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Joint Position and Travel Path Optimization for Energy Efficient Wireless Data Gathering Using Unmanned Aerial Vehicles

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Abstract—Unmanned aerial vehicles (UAVs) or drones have attracted growing interest in the last few years for multiple applications; thanks to their advantages in terms of mobility, easy movement, and flexible positioning. In UAV-based communications, mobility and higher line-of-sight probability represent opportunities for the flying UAVs while the limited battery capacity remains its major challenge. Thus, they can be employed for specific applications where their permanent presence is not mandatory. Data gathering from wireless sensor networks is one of these applications. This paper proposes an energy-efficient solution minimizing the UAV and/or sensors energy consumption while accomplishing a tour to collect data from the spatially distributed wireless sensors. The objective is to determine the positions of the UAV “stops” from which it can collect data from a subset of sensors located in the same neighborhood and find the path that the UAV should follow to complete its data gathering tour in an energy-efficient manner. A non-convex optimization problem is first formulated then, an efficient and low-complex technique is proposed to iteratively achieve a sub-optimal solution. The initial problem is decomposed into three sub-problems: The first sub-problem optimizes the positioning of the stops using linearization. The second one determines the sensors assignment to stops using clustering. Finally, the path among these stops is optimized using the travel salesman problem. Selected numerical results show the behavior of the UAV versus various system parameters and that the achieved energy is considerably reduced compared to the one of existing approaches.

Index Terms—3D positioning, path planning, unmanned aerial vehicle-based communications, wireless sensors.

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I. INTRODUCTION

WIRELESS sensor networks (WSNs) have attracted a lot of interest due to the advantages they offer in terms of infrastructure installation cost and reconfiguration flexibility [1]. While the development of wireless communication technologies was an important factor for the large-scale spread of these sensors, new challenges in terms of networks capacity to accommodate their data traffic arise [2]. Taking into consideration the characteristics of their traffic (low data rates, periodicity, etc.), optimizing the information gathering has been the subject of active research. Very efficient approaches [3]–[5] were proposed based on clustering, multihop relaying, context awareness, etc. With the emergence of Internet of Things (IoT), the deployment of smart sensors is exponentially increasing. The task of information collection is then becoming much more challenging given that the network capacity is already saturated with the increase and diversification of other wireless services [6]. Therefore, the need for revolutionary solutions to reduce the dependency on the network infrastructure arises.

Thanks to their mobility and flexibility, the use of remote controlled and automated micro unmanned aerial vehicles (UAVs), also known as drones¹, has gained much popularity in different domains. Their recent development allowed the considerable reduction of their production cost which makes them affordable for a variety of civil and public applications such as traffic monitoring, border surveillance, disaster management, public safety, health and environmental services; to name a few [7]–[9].

Since they can be equipped with communication interfaces allowing them to interact with other ground and flying nodes, lightweight drones can be employed to perform data gathering from the wireless sensors. However, their finite battery storage represents a major constraint that limits their energy supply and thus, their service time. Hence, the drones can only be used for specific applications that do not require permanent infrastructure presence such as delay-tolerant and on-demand applications. Collecting information of a sensor network belongs to these types of applications. Examples of practical usages include the periodic data collection from sensor networks located in remote areas like mountains and farms or from road side units to reduce the traffic load for vehicular ad-hoc networks (VANETs).

¹Note that the terms “UAV” and “drone” are used interchangeably throughout the paper.

74 On the other hand, the drones' mobility and flexibility in
 75 three-dimensional (3D) positioning represent major advantages
 76 that allow them to complete the task of data collection in a reli-
 77 able manner while profiting from reduced path losses [9], [10].
 78 Thus, an optimization of the path for efficient data collection
 79 is required. Specifically, this path should address the trade-off
 80 between the flight duration and the communication reliability
 81 to fulfill the required task with minimum energy consumption.
 82 Indeed, sending the drone to positions close to the sensors may
 83 reduce the communication time as higher data rates can be
 84 achieved but this might lead to additional energy consumption
 85 due to extra traveled distances. On the contrary, minimizing the
 86 navigation energy by collecting data from farther positions re-
 87 sults in a degradation of the communication channel and thus,
 88 higher transmission time is required which may lead to the de-
 89 pletion of the sensors' energy. Thus, it is important to optimize
 90 the UAV path by efficiently planning the UAV collection tour.

91 A. Related Work

92 Data gathering in WSNs has attracted a lot of attention during
 93 the last decade. Several solutions have been proposed to collect
 94 messages from spatially distributed sensors to deliver them to a
 95 central node known as "sink". In general, the existing solutions
 96 can be classified into two categories: routing-based solution and
 97 mobile sink-based solution.

98 Recently, multiple routing protocols have been proposed to
 99 ensure fast, reliable, and/or energy efficient data collection
 100 [11]–[13]. In [11], the authors proposed a distributed routing
 101 algorithm aiming to ensure a balance between latency and en-
 102 ergy consumption. The objective is to determine the routing
 103 through which the data need to be forwarded such that a global
 104 network utility including the energy consumption and the end-
 105 to-end delay is optimized. Another protocol focusing on com-
 106 bining clustering and routing has been proposed in [12]. The
 107 idea consists of selecting multiple cluster-heads which are re-
 108 sponsible in collecting data from multiple groups of sensors. A
 109 routing path connecting these cluster-heads is then, established
 110 to forward the data to the sink. The clustering procedure is per-
 111 formed while taking into account the network life time and the
 112 limited range of the deployed sensors. Data aggregation is also
 113 investigated as a solution to reduce the signaling overhead when
 114 establishing routing paths in WSNs. In [13], three modes of data
 115 aggregation are studied. The first mode named full-aggregation
 116 where an intermediate node aggregates all the received data in
 117 addition to its own data in a single message and forwards it to
 118 the next hop. The second, non-aggregation mode, in which data
 119 is forwarded separately without any aggregation. Finally, the
 120 hybrid aggregation where data aggregation is subject to a cer-
 121 tain threshold. For each aggregation mode, a data-gathering tree
 122 is constructed such that the lifetime of sensors is maximized.

123 The implementation of routing protocols requires the exist-
 124 ence of direct communication links between multiple nodes
 125 in WSNs which are not always available in practice especially
 126 for lightly-powered sensors and in remote areas. Hence, mo-
 127 bile sink-based solutions are proposed. In this case, a ground
 128 node will permeate all sensors and collect their data. The most

challenging part in this method is to determine the path that
 the mobile sink has to follow to complete the data gathering
 mission [14]–[17].

