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

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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*—Unnamed 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 drones[1], 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).

[1]Note that the terms "UAV" and "drone" are used interchangeably throughout the paper.

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

### A. Related Work

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

Recently, multiple routing protocols have been proposed to ensure fast, reliable, and/or energy efficient data collection [11]–[13]. In [11], the authors proposed a distributed routing algorithm aiming to ensure a balance between latency and energy consumption. The objective is to determine the routing through which the data need to be forwarded such that a global network utility including the energy consumption and the end-to-end delay is optimized. Another protocol focusing on combining clustering and routing has been proposed in [12]. The idea consists of selecting multiple cluster-heads which are responsible in collecting data from multiple groups of sensors. A routing path connecting these cluster-heads is then, established to forward the data to the sink. The clustering procedure is performed while taking into account the network life time and the limited range of the deployed sensors. Data aggregation is also investigated as a solution to reduce the signaling overhead when establishing routing paths in WSNs. In [13], three modes of data aggregation are studied. The first mode named full-aggregation where an intermediate node aggregates all the received data in addition to its own data in a single message and forwards it to the next hop. The second, non-aggregation mode, in which data is forwarded separately without any aggregation. Finally, the hybrid aggregation where data aggregation is subject to a certain threshold. For each aggregation mode, a data-gathering tree is constructed such that the lifetime of sensors is maximized.

The implementation of routing protocols requires the existence of direct communication links between multiple nodes in WSNs which are not always available in practice especially for lightly-powered sensors and in remote areas. Hence, mobile sink-based solutions are proposed. In this case, a ground 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].

In [14], the authors proposed an algorithm based on travel salesman problem (TSP) to determine the locations that the mobile sink needs to visit in order to collect data from multiple sensors sharing overlapping areas based on their communication ranges. Similarly, in [15], a tree-based approach is proposed to collect data from different sensors. The WSN is divided into multiple clusters where the cluster-head collects data from multiple sensors within the cluster to forward it to the moving sink. Hence, routing and mobile sink-based solutions can be jointly implemented together as studied in [16]. The authors proposed a clue-based data collection routing where the mobile sink moves randomly and informs sensors about its presence so it can collect data from the neighborhood defined by a limited number of hops. A tradeoff between mobile sink mobility and routing protocol overhead has been reached in [17]. Starting from the fact that the ground sink cannot move freely, the authors proposed an energy-efficient data gathering protocol that uses the moving mobile sink and coordinates to establish data reporting routes in a proactive manner. Hence, according to the known trajectory of the ground sink, the sensors can determine their future locations and hence, decide where to forward their data so it can be collected.

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

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

Most of the aforementioned studies focused on the performance of the UAV-assisted WSNs but neglected the challenges related to UAVs especially in terms of energy limitation. In this work, we aim at optimizing the data collection procedure such

TABLE I
TABLE OF NOTATIONS

| Parameter | Notation |
|---|---|
| $\boldsymbol{S}_k$ | $k$-th sensor 3D position |
| $\boldsymbol{X}_c$ | $c$-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 $\boldsymbol{X}_c$ to $\boldsymbol{X}_{c'}$ |
| $E_{c,k}^{stop}$ | energy consumed by the drone to collect data from $\boldsymbol{S}_k$ at stop $\boldsymbol{X}_c$ |
| $E_{\boldsymbol{S}_k}$ | energy consumption of the sensor $\boldsymbol{S}_k$ |

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

## B. Contributions

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

- We design a framework for energy efficient data collection from a WSN using a flying UAV. Unlike existing studies, our approach takes into account the total energy consumption of the UAV tour both for travel as well as hovering for data collection by considering the communication data rate between the sensors and the UAV. Then, we formulate a joint optimization problem to determine the UAV stops positions, the sensors to send data at each stop, and the itinerary that the UAV should follow to ensure data collection from all sensors with minimum energy consumption while respecting their energy availability requirements.
- Due to the complexity and non-convexity of the problem, we derive a sub-optimal but deterministic solution based on decomposition of the problem and propose a procedure to solve each sub-problem separately. The optimization of the locations of the UAV stops as well as the selected sensors to transmit at each stop is formulated as a clustering problem where the stops' positions are determined using linear relaxation of the objective function while the itinerary between the stops is optimized using a TSP algorithm.
- We present some selected numerical results that show the efficiency of the proposed approach. Specifically, we compare it with previously proposed solution based on a TSP with neighborhood (TSP-N) approach that optimizes the itinerary of the UAV such that it travels through the neighborhoods of the sensors.

