

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

*Original*

Joint Position and Travel Path Optimization for Energy Efficient Wireless Data Gathering Using Unmanned Aerial Vehicles / Ghorbel, M. B.; RODRIGUEZ DUARTE, DAVID ORLANDO; Ghazzai, H.; Hossain, M. J.; Menouar, H. - In: IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY. - ISSN 0018-9545. - ELETTRONICO. - 68:3(2019), pp. 2165-2175. [10.1109/TVT.2019.2893374]

*Availability:*

This version is available at: 11583/2805014 since: 2020-03-23T12:27:09Z

*Publisher:*

Institute of Electrical and Electronics Engineers Inc.

*Published*

DOI:10.1109/TVT.2019.2893374

*Terms of use:*

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

*Publisher copyright*

IEEE postprint/Author's Accepted Manuscript

©2019 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collecting works, for resale or lists, or reuse of any copyrighted component of this work in other works.

(Article begins on next page)

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

Mahdi Ben Ghorbel <sup>1</sup>, *Member, IEEE*, David Rodríguez-Duarte, Hakim Ghazzai, *Member, IEEE*,  
Md. Jahangir Hossain <sup>2</sup>, *Senior Member, IEEE*, and Hamid Menouar, *Senior Member, IEEE*

**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.

Manuscript received June 8, 2018; revised November 1, 2018; accepted January 11, 2019. This work was supported under Grant National Priorities Research Program 9-257-1-056 from the Qatar National Research Fund (a member of The Qatar Foundation). The review of this paper was coordinated by Prof. W. Song. This paper was presented in part at the IEEE 87th Vehicular Technology Conference, Porto, Portugal, June 2018. (*Corresponding author: Mahdi Ben Ghorbel.*)

M. Ben Ghorbel was with the School of Engineering, University of British Columbia, Vancouver, BC V6T 1Z4, Canada, and now with the Exfo Inc., Quebec City, QC G1M 2K2, Canada (e-mail: mahdi.ben-ghorbel@exfo.com).

D. Rodríguez-Duarte was with the School of Engineering, University of British Columbia, Vancouver, BC V6T 1Z4, Canada, and now with the Department of Electronics and Telecommunications, Politecnico di Torino, Torino 10125, Italy (e-mail: david.rodriguez@polito.it).

H. Ghazzai is with the School of Systems and Enterprises, Stevens Institute of Technology, Hoboken, NJ 07030 USA (e-mail: hghazzai@stevens.edu).

Md. J. Hossain is with the School of Engineering, University of British Columbia, Kelowna, BC V1V 1V7, Canada (e-mail: jahangir.hossain@ubc.ca).

H. Menouar is with the Qatar Mobility Innovations Center, Qatar University, Doha 2713, Qatar (e-mail: hamidm@qmic.com).

Digital Object Identifier 10.1109/TVT.2019.2893374

## 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 drones<sup>1</sup>, 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).

<sup>1</sup>Note 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

<sup>2</sup>We use  $S_k$  to denote both the  $k$ -th sensor and its 3D position.

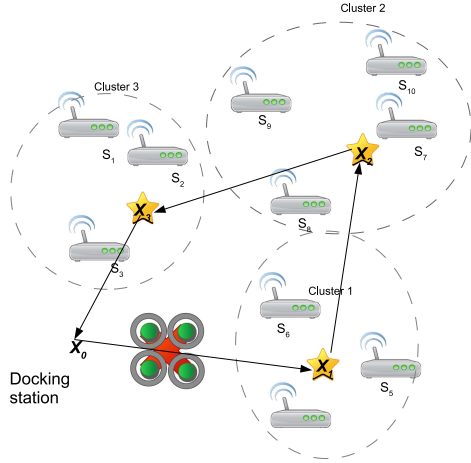


Fig. 1. UAV wireless data collection scheme for  $N = 3$ .