129 In [14], the authors proposed an algorithm based on travel
 130 salesman problem (TSP) to determine the locations that the mo-
 131 bile sink needs to visit in order to collect data from multiple
 132 sensors sharing overlapping areas based on their communica-
 133 tion ranges. Similarly, in [15], a tree-based approach is proposed
 134 to collect data from different sensors. The WSN is divided into
 135 multiple clusters where the cluster-head collects data from mul-
 136 tiple sensors within the cluster to forward it to the moving sink.
 137 Hence, routing and mobile sink-based solutions can be jointly
 138 implemented together as studied in [16]. The authors proposed a
 139 clue-based data collection routing where the mobile sink moves
 140 randomly and informs sensors about its presence so it can col-
 141 lect data from the neighborhood defined by a limited number
 142 of hops. A tradeoff between mobile sink mobility and routing
 143 protocol overhead has been reached in [17]. Starting from the
 144 fact that the ground sink cannot move freely, the authors pro-
 145 posed an energy-efficient data gathering protocol that uses the
 146 moving mobile sink and coordinates to establish data reporting
 147 routes in a proactive manner. Hence, according to the known
 148 trajectory of the ground sink, the sensors can determine their
 149 future locations and hence, decide where to forward their data
 150 so it can be collected.

151 Thanks to the rapid development of the mirco-UAV technol-
 152 ogy, their use becomes very practical for the data gathering
 153 task. Indeed, as discussed earlier, unlike the ground mobile
 154 sink, the UAVs are characterized by a free and fast mobility
 155 unaffected by the ground topography. Moreover, they provide
 156 a better channel quality thanks to their high altitude. Hence,
 157 they can be exploited as flying data collectors that are able
 158 to reach the sensors independently of the ground topology.
 159 Some studies have investigated the use of drones with sensor
 160 networks [18]–[21].

161 For instance, the authors of [20] studied the case of randomly
 162 deployed moving sensors along a pre-know UAV path. Data
 163 collection protocols for this dynamic WSN topology are ana-
 164 lyzed while taking into account the achieved data rate and the
 165 contact duration time. Most of the studies tackling this prob-
 166 lem are aiming to optimize the UAV path based on different
 167 metrics. In [21], the chosen metric is the maximization of the
 168 system throughput by eliminating redundant data transmissions
 169 through a priority-based frame selection scheme that associates
 170 a lower contention window range to the high-priority frame and
 171 vice versa. In this way, the packet collision is reduced and the
 172 throughput is enhanced. In [19], another priority-based scheme
 173 is proposed by giving priority to sensors located close to the
 174 UAV. It has been shown that the proposed method achieves a
 175 certain energy saving gain and increases the lifetime of the sen-
 176 sors. Data aggregation has also been employed with UAV [18]
 177 with the objective to achieve energy-efficient communication
 178 links between sensors and UAVs.

179 Most of the aforementioned studies focused on the perfor-
 180 mance of the UAV-assisted WSNs but neglected the challenges
 181 related to UAVs especially in terms of energy limitation. In this
 182 work, we aim at optimizing the data collection procedure such
 183
 184
 185

TABLE I
TABLE OF NOTATIONS

Parameter	Notation
S_k	k -th sensor 3D position
X_c	c -th drone collection stop 3D position
$x_{c,k}$	index for k -th sensor collection at stop c
$y_{c,c'}$	index for drone's travel path
$T_{k,c}^{com}$	communication time of k -th sensor to drone at stop c
$T_{c,c'}^{fly}$	flight time between the drone collection stops c and c'
$E_{c,c'}^{flight}$	energy consumed by the drone to fly from X_c to $X_{c'}$
$E_{c,k}^{stop}$	energy consumed by the drone to collect data from S_k at stop X_c
E_{S_k}	energy consumption of the sensor S_k

186 that efficient data collection is ensured and the drone energy
187 consumption is minimized.

188 B. Contributions

189 In this paper, we investigate the usage of a UAV for data
190 collection in WSNs. The main contributions of the present work
191 can be summarized as follows:

- 192 • We design a framework for energy efficient data collection
193 from a WSN using a flying UAV. Unlike existing studies,
194 our approach takes into account the total energy consump-
195 tion of the UAV tour both for travel as well as hovering
196 for data collection by considering the communication data
197 rate between the sensors and the UAV. Then, we formulate
198 a joint optimization problem to determine the UAV stops
199 positions, the sensors to send data at each stop, and the
200 itinerary that the UAV should follow to ensure data collec-
201 tion from all sensors with minimum energy consumption
202 while respecting their energy availability requirements.
- 203 • Due to the complexity and non-convexity of the problem,
204 we derive a sub-optimal but deterministic solution based
205 on decomposition of the problem and propose a procedure
206 to solve each sub-problem separately. The optimization
207 of the locations of the UAV stops as well as the selected
208 sensors to transmit at each stop is formulated as a cluster-
209 ing problem where the stops' positions are determined
210 using linear relaxation of the objective function while
211 the itinerary between the stops is optimized using a TSP
212 algorithm.
- 213 • We present some selected numerical results that show the
214 efficiency of the proposed approach. Specifically, we com-
215 pare it with previously proposed solution based on a TSP
216 with neighborhood (TSP-N) approach that optimizes the
217 itinerary of the UAV such that it travels through the neigh-
218 borhoods of the sensors.

219 In our previous work, [22], we proposed an initial investiga-
220 tion of the problem that does not take into account the sensors
221 energy constraints and their weights in the objective function.
222 In this paper, we have also enhanced the proposed solution by
223 investigating the mutual dependence between the different UAV
224 stop positions on the total consumption energy.

225 C. Paper Outline

226 The paper is organized as follows. Section II presents the sys-
227 tem model and the problem formulation. The joint clustering-

TSP solution is presented in Section III with discussion of each
sub-problem and details of the proposed algorithm. Selected
simulation results are provided in Section IV. Finally, conclu-
sions are drawn in Section V. Notations used throughout this
paper are summarized in Table I.

233 II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a set of K wireless sensors $\{S_1, \dots, S_K\}$ lo-
cated in a sub-region $\Omega \subseteq \mathbb{R}^3$. We assume that each sensor's
position $S_k \in \Omega^2$ is known and that each node is equipped with
a single omni-directional antenna. The assumption of pre-known
positions of the sensors is a typical assumption in the literature.
In practice, if the sensors are fixed, their positions can be ob-
tained. In particular, if the sensors belong to the same operator
who is also managing the drone, the fixed locations can be ob-
tained beforehand and can be saved in a data base. Moreover,
for more general scenarios, recent advances in localization tech-
niques allow accurate real-time knowledge of mobile sensors'
locations in outdoor and indoor environments with high preci-
sion. We consider a delay-tolerant application scenario where
each sensor S_k has transfer a message of size M_k bits during
the period of interest. However, due to powering constraints,
each sensor has a limited energy E_k^{max} to complete its data
transmission. We consider that each sensor transmits its signal
with a constant transmit power equal to P_T (in Watts) over the
bandwidth B .