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

## C. Paper Outline

The paper is organized as follows. Section II presents the system 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, conclusions are drawn in Section V. Notations used throughout this paper are summarized in Table I.

# II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a set of $K$ wireless sensors $\{\boldsymbol{S}_1, \ldots, \boldsymbol{S}_K\}$ located in a sub-region $\Omega \subseteq \mathbb{R}^3$. We assume that each sensor's position $\boldsymbol{S}_k \in \Omega$[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 obtained. In particular, if the sensors belong to the same operator who is also managing the drone, the fixed locations can be obtained beforehand and can be saved in a data base. Moreover, for more general scenarios, recent advances in localization techniques allow accurate real-time knowledge of mobile sensors' locations in outdoor and indoor environments with high precision. We consider a delay-tolerant application scenario where each sensor $\boldsymbol{S}_k$ 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 $\boldsymbol{X}_0$ where $\boldsymbol{X}_0$ 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 $\boldsymbol{X}_c$, $\forall c = 1, \ldots, N$, 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 $\mathcal{C}_c$ the subset of sensors that their data is collected by the drone at the stop $\boldsymbol{X}_c$. 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

[2]We use $\boldsymbol{S}_k$ to denote both the $k$-th sensor and its 3D position.

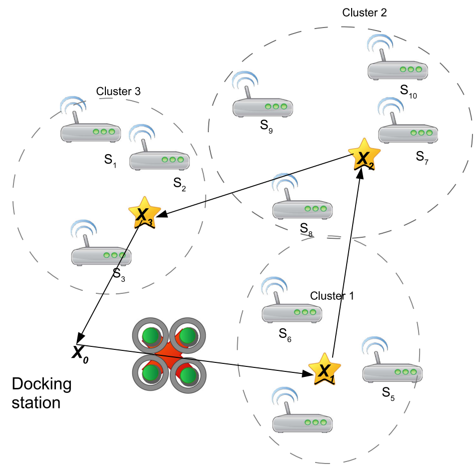


Fig. 1. UAV wireless data collection scheme for $N = 3$.

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

### A. Channel Model

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

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

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

where $PL_{\text{A-G}}\left(\boldsymbol{S},\boldsymbol{X}\right)$ is the average channel pathloss We consider a probabilistic air-to-ground path loss model as in [23]. The average path-loss between a sensor $\boldsymbol{S}$ and the UAV located at a position $\boldsymbol{X}$ is then expressed as:

$$\begin{aligned} PL_{\text{A-G}}\left(\boldsymbol{S},\boldsymbol{X}\right) &= p_{\text{LoS}}\left(\boldsymbol{S},\boldsymbol{X}\right)PL_{\text{LoS}}\left(\boldsymbol{S},\boldsymbol{X}\right) \\ &\quad + \left[1-p_{\text{LoS}}\left(\boldsymbol{S},\boldsymbol{X}\right)\right]PL_{\text{NLoS}}\left(\boldsymbol{S},\boldsymbol{X}\right), \end{aligned} \quad (2)$$