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  $\alpha$  and  $\beta$  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

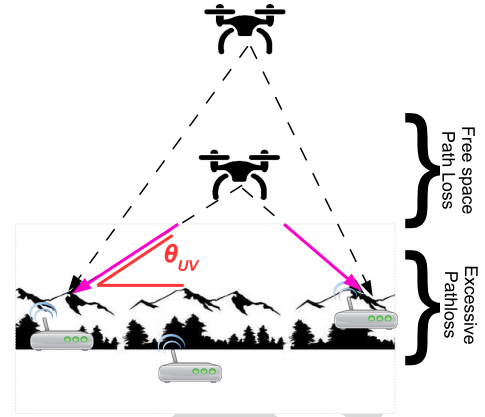


Fig. 2. UAV radio propagation model.

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  $\eta$  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.,  $\xi_{LoS}$  is the mean value 307  
of excessive path loss in LoS and  $\xi_{NLoS}$  is the mean value of 308  
excessive path loss in NLoS). 309

### B. Drone Power Consumption Model 310

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  $\rho$  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.  $P_{\text{full}}$  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  $P_{\text{com}}$ . 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 posi-  
 342 tions 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 sen-  
 349 sors 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 in-  
 352 dex 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).  $R_k^{\text{min}}$  and  
 373  $R_k^{\text{max}}$  are respectively the minimum and maximum decoding  
 374 and transmission rate for the  $k$ -th sensor.<sup>3</sup> Finally,  $\rho_k$  is a weight  
 375 associated to the energy consumed by the  $k$ -th sensor in the  
 376 objective function<sup>4</sup> 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:

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

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

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

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

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

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

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

<sup>4</sup>the 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  
417 matrix transpose operator while  $\nabla_{\mathbf{X}}(\cdot)$  is the gradient operator  
418 with regards to the vector  $\mathbf{X}$ .  
419  
420

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

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

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

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

433 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  
434 composed by concatenation of the  $N$  collection stops' 3D posi-  
435 tions, while  $\mathbf{\Lambda}$  is a  $3N \times 3N$  matrix defined as follows:

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

436 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  
437 hand side of the equality (18),  $\mathbf{\Theta}$  is a  $3N \times 1$  vector defined  
438 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.

456 **B. Clusters Assignment Sub-Problem**

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

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

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

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

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:

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

467 **C. Path Planing Sub-Problem**

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

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

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

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

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

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

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.

477 **D. Joint Optimization Algorithm**

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

TABLE II  
SYSTEM PARAMETERS

Parameter	Value	Parameter	Value
$P_T$ (dBm/Hz)	21	$N_0$ (dBm/Hz)	-174
$f_c$ (GHz)	2	$\eta$	3
$\alpha$	10	$\beta$	0.03
$\xi_{LoS}$ (dB)	0	$\xi_{NLoS}$ (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  $1 \times 1$  km<sup>2</sup> 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

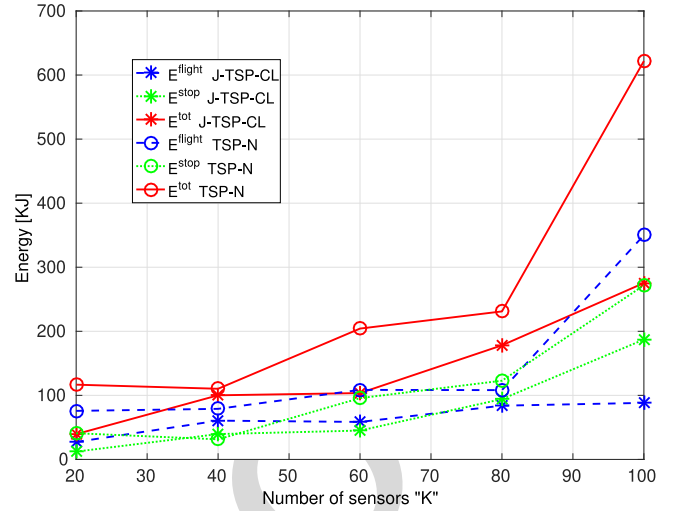


Fig. 3. Comparison between the proposed approach “J-TSP-CL” and the “TSP-N” algorithm energy consumption as a function of the number of sensors.