We denote by D the UAV which is responsible of collecting
data from the sensors. Initially, the drone is assumed to be placed
at its docking station position X_0 where X_0 represents the 3D
geographical coordinates of the initial position to which it has to
return back after completing the data collection. The objective
is to find the set of N stop positions $X_c, \forall c = 1, \dots, N$, where
the drone should stop to collect data from the sensors as shown
in Fig. 1. At each stop, the drone collects data from a subset
of sensors using a time division multiple access scheme. We
denote by the cluster C_c the subset of sensors that their data
is collected by the drone at the stop X_c . We assume that the
drone moves with a fixed speed v_D and receives data only when
hovering at one of the stops in order to allow efficient channel
estimation and avoid interference and Doppler effects. Since we
are considering delay tolerant applications, the collected data is

²We use S_k to denote both the k -th sensor and its 3D position.

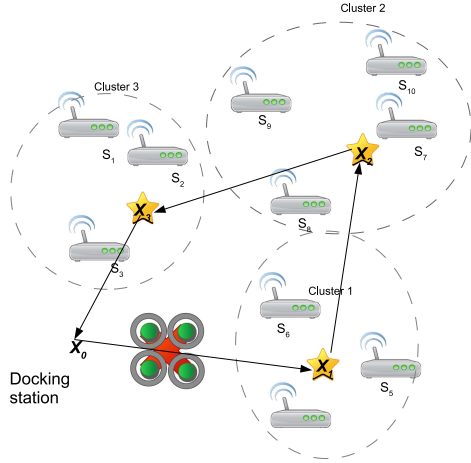


Fig. 1. UAV wireless data collection scheme for $N = 3$.

268 only forwarded to the sink when the drone returns to its docking
269 station.

270 A. Channel Model

271 The objective is to efficiently optimize the drone's path plan,
272 the overall transmission time is relatively long compared to
273 the channel coherence time. Hence, we focus on the system's
274 performance based on its average statistics rather than the in-
275 stantaneous ones which is not possible for this framework due
276 to the larger drones' flying time compared to the channel co-
277 herence time, usually measured in milliseconds. Therefore, we
278 only consider the large-scale path loss effect in the channel
279 gain's expressions.

280 The average data rate for the communication between a sensor
281 \mathbf{S} 's and the drone located at a position \mathbf{X} is denoted by
282 $\mathcal{R}(\mathbf{S}, \mathbf{X})$ defined by:

$$\mathcal{R}(\mathbf{S}, \mathbf{X}) = B \log_2 \left(1 + \frac{P_T}{PL_{A-G}(\mathbf{S}, \mathbf{X}) N_0} \right) \quad (1)$$

283 where $PL_{A-G}(\mathbf{S}, \mathbf{X})$ is the average channel pathloss. We con-
284 sider a probabilistic air-to-ground path loss model as in [23].
285 The average path-loss between a sensor \mathbf{S} and the UAV located
286 at a position \mathbf{X} is then expressed as:

$$PL_{A-G}(\mathbf{S}, \mathbf{X}) = p_{LoS}(\mathbf{S}, \mathbf{X}) PL_{LoS}(\mathbf{S}, \mathbf{X}) + [1 - p_{LoS}(\mathbf{S}, \mathbf{X})] PL_{NLoS}(\mathbf{S}, \mathbf{X}), \quad (2)$$

287 where $p_{LoS}(\mathbf{S}, \mathbf{X})$ represents the probability of LoS between
288 the sensor \mathbf{S} and the drone at position \mathbf{X} . This probability
289 depends on the environment and elevation angle. As shown
290 in [10], it can be expressed as follows

$$p_{LoS}(\mathbf{S}, \mathbf{X}) = \frac{1}{1 + \alpha \exp(-\beta[\theta(\mathbf{S}, \mathbf{X}) - \alpha])}, \quad (3)$$

291 where $\theta(\mathbf{S}, \mathbf{X})$ is the elevation angle of the drone in the posi-
292 tion \mathbf{X} with regards to the sensor \mathbf{S} as shown in Fig. 2 while
293 α and β are parameters that depend on the urban environment,
294 notably the percentage of build-up area to the total land area,
295 the number of buildings and obstacles per unit area, and the

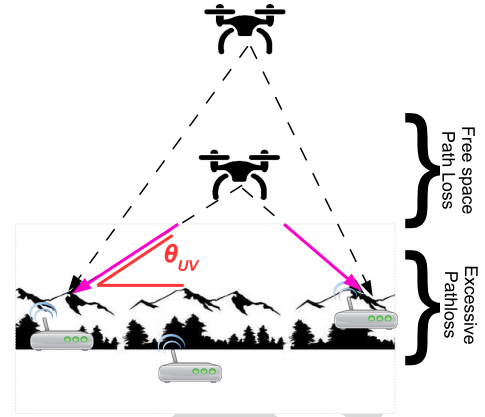


Fig. 2. UAV radio propagation model.

statistical distribution of their heights. The authors in [10] de- 296
rived an empirical method to compute these parameters as 297
a function of the urban environment characteristics. Finally, 298
 $PL_{LoS}(\mathbf{S}, \mathbf{X})$ and $PL_{NLoS}(\mathbf{S}, \mathbf{X})$ are the average path losses 299
for LoS and non line-of-sight (NLoS) environments, respec- 300
tively, expressed as: 301

$$PL_{LoS}(\mathbf{S}, \mathbf{X}) = 10\eta \log_{10} \left(\frac{4\pi f_c}{c} \|\mathbf{S} - \mathbf{X}\|_2 \right) + \xi_{LoS}, \quad (4)$$

$$PL_{NLoS}(\mathbf{S}, \mathbf{X}) = 10\eta \log_{10} \left(\frac{4\pi f_c}{c} \|\mathbf{S} - \mathbf{X}\|_2 \right) + \xi_{NLoS}, \quad (5)$$

where the first component represents the free-space path loss 302
with η the path loss exponent, f_c the carrier frequency, c the light 303
celerity, and $\|\mathbf{V}\|_2$ the norm-2 of the vector \mathbf{V} (i.e., $\|\mathbf{S} - \mathbf{X}\|_2$ 304
is the euclidian distance that separates the positions \mathbf{S} and \mathbf{X}). 305
On the other hand, the second component represents the mean 306
value of the excessive path loss (i.e., ξ_{LoS} is the mean value 307
of excessive path loss in LoS and ξ_{NLoS} is the mean value of 308
excessive path loss in NLoS). 309

B. Drone Power Consumption Model

The power consumption of the drone in the data collection 311
trip can be decomposed into two main cases, namely flight and 312
communication modes. The consumed power in the flight mode 313
contains two main parts: the first ensures hovering while the 314
other allows motion. 315

The hover power is written as a function of the drone's mass 316
 m_{tot} as well as the radius and the number of propellers r_p and 317
 n_p , respectively, [24]: 318

$$P_{hov} = \sqrt{\frac{(m_{tot}g)^3}{2\pi r_p^2 n_p \rho}}, \quad (6)$$

where g and ρ are respectively the earth gravity and air density. 319

The movement power for transition from a position to another 320
is assumed to be linear function of the drone speed v_D (assumed 321
to be constant) and can be written as 322

$$P_{tr} = \frac{P_{full} - P_s}{v_{max}} v_D + P_s, \quad (7)$$

323 where v_{\max} is the maximum speed of the drone. P_{full} and P_s
 324 are the hardware power levels when the drone is moving at full
 325 speed and when the drone stops in a fixed position (i.e., $v_D = 0$),
 326 respectively.