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

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

where $\theta(\boldsymbol{S},\boldsymbol{X})$ is the elevation angle of the drone in the position $\boldsymbol{X}$ with regards to the sensor $\boldsymbol{S}$ as shown in Fig. 2 while $\alpha$ and $\beta$ are parameters that depend on the urban environment, notably the percentage of build-up area to the total land area, the number of buildings and obstacles per unit area, and the statistical distribution of their heights. The authors in [10] derived an empirical method to compute these parameters as a function of the urban environment characteristics. Finally, $PL_{\text{LoS}}\left(\boldsymbol{S},\boldsymbol{X}\right)$ and $PL_{\text{NLoS}}\left(\boldsymbol{S},\boldsymbol{X}\right)$ are the average path losses for LoS and non line-of-sight (NLoS) environments, respectively, expressed as:

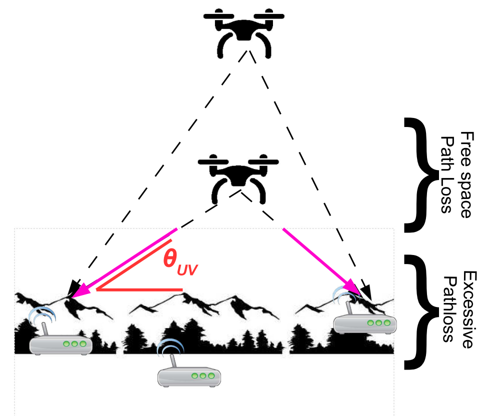


Fig. 2. UAV radio propagation model.

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

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

where the first component represents the free-space path loss with $\eta$ the path loss exponent, $f_c$ the carrier frequency, $c$ the light celerity, and $||\boldsymbol{V}||_2$ the norm-2 of the vector $\boldsymbol{V}$ (i.e., $||\boldsymbol{S}-\boldsymbol{X}||_2$ is the euclidian distance that separates the positions $\boldsymbol{S}$ and $\boldsymbol{X}$). On the other hand, the second component represents the mean value of the excessive path loss (i.e., $\xi_{\text{LoS}}$ is the mean value of excessive path loss in LoS and $\xi_{\text{NLoS}}$ is the mean value of excessive path loss in NLoS).

### B. Drone Power Consumption Model

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

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

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

where $g$ and $\rho$ are respectively the earth gravity and air density.

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

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

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

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

## *C. Problem Formulation*

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

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

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

$$\mathcal{O} = E_D + \sum_{k=1}^{K} \rho_k E_{\boldsymbol{S}_k}. \tag{8}$$

$E_D$ is the energy consumed by the drone during the data collection trip, written as:

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

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

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

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

On the other hand, $E_{c,k}^{stop}$ is the energy consumed by the drone when collecting data of the sensor $\boldsymbol{S}_k$ at the stop $\boldsymbol{X}_c$, which is written as:

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

where $T_{k,c}^{com} = M_k / \langle \mathcal{R}(\boldsymbol{S}_k, \boldsymbol{X}_c)\rangle_{R_k^{min}}^{R_k^{max}}$ corresponds to the time needed to transfer the data of the sensor $\boldsymbol{S}_k$ to the drone at position $\boldsymbol{X}_c$. This communication time depends on the amount of data $M_k$ that the sensor $\boldsymbol{S}_k$ has to transfer and the average data rate $\mathcal{R}(\boldsymbol{S}_k, \boldsymbol{X}_c)$ for the sensor $\boldsymbol{S}_k$'s transmission to the drone at position $\boldsymbol{X}_c$ which was defined in Eq. (1). $R_k^{min}$ and $R_k^{max}$ are respectively the minimum and maximum decoding and transmission rate for the $k$-th sensor.[3] Finally, $\rho_k$ is a weight associated to the energy consumed by the $k$-th sensor in the objective function[4] and $E_{\boldsymbol{S}_k}$ is the energy consumed by the $k$-th sensor to complete its data transmission, written as:

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

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

The optimization problem is then written as follows:

$$\underset{\substack{\{\boldsymbol{X}_c \in \Omega\}_{1\le c\le N}\\ \{x_{c,k}\in\{0,1\}\}_{1\le c\le N,\ 1\le k\le K}\\ \{y_{c,c'}\in\{0,1\}\}_{0\le c\le N,\ 0\le c'\le N}\\ \{u_c\in\mathbb{Z}\}_{0\le c\le N}}}{\text{minimize}} \quad E_D + \sum_{k=1}^{K} \rho_k E_{\boldsymbol{S}_k} \tag{13a}$$