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

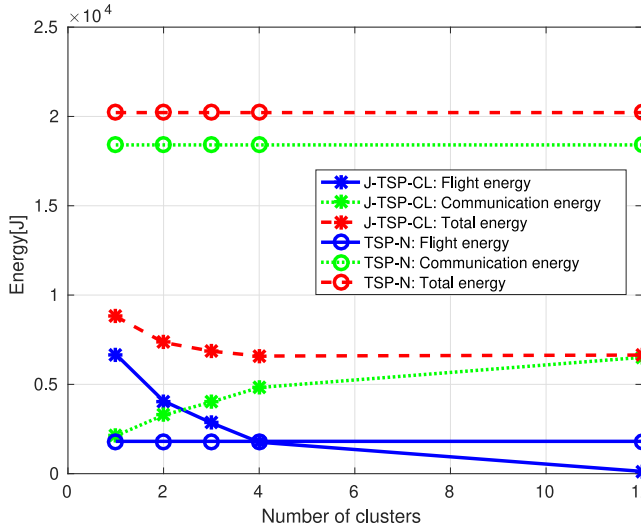


Fig. 4. Energy consumption as a function of the number of steps.

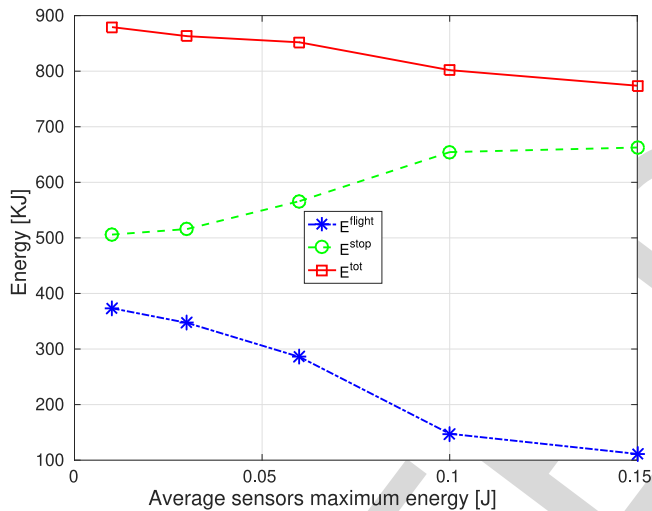


Fig. 5. Energy consumption as a function of the sensors available energy.

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 op-  
 568 timal 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.

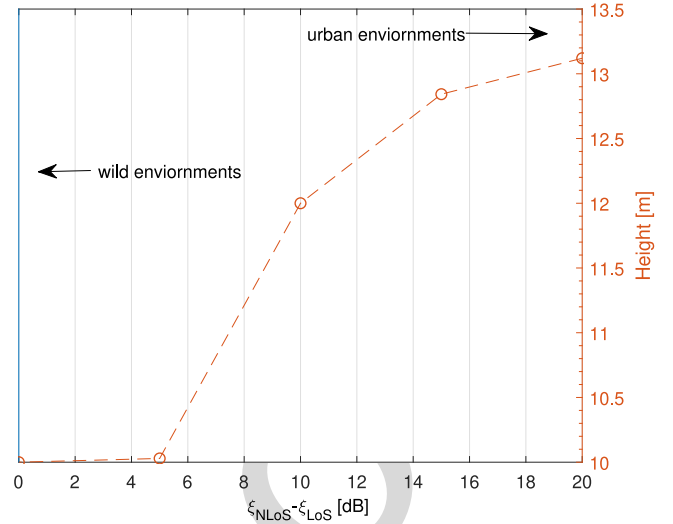


Fig. 6. UAV altitude as a function of the LoS/NLoS pathloss difference.