327 On the other hand, in the communication mode, the drone
 328 is assumed to hover at a fixed position. Thus, the consumed
 329 power is composed of the hovering power and a communication
 330 and signal processing power. The first component is the same
 331 introduced in (6) while the second one is assumed to be constant
 332 and denoted by P_{com} . In this paper, we are rather focusing on the
 333 access and operation parts of the drone. We are not investigating
 334 in details the signaling and overhead parts. This is because,
 335 in terms of energy consumption, the operation energy is more
 336 important than the overhead one as the signaling is happening
 337 for very short periods of the order of milliseconds while the
 338 network access operation occurs over long time slots of the
 339 order of minutes.

340 C. Problem Formulation

341 The drone's tour consists of moving around a number of positions
 342 called "collection stops" and denoted by $\{\mathbf{X}_1, \dots, \mathbf{X}_N\}$,
 343 where the drone hovers at each stop to receive data from a subset
 344 of the sensors as shown in Fig. 1. For that, we aim to optimize
 345 the positions of the collection stops, the subset of sensors that
 346 will transfer data at each stop, and the itinerary that the drone
 347 should follow to navigate between the stops.

348 We denote by $x_{c,k}$ the variables indicating the subset of sensors
 349 that will transfer their data to the Drone at each collection
 350 stop (i.e., $x_{c,k} = 1$ if the sensor's data is collected at the stop
 351 \mathbf{X}_c , and $x_{c,k} = 0$ otherwise.). We also denote by $y_{c,c'}$ the index
 352 variables for the UAV's itinerary (i.e., $y_{c,c'} = 1$ if the UAV
 353 moves from stop \mathbf{X}_c towards stop $\mathbf{X}_{c'}$, and $y_{c,c'} = 0$ otherwise).

354 The objective is written as the weighted sum of the energy
 355 consumed by the drone and the different sensors to complete
 356 the data collection.

$$O = E_D + \sum_{k=1}^K \rho_k E_{S_k}. \quad (8)$$

357 E_D is the energy consumed by the drone during the data collec-
 358 tion trip, written as:

$$E_D = \sum_{c=1}^N \sum_{k=1}^K x_{c,k} E_{c,k}^{\text{stop}} + \sum_{c=0}^N \sum_{\substack{c'=0 \\ c' \neq c}}^N y_{c,c'} E_{c,c'}^{\text{flight}}, \quad (9)$$

359 where $E_{c,c'}^{\text{flight}}$ is the drone's energy consumption when flying
 360 from a location \mathbf{X}_c to another $\mathbf{X}_{c'}$, expressed as follows:

$$\begin{aligned} E_{c,c'}^{\text{flight}} &= (P_{\text{hov}} + P_{\text{tr}}) \times T_{c,c'}^{\text{flight}} \\ &= \frac{(P_{\text{hov}} + P_{\text{tr}}) \|\mathbf{X}_c - \mathbf{X}_{c'}\|_2}{v_D}, \end{aligned} \quad (10)$$

361 with $T_{c,c'}^{\text{flight}} = \|\mathbf{X}_c - \mathbf{X}_{c'}\|_2 / v_D$ representing the drone's trip
 362 time from the position \mathbf{X}_c to the position $\mathbf{X}_{c'}$ and v_D is the
 363 drone's speed supposed constant along the trip.

364 On the other hand, $E_{c,k}^{\text{stop}}$ is the energy consumed by the drone
 365 when collecting data of the sensor S_k at the stop \mathbf{X}_c , which is

written as:

$$\begin{aligned} E_{c,k}^{\text{stop}} &= (P_{\text{hov}} + P_{\text{com}}) \times T_{k,c}^{\text{com}} \\ &= \frac{M_k (P_{\text{hov}} + P_{\text{com}})}{\langle \mathcal{R}(S_k, \mathbf{X}_c) \rangle_{R_k^{\text{min}}}^{R_k^{\text{max}}}}, \end{aligned} \quad (11)$$

367 where $T_{k,c}^{\text{com}} = M_k / \langle \mathcal{R}(S_k, \mathbf{X}_c) \rangle_{R_k^{\text{min}}}^{R_k^{\text{max}}}$ corresponds to the time
 368 needed to transfer the data of the sensor S_k to the drone at
 369 position \mathbf{X}_c . This communication time depends on the amount
 370 of data M_k that the sensor S_k has to transfer and the average
 371 data rate $\mathcal{R}(S_k, \mathbf{X}_c)$ for the sensor S_k 's transmission to the
 372 drone at position \mathbf{X}_c which was defined in Eq. (1). R_k^{min} and
 373 R_k^{max} are respectively the minimum and maximum decoding
 374 and transmission rate for the k -th sensor.³ Finally, ρ_k is a weight
 375 associated to the energy consumed by the k -th sensor in the
 376 objective function⁴ and E_{S_k} is the energy consumed by the k -th
 377 sensor to complete its data transmission, written as:

$$\begin{aligned} E_{S_k} &= P_T \times \sum_{c=1}^N x_{c,k} T_{k,c}^{\text{com}} \\ &= \frac{P_T M_k}{\sum_{c=1}^N x_{c,k} \langle \mathcal{R}(S_k, \mathbf{X}_c) \rangle_{R_k^{\text{min}}}^{R_k^{\text{max}}}}, \end{aligned} \quad (12)$$

378 where P_T is the sensor's transmit power and $T_{k,c}^{\text{com}} =$
 379 $M_k / \langle \mathcal{R}(S_k, \mathbf{X}_c) \rangle_{R_k^{\text{min}}}^{R_k^{\text{max}}}$ is the average time to send the M_k
 380 amount of data to the drone at the collection stop \mathbf{X}_c .