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

$$\sum_{\substack{c=0\\c\neq c'}}^{N} y_{c,c'} = 1,\ 0 \le c' \le N; \tag{13c}$$

$$\sum_{\substack{c'=0\\c'\neq c}}^{N} y_{c,c'} = 1,\ 0 \le c \le N; \tag{13d}$$

$$u_c - u_{c'} + (N+1) y_{c,c'} \le N, \quad 1 \le c \ne c' \le N; \tag{13e}$$

$$E_{\boldsymbol{S}_k} \le E_k^{max},\ 1 \le k \le K, \tag{13f}$$

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

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

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

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

## III. Optimization Approach

In this section, we present the proposed problem decomposition approach to solve the non-convex optimization problem formulated in (13). We aim first to propose a procedure to determine the UAV stops locations then, determine the sensors associated to each of the UAV stops, and finally the UAV itinerary between the stops to complete its data gathering tour. Following that, an iterative algorithm is developed to combine these procedures and jointly optimize the UAV tour.

### A. Collection Stops Optimization Sub-Problem

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

$$\underset{\{\boldsymbol{X}_c \in \Omega\}_{1\le c\le N}}{\arg\min} \quad E_D + \sum_{k=1}^{K} \rho_k E_{\boldsymbol{S}_k} \tag{14a}$$

$$\text{subject to} \quad E_{\boldsymbol{S}_k} \le E_k^{max},\ 1 \le k \le K. \tag{14b}$$

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

$$\underset{\{\boldsymbol{X}_c \in \Omega\}_{1\le c\le N}}{\arg\min} \sum_{c=1}^{N}\sum_{k=1}^{K} x_{c,k}\left(\omega_{c,k}^{com}\right)^t (\boldsymbol{X}_c - \boldsymbol{S}_k) + \sum_{c=0}^{N}\sum_{\substack{c'=0\\ c'\neq c}}^{N} y_{c,c'}\left(\omega_{c,c'}^{fly}\right)^t (\boldsymbol{X}_c - \boldsymbol{X}_{c'}) \tag{15a}$$

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

with

$$\begin{aligned} \omega_{c,k}^{com} &= (P_{hov} + P_{com} + \rho_k P_T)\, \nabla_{\boldsymbol{X}_c}\left(T_{c,k}^{com}\right), \\ \omega_{c,c'}^{fly} &= (P_{hov} + P_{tr})\, \nabla_{\boldsymbol{X}_c}\left(T_{c,k}^{flight}\right). \end{aligned} \tag{16}$$

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

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 limited area [25], [26]. In our case, the set of points are the sensors from which the data is collected and the neighboring collection stops. Solving this problem involves an iterative update of the searched position within the constrained neighborhood until convergence is reached [27]. Ideally, each collection position $\boldsymbol{X}_c$ coincides with the weighted median of the neighboring stops and the sensors which can be written as follows:

$$\boldsymbol{X}_c = \frac{\sum_{k=1}^{K} x_{c,k}\omega_{c,k}^{com}\boldsymbol{S}_k + \sum_{\substack{c'=0\\ c'\neq c}}^{N} y_{c,c'}\omega_{c,c'}^{fly}\boldsymbol{X}_{c'}}{\sum_{k=1}^{K} x_{c,k}\omega_{c,k}^{com} + \sum_{\substack{c'=0\\ c'\neq c}}^{N} y_{c,c'}\omega_{c,c'}^{fly}},\ \forall c = 1, .., N, \tag{17}$$