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

## ACKNOWLEDGMENT

The statements made herein are solely the responsibility of  
 607 the authors.  
 608

## REFERENCES

- 609
- 610 [1] C.-Y. Chong and S. P. Kumar, "Sensor networks: Evolution, opportunities,  
611 and challenges," *Proc. IEEE*, vol. 91, no. 8, pp. 1247–1256, Aug. 2003.
- 612 [2] M. Bagaa, Y. Challal, A. Ksentini, A. Derhab, and N. Badache, "Data  
613 aggregation scheduling algorithms in wireless sensor networks: Solutions  
614 and challenges," *IEEE Commun. Surv. Tut.*, vol. 16, no. 3, pp. 1339–1368,  
615 Third Quarter 2014.
- 616 [3] R. Prabha, M. V. Ramesh, V. P. Rangan, P. V. Ushakumari, and  
617 T. Hemalatha, "Energy efficient data acquisition techniques using con-  
618 text aware sensing for landslide monitoring systems," *IEEE Sensors J.*,  
619 vol. 17, no. 18, pp. 6006–6018, Sep. 2017.
- 620 [4] C. F. Cheng, L. H. Li, and C. C. Wang, "Data gathering with minimum  
621 number of relay packets in wireless sensor networks," *IEEE Sensors J.*,  
622 vol. 17, no. 21, pp. 7196–7208, Nov. 2017.
- 623 [5] M. Zhao, Y. Yang, and C. Wang, "Mobile data gathering with load balanced  
624 clustering and dual data uploading in wireless sensor networks," *IEEE  
625 Trans. Mobile Comput.*, vol. 14, no. 4, pp. 770–785, Apr. 2015.
- 626 [6] M. Ruiz, E. Alvarez, A. Serrano, and E. Garcia, "The convergence be-  
627 tween wireless sensor networks and the Internet of Things; challenges  
628 and perspectives: A survey," *IEEE Latin America Trans.*, vol. 14, no. 10,  
629 pp. 4249–4254, Oct. 2016.
- 630 [7] M. Gharibi, R. Boutaba, and S. L. Waslander, "Internet of drones," *IEEE  
631 Access*, vol. 4, pp. 1148–1162, Mar. 2016.
- 632 [8] H. Menouar, I. Guvenç, K. Akkaya, A. S. Uluagac, A. Kadri, and  
633 A. Tuncer, "UAV-enabled intelligent transportation systems for the smart  
634 city: Applications and challenges," *IEEE Commun. Mag.*, vol. 55, no. 3,  
635 pp. 22–28, Mar. 2017.
- 636 [9] H. Ghazzai, M. B. Ghorbel, A. Kadri, M. J. Hossain, and H. Menouar,  
637 "Energy-efficient management of unmanned aerial vehicles for underlay  
638 cognitive radio systems," *IEEE Trans. Green Commun. Netw.*, vol. 1, no. 4,  
639 pp. 434–443, Dec. 2017.
- 640 [10] A. Al-Hourani, S. Kandeepan, and S. Lardner, "Optimal LAP altitude  
641 for maximum coverage," *IEEE Wireless Commun. Lett.*, vol. 3, no. 6,  
642 pp. 569–572, Dec. 2014.
- 643 [11] F. Liu, Y. Wang, M. Lin, K. Liu, and D. Wu, "A distributed routing  
644 algorithm for data collection in low-duty-cycle wireless sensor networks,"  
645 *IEEE Internet Things J.*, vol. 4, no. 5, pp. 1420–1433, Oct. 2017.
- 646 [12] Z. Xu, L. Chen, C. Chen, and X. Guan, "Joint clustering and routing  
647 design for reliable and efficient data collection in large-scale wireless  
648 sensor networks," *IEEE Internet Things J.*, vol. 3, no. 4, pp. 520–532,  
649 Aug. 2016.
- 650 [13] F. Zhou, Z. Chen, S. Guo, and J. Li, "Maximizing lifetime of data-gathering  
651 trees with different aggregation modes in WSNs," *IEEE Sensors J.*, vol. 16,  
652 no. 22, pp. 8167–8177, Nov. 2016.
- 653 [14] C. F. Cheng and C. F. Yu, "Data gathering in wireless sensor networks:  
654 A combine-TSP-reduce approach," *IEEE Trans. Veh. Technol.*, vol. 65,  
655 no. 4, pp. 2309–2324, Apr. 2016.
- 656 [15] C. Zhu, S. Wu, G. Han, L. Shu, and H. Wu, "A tree-cluster-based data-  
657 gathering algorithm for industrial WSNs with a mobile sink," *IEEE Access*,  
658 vol. 3, pp. 381–396, Apr. 2015.