The optimization problem is then written as follows:

$$\begin{aligned} &\text{minimize} && E_D + \sum_{k=1}^K \rho_k E_{S_k} && (13a) \\ &\{\mathbf{X}_c \in \Omega\}_{1 \leq c \leq N} \\ &\{x_{c,k} \in \{0, 1\}\}_{\substack{1 \leq c \leq N \\ 1 \leq k \leq K}} \\ &\{y_{c,c'} \in \{0, 1\}\}_{\substack{0 \leq c \leq N \\ 0 \leq c' \leq N}} \\ &\{u_c \in \mathbb{Z}\}_{0 \leq c \leq N} \end{aligned}$$

$$\text{subject to} \quad \sum_{c=1}^N x_{c,k} = 1, \quad 1 \leq k \leq K; \quad (13b)$$

$$\sum_{\substack{c=0 \\ c \neq c'}}^N y_{c,c'} = 1, \quad 0 \leq c' \leq N; \quad (13c)$$

$$\sum_{\substack{c'=0 \\ c' \neq c}}^N y_{c,c'} = 1, \quad 0 \leq c \leq N; \quad (13d)$$

$$\begin{aligned} u_c - u_{c'} + (N+1)y_{c,c'} &\leq N, \\ &1 \leq c \neq c' \leq N; \end{aligned} \quad (13e)$$

$$E_{S_k} \leq E_k^{\text{max}}, \quad 1 \leq k \leq K, \quad (13f)$$

³ $\langle u \rangle_{u_{\text{min}}}^{u_{\text{max}}}$ is defined as $\begin{cases} u_{\text{min}}, & \text{if } u < u_{\text{min}} \\ u, & \text{if } u_{\text{min}} \leq u \leq u_{\text{max}} \\ u_{\text{max}}, & \text{if } u > u_{\text{max}}. \end{cases}$

⁴the weights can be set by the operator depending on its priorities, affinities, and operation requirements.

382 where u_c are dummy variables added to guarantee that the drone
383 travels through all stops only once in a closed loop. Equal-
384 ity (13b) constrains the data of each sensor to be collected at
385 one stop while the constraints (13c), (13d), and (13e) ensure
386 a closed loop of the drone's itinerary. Finally, (13f) guarantees
387 that energies consumed by the sensors does not exceed their
388 energy levels denoted as E_k^{max} for the k -th sensor.

389 This is a mixed integer non-linear programming problem
390 (MINLP). Even for fixed integer variables (i.e., $x_{c,k}$ and $y_{c,c'}$),
391 the problem remains non-convex as a function of the UAV stop
392 positions (\mathbf{X}_c), notably due to the expression of the communi-
393 cation time given in Eq. (11). Hence, optimal solutions is very
394 difficult to reach. Thus, we propose to devise a sub-optimal solu-
395 tion that decomposes the problem into three sub-problems such
396 that each variable is separately optimized. Then, an iterative
397 approach is adopted to reach a global solution.

398 III. OPTIMIZATION APPROACH

399 In this section, we present the proposed problem decompo-
400 sition approach to solve the non-convex optimization problem
401 formulated in (13). We aim first to propose a procedure to de-
402 termine the UAV stops locations then, determine the sensors as-
403 sociated to each of the UAV stops, and finally the UAV itinerary
404 between the stops to complete its data gathering tour. Follow-
405 ing that, an iterative algorithm is developed to combine these
406 procedures and jointly optimize the UAV tour.

407 A. Collection Stops Optimization Sub-Problem

408 Assuming known path ($y_{c,c'}, \forall c, c'$) and the subset of sensors
409 that will transfer data at each UAV stop ($x_{c,k}, \forall c, k$), we aim
410 to optimize the collection stops 3D positions. Hence, the sub-
411 problem is written as:

$$\arg \min_{\{\mathbf{X}_c \in \Omega\}_{1 \leq c \leq N}} E_D + \sum_{k=1}^K \rho_k E_{S_k} \quad (14a)$$

$$\text{subject to } E_{S_k} \leq E_k^{max}, 1 \leq k \leq K. \quad (14b)$$

412 Since this sub-problem is non-convex, we propose to find an
413 approximate solution through a linearization of the objective
414 function with regards to the stop positions. The approximated
415 problem is written as

$$\arg \min_{\{\mathbf{X}_c \in \Omega\}_{1 \leq c \leq N}} \sum_{c=1}^N \sum_{k=1}^K x_{c,k} (\omega_{c,k}^{com})^t (\mathbf{X}_c - \mathbf{S}_k) \\ + \sum_{c=0}^N \sum_{\substack{c'=0 \\ c' \neq c}}^N y_{c,c'} (\omega_{c,c'}^{fly})^t (\mathbf{X}_c - \mathbf{X}_{c'}) \quad (15a)$$

$$\text{subject to } x_{c,k} PL_{A-G}(\mathbf{S}_k, \mathbf{X}_c) \leq \frac{P_T/N_0}{2^{(P_T M_k)/(B E_k^{max})} - 1}, \\ 1 \leq k \leq K, 1 \leq c \leq N; \quad (15b)$$

with

$$\omega_{c,k}^{com} = (P_{hov} + P_{com} + \rho_k P_T) \nabla_{\mathbf{X}_c} (T_{c,k}^{com}), \\ \omega_{c,c'}^{fly} = (P_{hov} + P_{tr}) \nabla_{\mathbf{X}_c} (T_{c,k}^{flight}). \quad (16)$$

In the remainder of the paper, we denote $PL_k^{max} \triangleq \frac{P_T/N_0}{2^{(P_T M_k)/(B E_k^{max})} - 1}$. Note that the superscript $(\cdot)^t$ indicates the
matrix transpose operator while $\nabla_{\mathbf{X}}(\cdot)$ is the gradient operator
with regards to the vector \mathbf{X} .

We remark that each collection stop corresponds to a known
problem in the literature called the constrained Weber problem
that searches the weighted median of a set of points within a lim-
ited area [25], [26]. In our case, the set of points are the sensors
from which the data is collected and the neighboring collec-
tion stops. Solving this problem involves an iterative update
of the searched position within the constrained neighborhood
until convergence is reached [27]. Ideally, each collection posi-
tion \mathbf{X}_c coincides with the weighted median of the neighboring
stops and the sensors which can be written as follows:

$$\mathbf{X}_c = \frac{\sum_{k=1}^K x_{c,k} \omega_{c,k}^{com} \mathbf{S}_k + \sum_{\substack{c'=0 \\ c' \neq c}}^N y_{c,c'} \omega_{c,c'}^{fly} \mathbf{X}_{c'}}{\sum_{k=1}^K x_{c,k} \omega_{c,k}^{com} + \sum_{\substack{c'=0 \\ c' \neq c}}^N y_{c,c'} \omega_{c,c'}^{fly}}, \forall c = 1, \dots, N, \quad (17)$$

