration with Continuous Coverage.

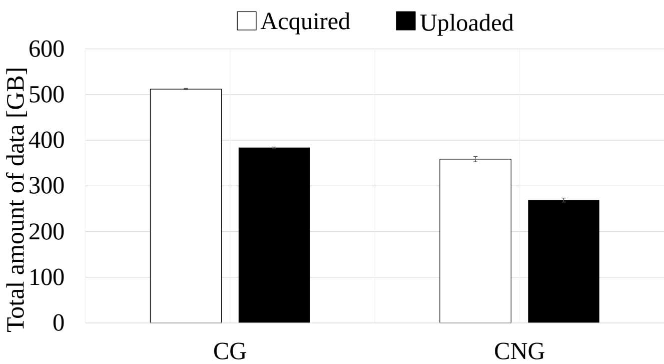


Fig. 4: Comparison among Acquired and Offloaded data in CG and CNG conditions in the 128 GB Configuration, U_1, ε_1, α_3.

will diffusely investigate channel models and their variability over time. At the same time, the missions will involve swarms of coordinated drones. Moreover, the proposed solution can be further improved optimizing the ratio between acquired and uploaded data.

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