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

$$\boldsymbol{\Lambda}\,\tilde{\boldsymbol{X}} = \boldsymbol{\Theta}, \tag{18}$$

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

$$\boldsymbol{\Lambda} = \begin{bmatrix} \boldsymbol{\Phi}_1 & \dots & -y_{1,c}\omega_{1,c}^{fly} & \dots & -y_{1,N}\omega_{1,N}^{fly} \\ \vdots & \ddots & \vdots & \dots & \vdots \\ -y_{c,1}\omega_{c,1}^{fly} & \dots & \boldsymbol{\Phi}_c & \dots & -y_{c,N}\omega_{c,N}^{fly} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -y_{N,1}\omega_{N,1}^{fly} & \dots & -y_{N,c}\omega_{N,c}^{fly} & \dots & \boldsymbol{\Phi}_N \end{bmatrix} \tag{19}$$

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

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

**Algorithm 1:** UAV Stops Optimization Algorithm.

Choose a random initial set of stop positions of the UAV that satisfies the constraints (15b).
**while** $||\boldsymbol{X}_c^{(t+1)} - \boldsymbol{X}_c^{(t)}|| > \epsilon, \ \forall c$ **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**

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

$$\boldsymbol{X}_c = \underset{\boldsymbol{X} \in \bigcap_{k|x_{c,k}=1} \mathbb{F}_r(\boldsymbol{S}_k)}{\arg\min} ||\boldsymbol{X} - \boldsymbol{X}_c||_2, \tag{21}$$

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

On the other hand, for a better approximation of the original objective function, we update the weights $\omega^{com}$ and $\omega^{fly}$ by recomputing the gradients at each iteration using the new positions to seek close-optimality of the solution.

## B. Clusters Assignment Sub-Problem

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

$$\underset{\{x_{c,k} \in \{0,1\}\}_{\substack{1 \leq c \leq N \\ 1 \leq k \leq K}}}{\arg\min} \sum_{c=1}^{N} \sum_{k=1}^{K} x_{c,k} E_{c,k}^{stop} + \rho_k E_{\boldsymbol{S}_k} \tag{22a}$$

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

$$E_{\boldsymbol{S}_k} \leq E_k^{max}, \ 1 \leq k \leq K. \tag{22c}$$

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

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

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

Initialize collection stops $\boldsymbol{X}_c^{(0)}, \ \forall c$.
**while** $||\boldsymbol{X}_c^{(t+1)} - \boldsymbol{X}_c^{(t)}|| > \epsilon, \ \forall c$ **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 $\omega_{c,f}^{fly}$.
- 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**

## C. Path Planing Sub-Problem

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

$$\underset{\substack{\{y_{c,c'} \in \{0,1\}\}_{\substack{0 \leq c \leq N \\ 0 \leq c' \leq N}} \\ \{u_c \in \mathbb{Z}\}_{0 \leq c \leq N}}}{\arg\min} \sum_{c=0}^{N} \sum_{\substack{c'=0 \\ c' \neq c}}^{N} y_{c,c'} E_{c,c'}^{flight} \tag{24a}$$

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

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

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

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

## D. Joint Optimization Algorithm

Now that we presented convenient procedures to solve each variable efficiently. We develop a global algorithm that jointly solves the problem and determines the stops positions, the sensors assignment, and the path using an iterative approach as presented in the joint Clustering-TSP Algorithm 2. The approach 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 |
| $\xi_{\text{LoS}}$ (dB) | 0 | $\xi_{\text{NLoS}}$ (dB) | 20 |
| $P_{com}(W)$ | 0.0126 | $P_{\text{full}}$ (W) | 5 |
| $v_d = v_{\max}$ (m/s) | 15 | $P_s$ (W) | 0 |
| $B$ kHz | 15 | $m_{\text{tot}}$ (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 |

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

### E. Effect of the Number of Stops/Clusters

We note that Algorithm 2 considers a fixed number of collection stops $N$. On one hand, we should note that this number is lower bounded by the minimum needed stops to cover all the sensors. This lower bound can be computed through the intersection of all the regions that satisfy the energy constraints of all sensors. This can be written as:

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

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

## IV. RESULTS AND DISCUSSION

In this section, we investigate the impact of some parameters on the system performance. We consider a bounded area of size $1 \times 1$ km$^2$ where $K = 100$ ground sensors are randomly placed in the area following a uniform distribution. A quadcopter drone is initially placed at the center of the area targeting to collect data from the $K$ sensors. We assume that the locations and size of data to transmit for each sensor are a-priori known. The channel and energy consumption models' parameters are given in Table II [24], [29] unless mentioned otherwise. For the objective function, without loss of generality, we consider equal weights for all sensors' energy $\rho_k = \rho = \frac{1}{K}, \forall k$. We compare

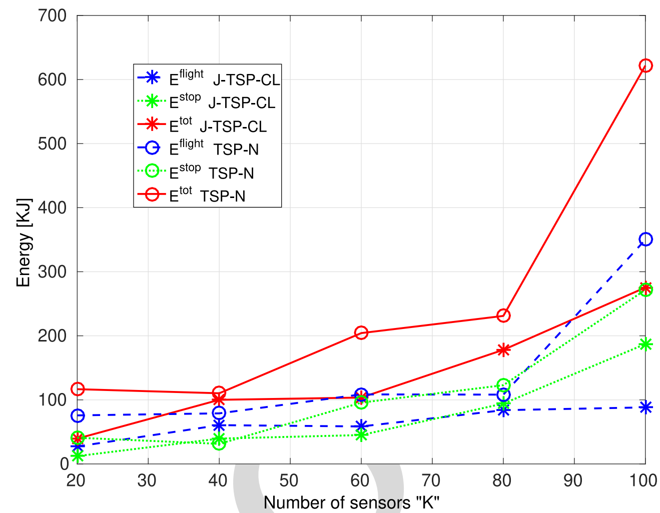


Fig. 3. Comparison between the proposed approach "J-TSP-CL" and the "TSP-N" algorithm energy consumption as a function of the number of sensors.

the performance of our algorithm that we denote by "J-TSP-CL" to the performance obtained using a TSP with neighborhood (TSP-N) based approach that determines the minimum path to travel across the neighborhood of the sensors using the algorithm introduced in [30]. In this algorithm, for each sensor, a neighborhood area is defined. This region characterizes the area where a UAV can receive the sensor's data reliably. The objective of the algorithm is then to optimize the path of the UAV such that it flies over all neighborhood regions of the transmitting sensors. However, this solution does not account for the effect of the UAV's positions on the data rate, and thus on the time needed to complete the transmissions. Additionally, it requires a discretization of the environment to obtain the global solution.

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

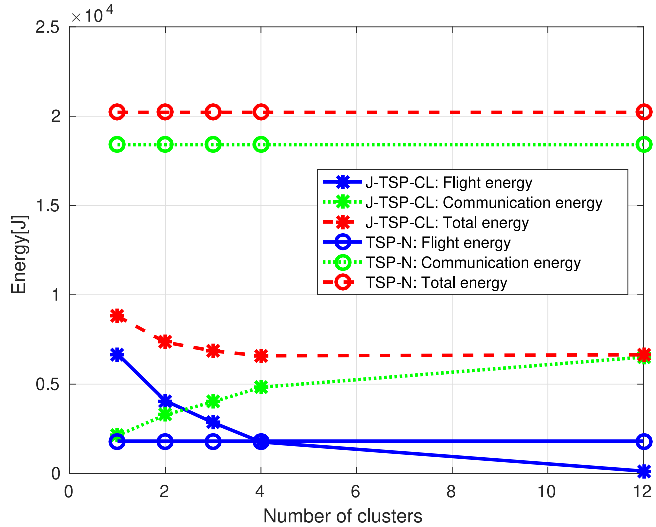


Fig. 4. Energy consumption as a function of the number of stops.