From that we can deduce that the optimal set of positions is the
solution of a linear system:

$$\mathbf{\Lambda} \tilde{\mathbf{X}} = \mathbf{\Theta}, \quad (18)$$

where $\tilde{\mathbf{X}} = [\mathbf{X}_1 \mathbf{X}_2 \dots \mathbf{X}_c \dots \mathbf{X}_N]^t$ is a $3N \times 1$ vector
composed by concatenation of the N collection stops' 3D posi-
tions, while $\mathbf{\Lambda}$ is a $3N \times 3N$ matrix defined as follows:

$$\mathbf{\Lambda} = \begin{bmatrix} \Phi_1 & \dots & -y_{1,c} \omega_{1,c}^{fly} & \dots & -y_{1,N} \omega_{1,N}^{fly} \\ \vdots & \ddots & \vdots & \dots & \vdots \\ -y_{c,1} \omega_{c,1}^{fly} & \dots & \Phi_c & \dots & -y_{c,N} \omega_{c,N}^{fly} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -y_{N,1} \omega_{N,1}^{fly} & \dots & -y_{N,c} \omega_{N,c}^{fly} & \dots & \Phi_N \end{bmatrix} \quad (19)$$

with $\Phi_c = \sum_{\substack{c'=0 \\ c' \neq c}}^N y_{c,c'} \omega_{c,c'}^{fly} + \sum_{k=1}^K x_{c,k} \omega_{c,k}^{com}$. On the right
hand side of the equality (18), $\mathbf{\Theta}$ is a $3N \times 1$ vector defined
as:

$$\mathbf{\Theta} = \begin{bmatrix} y_{1,0} \omega_{1,0}^{fly} \mathbf{X}_0 + \sum_{k=1}^K x_{1,k} \omega_{1,k}^{com} \mathbf{S}_k \\ y_{2,0} \omega_{2,0}^{fly} \mathbf{X}_0 + \sum_{k=1}^K x_{2,k} \omega_{2,k}^{com} \mathbf{S}_k \\ \vdots \\ y_{c,0} \omega_{c,0}^{fly} \mathbf{X}_0 + \sum_{k=1}^K x_{c,k} \omega_{c,k}^{com} \mathbf{S}_k \\ \vdots \\ y_{N,0} \omega_{N,0}^{fly} \mathbf{X}_0 + \sum_{k=1}^K x_{N,k} \omega_{N,k}^{com} \mathbf{S}_k \end{bmatrix} \quad (20)$$

Algorithm 1: UAV Stops Optimization Algorithm.

Choose a random initial set of stop positions of the UAV that satisfies the constraints (15b).

while $\|\mathbf{X}_c^{(t+1)} - \mathbf{X}_c^{(t)}\| > \epsilon, \forall c$ **do**

- Update the weights $\omega_{c,k}^{com}$ and $\omega_{c,k}^{fly}$ using (16).
- Compute the positions of the UAV stops using (18).
- For each collection stop position, check that the constraints (15b) are satisfied or choose the closest solution that satisfies them using (21).
- $t := t + 1$.

end while

439 Thus, the positioning of the collection stops can be found
440 through Algorithm 1 where the locations of the UAV stops are
441 iteratively updated until convergence is reached. We note that
442 since the obtained positions must satisfy the sensors energy
443 constraints as in (15b), we check at every iteration whether each
444 stop satisfies them with regards to its relative sensors. Otherwise,
445 we choose the closest position at which these constraints are
446 satisfied. This can be done through a local neighborhood search
447 algorithm that determines the new position \mathbf{X}_c as follows:

$$\mathbf{X}_c = \arg \min_{\mathbf{X} \in \bigcap_{k|x_{c,k}=1} \mathbb{F}_r(\mathbf{S}_k)} \|\mathbf{X} - \mathbf{X}_c\|_2, \quad (21)$$

448 where $\mathbb{F}_r(\mathbf{S}_k) = \{\mathbf{X} \in \Omega | PL_{A-G}(\mathbf{S}_k, \mathbf{X}) \leq PL_k^{max}\}$ is the
449 “feasibility” region of the sensor \mathbf{S}_k in which the drone can
450 receive the total sensor’s data while not violating its energy and
451 rate constraints.

452 On the other hand, for a better approximation of the origi-
453 nal objective function, we update the weights $\omega_{c,k}^{com}$ and $\omega_{c,k}^{fly}$
454 by recomputing the gradients at each iteration using the new
455 positions to seek close-optimality of the solution.

B. Clusters Assignment Sub-Problem

456 In this step, we propose to determine for each stop, the subset
457 of sensors for which data is collected. This is mathematically
458 equivalent to determining the index variables $\{x_{c,k}, \forall c, k\}$. By
459 fixing the other variables, we obtain the following sub-problem:
460

$$\arg \min_{\{x_{c,k} \in \{0,1\} | 1 \leq c \leq N, 1 \leq k \leq K\}} \sum_{c=1}^N \sum_{k=1}^K x_{c,k} E_{c,k}^{stop} + \rho_k E_{S_k} \quad (22a)$$

$$\text{subject to } \sum_{c=1}^N x_{c,k} = 1, 1 \leq k \leq K; \quad (22b)$$

$$E_{S_k} \leq E_k^{max}, 1 \leq k \leq K. \quad (22c)$$

461 This sub-problem can be independently solved and a direct
462 solution is derived for each sensor. Each sensor is assigned to
463 the collection stop that requires the lowest stop energy to collect
464 its data. Given the expression of $E_{c,k}^{stop}$ in (11), this is also
465 equivalent to the stop with highest average communication data

Algorithm 2: Joint Clustering-TSP Path Planning for Wireless Data Gathering.

Initialize collection stops $\mathbf{X}_c^{(0)}, \forall c$.

while $\|\mathbf{X}_c^{(t+1)} - \mathbf{X}_c^{(t)}\| > \epsilon, \forall c$ **do**

- Determine sensors assignment to collection stops using (23).
- Determine the path between the collection stops using TSP.
- Update the weights $\omega_{c,k}^{com}$ and $\omega_{c,k}^{fly}$.
- Compute the locations of the UAV stops using (18).
- For each stop location, check that the constraints (15b) are satisfied or choose a close solution using (21).
- $t := t + 1$.

end while

rate:

$$x_{c,k} = \begin{cases} 1, & \text{if } c = \arg \min_{i=1..N} \mathcal{R}(\mathbf{S}_k, \mathbf{X}_i) \\ 0, & \text{otherwise.} \end{cases} \quad (23)$$

C. Path Planing Sub-Problem

467 In this step, we focus on optimizing the path between
468 the collection stops assuming that their positions ($\mathbf{X}_c, \forall c \in$
469 $\{1, \dots, N\}$) are fixed. The sub-problem then is simplified as
470 follows:
471

$$\arg \min_{\{y_{c,c'} \in \{0,1\} | 0 \leq c \leq N, 0 \leq c' \leq N\}} \sum_{c=0}^N \sum_{\substack{c'=0 \\ c' \neq c}}^N y_{c,c'} E_{c,c'}^{flight} \quad (24a)$$

$$\{u_c \in \mathbb{Z} | 0 \leq c \leq N\}$$

$$\text{subject to } \sum_{\substack{c=0 \\ c \neq c'}}^N y_{c,c'} = 1, 1 \leq c' \leq N; \quad (24b)$$

$$\sum_{\substack{c'=0 \\ c' \neq c}}^N y_{c,c'} = 1, 1 \leq c \leq N; \quad (24c)$$

$$u_c - u_{c'} + (N+1)y_{c,c'} \leq N, \\ 1 \leq c \neq c' \leq N. \quad (24d)$$

472 Due to the expression of the flight energy in (10), the sub-
473 problem can be simplified to a classic symmetric TSP. Since it
474 is a linear problem, classic linear programming algorithms or an
475 efficient heuristic such as the Christofides Algorithm [28] can
476 be used to find a close-optimal itinerary efficiently.