- 659 [16] G. Yang, H. Xu, X. He, L. Gao, Y. Geng, and C. Wu, "A clue based data  
660 collection routing protocol for mobile sensor networks," *IEEE Access*,  
661 vol. 4, pp. 8476–8486, Dec. 2016.
- 662 [17] X. Liu, H. Zhao, X. Yang, and X. Li, "SinkTrail: A proactive data reporting  
663 protocol for wireless sensor networks," *IEEE Trans. Comput.*, vol. 62,  
664 no. 1, pp. 151–162, Jan. 2013.
- 665 [18] A. Giorgetti, M. Lucchi, M. Chiani, and M. Z. Win, "Throughput per pass  
666 for data aggregation from a wireless sensor network via a UAV," *IEEE  
667 Trans. Aerosp. Electron. Syst.*, vol. 47, no. 4, pp. 2610–2626, Oct. 2011.
- 668 [19] S. Sotheara, K. Aso, N. Aomi, and S. Shimamoto, "Effective data gathering  
669 and energy efficient communication protocol in wireless sensor networks  
670 employing UAV," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Istanbul,  
671 Turkey, Apr. 2014, pp. 2342–2347.
- 672 [20] X. Ma, R. Kacimi, and R. Dhaou, "Fairness-aware UAV-assisted data  
673 collection in mobile wireless sensor networks," in *Proc. Int. Wireless  
674 Commun. Mobile Comput. Conf.*, Paphos, Cyprus, Sep. 2016, pp. 995–  
675 1001.
- 676 [21] S. Say, H. Inata, J. Liu, and S. Shimamoto, "Priority-based data gathering  
677 framework in UAV-assisted wireless sensor networks," *IEEE Sensors J.*,  
678 vol. 16, no. 14, pp. 5785–5794, Jul. 2016.
- 679 [22] M. B. Ghorbel, D. Rodriguez-Duarte, H. Ghazzai, M. J. Hossain, and  
680 H. Menouar, "Energy efficient data collection for wireless sensors using  
681 drones," in *Proc. IEEE 87th Veh. Technol. Conf.*, Porto, Portugal, Jun.  
682 2018, pp. 1–5.
- 683 [23] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Drone small cells in  
684 the clouds: Design, deployment and performance analysis," in *Proc. IEEE  
685 Global Commun. Conf.*, San Diego, CA, USA, Dec. 2015.
- 686 [24] J. V. Dries Hulens and T. Goedeme, "How to choose the best embedded  
687 processing platform for onboard UAV image processing," in *Proc. Int.  
688 Joint Conf. Comput. Vis., Imag. Comput. Graph. Theory Appl.*, Berlin,  
689 Germany, Mar. 2015.
- 690 [25] G. Wesolowsky, "The Weber problem: History and perspectives," *Address  
691 Sci.*, no. 1, pp. 5–23, 1993.
- 692 [26] E. Weiszfeld and F. Plastria, "On the point for which the sum of the dis-  
693 tances to n given points is minimum," *Ann. Operations Res.*, vol. 167, no. 1,  
694 pp. 7–41, 2009. [Online]. Available: <http://dx.doi.org/10.1007/s10479-008-0352-z>
- 695 [27] L. A. Kazakovtsev, "Algorithm for constrained Weber problem with fea-  
696 sible region bounded by arcs," *Facta Universitatis, Ser. Math. Inform.*,  
697 vol. 28, no. 3, pp. 271–284, 2013.
- 698 [28] N. Christofides and Carnegie-Mellon University Pittsburgh PA Manage-  
699 ment Sciences Research Group, "Worst-case analysis of a new heuristic for  
700 the travelling salesman problem," Defense Technical Information Center,  
701 Fort Belvoir, VA, USA, Tech. Rep. ADA025602, 1976. [Online]. Avail-  
702 able: <https://books.google.ca/books?id=2A7eygAACAAJ>
- 703 [29] G. Auer *et al.*, "D2.3 v2: Energy efficiency analysis of the reference  
704 systems, areas of improvements and target breakdown," Energy Aware  
705 Radio Network Technologies, Tech. Rep. INFSo-ICT-247733, Jan. 2011.
- 706 [30] J. Isaacs and J. Hespanha, "Dubins traveling salesman problem with neigh-  
707 borhoods: A graph-based approach," *Algorithms*, vol. 6, no. 1, p. 84–99,  
708 Feb. 2013. [Online]. Available: <http://dx.doi.org/10.3390/a6010084>
- 709