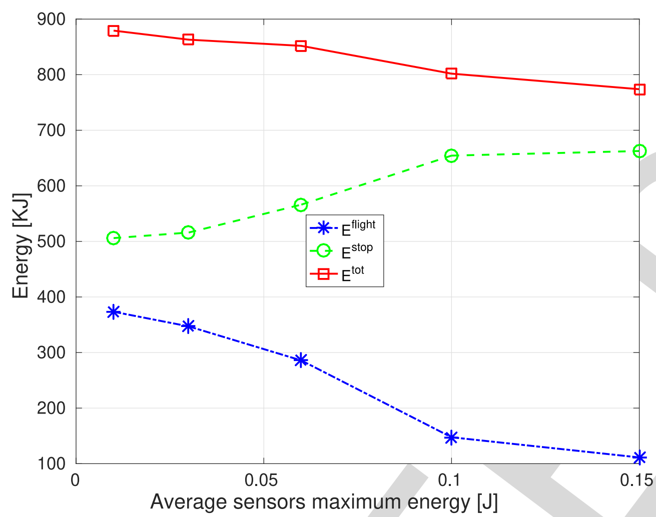


Fig. 5. Energy consumption as a function of the sensors available energy.

In order to further explain the effect of the trade-off between communication and flight times on the energy consumption, in Fig. 4 we fix the number of stops $N$ in our algorithm 'J-TSP-CL' and plot the consumed energy as a function of $N$. Since the number of sensors per cluster decreases with the number of stops, the communication time decreases with the increase of the number of stops and thus the energy consumed at stops continuously decreases. On the other hand, with the increase of the number of stops, more energy is needed to travel across them. Thus, $E^{flight}$ is continuously increasing with the number of stops. This trade-off results in an optimal number of stops $N^*$ that minimizes the global energy. For our set-up parameters, this optimal number is shown to be 4 clusters.

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

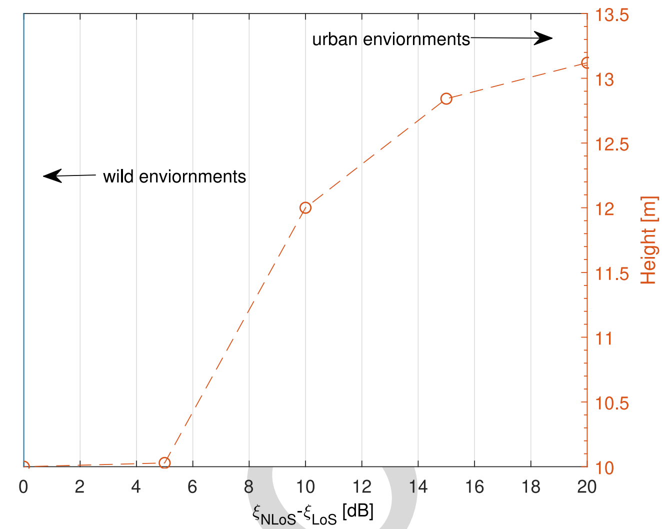


Fig. 6. UAV altitude as a function of the LoS/NLoS pathloss difference.

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

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

## V. Conclusion

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

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## References


[1] C.-Y. Chong and S. P. Kumar, "Sensor networks: Evolution, opportunities, and challenges," *Proc. IEEE*, vol. 91, no. 8, pp. 1247–1256, Aug. 2003.

[2] M. Bagaa, Y. Challal, A. Ksentini, A. Derhab, and N. Badache, "Data aggregation scheduling algorithms in wireless sensor networks: Solutions and challenges," *IEEE Commun. Surv. Tut.*, vol. 16, no. 3, pp. 1339–1368, Third Quater 2014.

[3] R. Prabha, M. V. Ramesh, V. P. Rangan, P. V. Ushakumari, and T. Hemalatha, "Energy efficient data acquisition techniques using context aware sensing for landslide monitoring systems," *IEEE Sensors J.*, vol. 17, no. 18, pp. 6006–6018, Sep. 2017.