D. Joint Optimization Algorithm

477 Now that we presented convenient procedures to solve each
478 variable efficiently. We develop a global algorithm that jointly
479 solves the problem and determines the stops positions, the sen-
480 sors assignment, and the path using an iterative approach as
481 presented in the joint Clustering-TSP Algorithm 2. The ap-
482 proach extends the previously presented UAV stops positioning
483

TABLE II
SYSTEM PARAMETERS

Parameter	Value	Parameter	Value
P_T (dBm/Hz)	21	N_0 (dBm/Hz)	-174
f_c (GHz)	2	η	3
α	10	β	0.03
ξ_{LoS} (dB)	0	ξ_{NLoS} (dB)	20
$P_{com}(W)$	0.0126	P_{full} (W)	5
$v_d = v_{max}$ (m/s)	15	P_s (W)	0
B kHz	15	m_{tot} (g)	500
r_p (cm)	20	n_p	4
M_k (Mo)	100	E_k^{max} (J)	0.016
R_k^{min} (Mbps)	0	R_k^{max} (Mbps)	100

484 Algorithm 1 to also update the assignment of sensors so clus-
485 ters are re-constructed at each iteration depending on the new
486 stops locations. Moreover, the itinerary is also updated at each
487 iteration as per the variation of these stops since these variables
488 are inter-dependent.

489 E. Effect of the Number of Stops/Clusters

490 We note that Algorithm 2 considers a fixed number of col-
491 lection stops N . On one hand, we should note that this number
492 is lower bounded by the minimum needed stops to cover all the
493 sensors. This lower bound can be computed through the inter-
494 section of all the regions that satisfy the energy constraints of
495 all sensors. This can be written as:

$$N^{min} = \min_{\mathbb{K}_i \in \mathcal{P}_K} \frac{|\mathbb{K}_i|}{\prod_{\mathbb{K} \in \mathbb{K}_i} \mathbb{1}_{\mathcal{I}_r(\mathbb{K})} \neq \emptyset}, \quad (25)$$

496 where \mathcal{P}_K is the set of all partitions of elements in $\{1, \dots, K\}$,
497 $|\cdot|$ denotes the cardinality of a set, and the operator $\mathbb{1}_e$ is the
498 identity function (i.e., it takes 1 when e is true and 0 otherwise).
499 Moreover $\mathcal{I}_r(\mathbb{K}) = \bigcap_{k \in \mathbb{K}} \mathbb{F}_r(\mathcal{S}_k)$ is the intersection of all fea-
500 sibility regions of the sensors in the set \mathbb{K} . On the other hand,
501 the maximum number of stops is equal to the number of sensors.
502 In this extreme situation, the drone would stop at a very close
503 location to every sensor to collect its data separately. This would
504 minimize the energy consumed at each stop but would cost much
505 higher flight energy to travel between all these stops. Thus, we
506 propose to start from the maximum number of stops and iter-
507 atively decrease the number of stops by removing one of the
508 stops if it results in reduction of the total energy consumption.

509 IV. RESULTS AND DISCUSSION

510 In this section, we investigate the impact of some parame-
511 ters on the system performance. We consider a bounded area of
512 size 1×1 km² where $K = 100$ ground sensors are randomly
513 placed in the area following a uniform distribution. A quad-
514 copter drone is initially placed at the center of the area targeting
515 to collect data from the K sensors. We assume that the locations
516 and size of data to transmit for each sensor are a-priori known.
517 The channel and energy consumption models' parameters are
518 given in Table II [24], [29] unless mentioned otherwise. For the
519 objective function, without loss of generality, we consider equal
520 weights for all sensors' energy $\rho_k = \rho = \frac{1}{K}, \forall k$. We compare

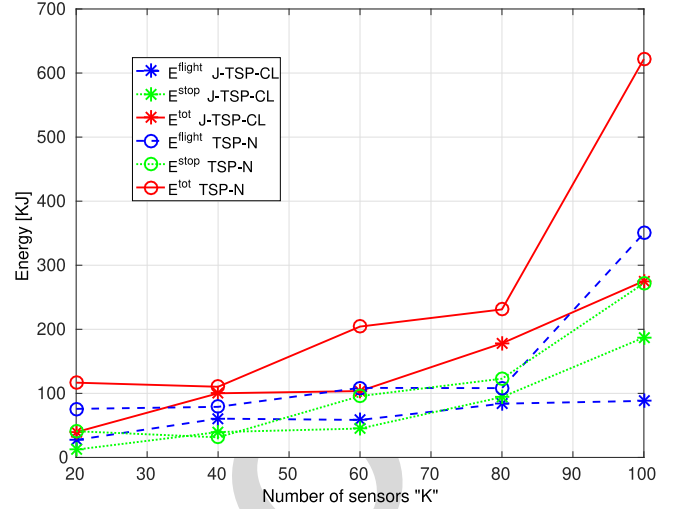


Fig. 3. Comparison between the proposed approach “J-TSP-CL” and the “TSP-N” algorithm energy consumption as a function of the number of sensors.

the performance of our algorithm that we denote by “J-TSP-CL” 521
to the performance obtained using a TSP with neighborhood 522
(TSP-N) based approach that determines the minimum path to 523
travel across the neighborhood of the sensors using the algo- 524
rithm introduced in [30]. In this algorithm, for each sensor, a 525
neighborhood area is defined. This region characterizes the area 526
where a UAV can receive the sensor’s data reliably. The objec- 527
tive of the algorithm is then to optimize the path of the UAV 528
such that it flies over all neighborhood regions of the transmit- 529
ting sensors. However, this solution does not account for the 530
effect of the UAV’s positions on the data rate, and thus on the 531
time needed to complete the transmissions. Additionally, it re- 532
quires a discretization of the environment to obtain the global 533
solution. 534

In Fig. 3, we plot the obtained energy consumption using 535
our algorithm compared to the one of the TSP-N algorithm as 536
a function of the number of active sensors (K). We observe 537
a net energy saving achieved via the proposed algorithm that 538
can reach 50% with only 100 sensors. Furthermore, the TSP- 539
N based algorithm energy consumption increases exponentially 540
with the increase of the number of sensors while our algorithm 541
ensures a linear increase through the control of the trade-off 542
between the flight and communication energies. In fact, when 543
the number of sensors is low, our algorithm sets the UAV to travel 544
very close to the sensors to collect the data rapidly (i.e., with 545
minimal energy at stops) while also keeping low travel energy. 546
However, when the number of sensors increases, the UAV starts 547
gathering data from larger distances; it consumes higher energy 548
when communicating but ensures higher saving in terms of flight 549
energy. In contrast, the TSP-N based algorithm fails to do this 550
trade-off between communication and flight times’ effects on 551
energy consumption. Since it does not account for the energy 552
consumption due to communication, the energy consumed at 553
the stops increases proportionally to the number of sensors. But, 554
more importantly, the flight energy continuously increase due to 555
the complication of finding a path that travels the neighborhoods. 556