**Mahdi Ben Ghorbel** (S'10–M'14) received the  
710 "Diplome d'Ingénieur" from Ecole Polytechnique de  
711 Tunisie, La Marsa, Tunisia, in 2009, and the Ph.D.  
712 degree in electrical engineering from the King Abdul-  
713 lah University of Science and Technology (KAUST),  
714 Thuwal, Saudi Arabia, in 2013. He is currently a  
715 Signal Processing Designer with Exfo Inc., Quebec  
716 city, QC, Canada. Before joining Exfo, he worked as  
717 a Postdoctoral Research Fellow with Qatar Univer-  
718 sity, Doha, Qatar, then with the University of British  
719 Columbia, Kelowna, BC, Canada between September  
720 2013 and July 2018. His research interests include resource allocation optimiza-  
721 tion and performance analysis for communication systems. He was the recipient  
722 of Excellency Fellowship for engineering studies from the Tunisian Government  
723 and the *majeur-de-promotion* award in June 2009. He was also the recipient of  
724 the Provost Award and the Discovery Fellowship to join KAUST in September  
725 2009. He has Co-Chaired several workshops in International Wireless Commu-  
726 nications and Mobile Computing Conference and WCNC conferences. He  
727 has served on the organization committee of many international conferences as  
728 a TPC member, including the IEEE International Conference on Communica-  
729 tions, Global Communications Conference, Vehicular Technology Conference,  
730 and WCNC, and a technical reviewer for many international IEEE journals.



**David Rodríguez-Duarte** received the B.Sc. and  
733 M.Sc. degrees in electronic engineering from Uni-  
734 versidad Nacional de Colombia, Bogota, Colombia,  
735 in 2013 and 2018, respectively. He is currently work-  
736 ing toward the Ph.D. degree with the Department of  
737 Electronics and Telecommunications, Politecnico di  
738 Torino, Torino, Italy, with the Applied Electromag-  
739 netics group. He is currently working on the develop-  
740 ment of a mobile device for imaging cerebrovascular  
741 diseases as a part of the European project EMER-  
742 ALD. For his masters thesis, he worked on the design  
743 of antennas for full-duplex wireless communications systems. From 2014 to  
744 2015, he collaborated in satellite mission Libertad 2 as a Young Researcher  
745 with the group in Control and Energy Nanosatellites, Universidad Sergio Ar-  
746 boleda, Bogota, Colombia. In 2017, he was visitor research with The University  
747 of British Columbia, Kelowna, BC, Canada, working on the usage of Unmanned  
748 Aerial Vehicle for information collection/dissemination in Wireless Sensor  
749 Networks, and funding by the Emerging Leaders in the Americas Program.  
750 His current research interest includes antenna design and microwave imaging  
751 system.