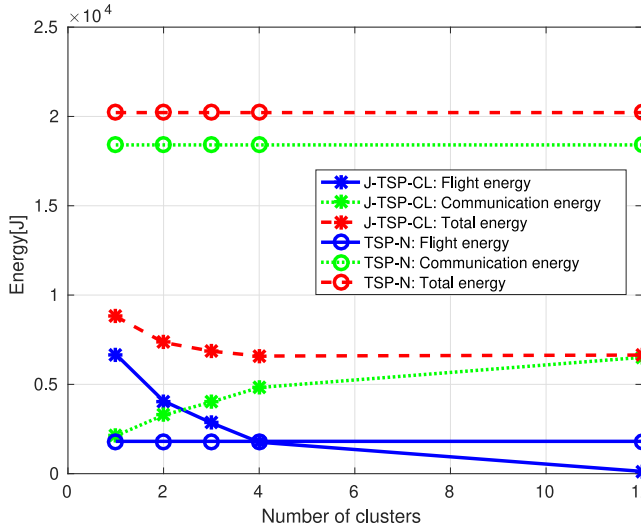


Fig. 4. Energy consumption as a function of the number of steps.

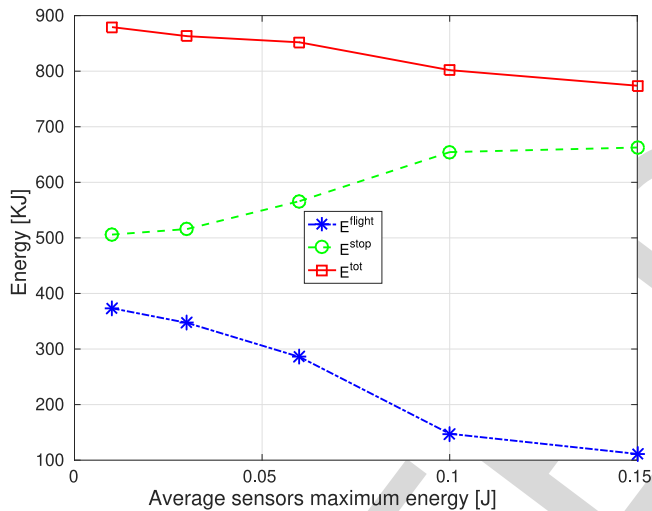


Fig. 5. Energy consumption as a function of the sensors available energy.

557 In order to further explain the effect of the trade-off between
 558 communication and flight times on the energy consumption,
 559 in Fig. 4 we fix the number of stops N in our algorithm
 560 ‘J-TSP-CL’ and plot the consumed energy as a function of
 561 N . Since the number of sensors per cluster decreases with
 562 the number of stops, the communication time decreases with
 563 the increase of the number of stops and thus the energy con-
 564 sumed at stops continuously decreases. On the other hand, with
 565 the increase of the number of stops, more energy is needed
 566 to travel across them. Thus, E^{flight} is continuously increas-
 567 ing with the number of stops. This trade-off results in an opti-
 568 mal number of stops N^* that minimizes the global energy.
 569 For our set-up parameters, this optimal number is shown to be
 570 4 clusters.

571 In Fig. 5, we focus on the effect of the sensors’ available
 572 energy. We vary the average available energy per sensor and
 573 show the result in terms of energy consumption. Increasing this
 574 energy relaxes the constraints for UAV stops and gives it more
 575 flexibility to ensure its data collection from larger distances.

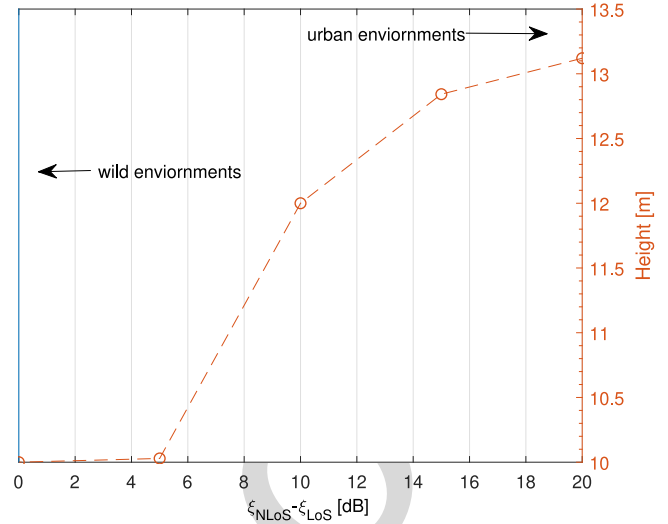


Fig. 6. UAV altitude as a function of the LoS/NLoS pathloss difference.

This results in an increase of the communication time (i.e.,
 576 increase of the stop energy) but at the same time, it ensures
 577 higher savings in flight distance/time which reduces the total
 578 energy consumption.
 579

In Fig. 6, we observe the behavior of the UAV in different
 580 simulation environments. We plot the average UAV height
 581 while varying the difference between NLoS and LoS excessive
 582 path losses ($\xi_{NLoS} - \xi_{LoS}$). For wild environments, LoS and
 583 NLoS are almost equal, the UAV flies only at low altitudes to
 584 reduce its flight energy consumption. Higher altitudes does not
 585 provide any benefit. As the difference between the path losses
 586 increases, we tend towards urban environments due to the higher
 587 shadowing and obstructions which increase the NLoS pathloss.
 588 Thus, the UAV is forced to fly at higher altitudes to take profit
 589 of the better channels using LoS in order to reduce its energy
 590 consumption.
 591

V. CONCLUSION

In this paper, we designed a framework for energy efficient
 593 data collection from WSNs using a mobile UAV. The proposed
 594 approach optimizes the UAV stops for data collection from
 595 neighboring sensors as well as the itinerary followed by the
 596 UAV in order to ensure efficient collection of all data with
 597 minimum energy consumption. The proposed algorithm iterates
 598 between clustering based approach to optimize the UAV
 599 stops positioning and the sensors collected per stop and a TSP
 600 procedure to determine the UAV path. The simulation results
 601 show the efficiency of the proposed approaches in provid-
 602 ing better results compared to existing approaches due to the
 603 joint optimization of the communication and flight energies
 604 consumption.
 605

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 608

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