754  
755  
756  
757  
758  
759  
760  
761  
762  
763  
764  
765  
766  
767  
768  
769  
770



**Hakim Ghazzai** (S'12–M'15) received the Diplome d'Ingenieur degree in telecommunication engineering with highest distinction and Master degree in high-rate transmission systems from the Ecole Supérieure des Communications de Tunis, Tunis, Tunisia, in 2010 and 2011, respectively, and the Ph.D. degree in electrical engineering from the King Abdullah University of Science and Technology, Thuwal, Saudi Arabia, in 2015. He is currently working as a Research Scientist with the Stevens Institute of Technology, Hoboken, NJ, USA. Before joining Stevens,

he worked as a Visiting Researcher with Karlstad University, Sweden and as a Research Scientist with Qatar Mobility Innovations Center, Doha, Qatar from 2015 to 2018. His general research interests are at the intersection of wireless networks, UAVs, Internet-of-Things, intelligent transportation systems, and optimization.

771  
772  
773  
774  
775  
776  
777  
778  
779  
780  
781  
782  
783  
784  
785  
786  
787  
788  
789  
790  
791  
792  
793  
794  
795  
796  
797



**Md. Jahangir Hossain** (S'04–M'08–SM'18) received the B.Sc. degree in electrical and electronics engineering from the Bangladesh University of Engineering and Technology (BUET), Dhaka, Bangladesh, the M.A.Sc. degree from the University of Victoria, Victoria, BC, Canada, and the Ph.D. degree from the University of British Columbia (UBC), Vancouver, BC, Canada.

He was a Lecturer with BUET. He was a Research Fellow with McGill University, Montreal, QC, Canada, the National Institute of Scientific Research,

Quebec, QC, Canada, and the Institute for Telecommunications Research, University of South Australia, Mawson Lakes, SA, Australia. His industrial experiences include a Senior Systems Engineer position with Redline Communications, Markham, ON, Canada, and a Research Intern position with Communication Technology Lab, Intel Inc., Hillsboro, OR, USA. He is currently an Associate Professor with the School of Engineering, UBC Okanagan campus, Kelowna, BC, Canada. His research interests include designing spectrally and power-efficient modulation schemes, quality of service issues and resource allocation in wireless networks, and optical wireless communications. He is serving as an Associate Editor for the IEEE COMMUNICATIONS SURVEYS AND TUTORIALS and an Editor for the IEEE TRANSACTIONS ON COMMUNICATIONS. He was also an Editor for the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS. He serves as a member of the Technical Program Committee of the IEEE International Conference on Communications and IEEE Global Telecommunications Conference.



**Hamid Menouar** (SM'16) received the Engineering degree in computer science from the University of Sciences and Technology Houari Boumediene, Algiers, Algeria, in 2003, the DEA (M.S.) degree in systems and information technologies from the University of Technology of Compiègne, Compiègne, France, in 2004, and the Ph.D. degree in computer science from Télécom ParisTech, called at that time Ecole Nationale Supérieure des Télécommunications, Paris, France, in 2008. From 2005 to 2010, he worked with Hitachi Europe, France as a Researcher then as

lead of the Cooperative Systems team. In late 2010, he moved to Qatar and joined Qatar Mobility Innovations Center where he works as a Senior R&D Expert and Product Manager, leading different projects and initiatives in the areas of connected and automated vehicles, intelligent transport systems, unmanned aerial vehicles, Internet of Things, smart mobility, etc.

798  
799  
800  
801  
802  
803  
804  
805  
806  
807  
808  
809  
810  
811  
812  
813  
814