[4] C. F. Cheng, L. H. Li, and C. C. Wang, "Data gathering with minimum number of relay packets in wireless sensor networks," *IEEE Sensors J.*, vol. 17, no. 21, pp. 7196–7208, Nov. 2017.

[5] M. Zhao, Y. Yang, and C. Wang, "Mobile data gathering with load balanced clustering and dual data uploading in wireless sensor networks," *IEEE Trans. Mobile Comput.*, vol. 14, no. 4, pp. 770–785, Apr. 2015.

[6] M. Ruiz, E. Alvarez, A. Serrano, and E. Garcia, "The convergence between wireless sensor networks and the Internet of Things; challenges and perspectives: A survey," *IEEE Latin America Trans.*, vol. 14, no. 10, pp. 4249–4254, Oct. 2016.

[7] M. Gharibi, R. Boutaba, and S. L. Waslander, "Internet of drones," *IEEE Access*, vol. 4, pp. 1148–1162, Mar. 2016.

[8] H. Menouar, I. Guvenç, K. Akkaya, A. S. Uluagac, A. Kadri, and A. Tuncer, "UAV-enabled intelligent transportation systems for the smart city: Applications and challenges," *IEEE Commun. Mag.*, vol. 55, no. 3, pp. 22–28, Mar. 2017.

[9] H. Ghazzai, M. B. Ghorbel, A. Kadri, M. J. Hossain, and H. Menouar, "Energy-efficient management of unmanned aerial vehicles for underlay cognitive radio systems," *IEEE Trans. Green Commun. Netw.*, vol. 1, no. 4, pp. 434–443, Dec. 2017.

[10] A. Al-Hourani, S. Kandeepan, and S. Lardner, "Optimal LAP altitude for maximum coverage," *IEEE Wireless Commun. Lett.*, vol. 3, no. 6, pp. 569–572, Dec. 2014.

[11] F. Liu, Y. Wang, M. Lin, K. Liu, and D. Wu, "A distributed routing algorithm for data collection in low-duty-cycle wireless sensor networks," *IEEE Internet Things J.*, vol. 4, no. 5, pp. 1420–1433, Oct. 2017.

[12] Z. Xu, L. Chen, C. Chen, and X. Guan, "Joint clustering and routing design for reliable and efficient data collection in large-scale wireless sensor networks," *IEEE Internet Things J.*, vol. 3, no. 4, pp. 520–532, Aug. 2016.

[13] F. Zhou, Z. Chen, S. Guo, and J. Li, "Maximizing lifetime of data-gathering trees with different aggregation modes in WSNs," *IEEE Sensors J.*, vol. 16, no. 22, pp. 8167–8177, Nov. 2016.

[14] C. F. Cheng and C. F. Yu, "Data gathering in wireless sensor networks: A combine-TSP-reduce approach," *IEEE Trans. Veh. Technol.*, vol. 65, no. 4, pp. 2309–2324, Apr. 2016.

[15] C. Zhu, S. Wu, G. Han, L. Shu, and H. Wu, "A tree-cluster-based data-gathering algorithm for industrial WSNs with a mobile sink," *IEEE Access*, vol. 3, pp. 381–396, Apr. 2015.

[16] G. Yang, H. Xu, X. He, L. Gao, Y. Geng, and C. Wu, "A clue based data collection routing protocol for mobile sensor networks," *IEEE Access*, vol. 4, pp. 8476–8486, Dec. 2016.

[17] X. Liu, H. Zhao, X. Yang, and X. Li, "SinkTrail: A proactive data reporting protocol for wireless sensor networks," *IEEE Trans. Comput.*, vol. 62, no. 1, pp. 151–162, Jan. 2013.

[18] A. Giorgetti, M. Lucchi, M. Chiani, and M. Z. Win, "Throughput per pass for data aggregation from a wireless sensor network via a UAV," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 47, no. 4, pp. 2610–2626, Oct. 2011.

[19] S. Sotheara, K. Aso, N. Aomi, and S. Shimamoto, "Effective data gathering and energy efficient communication protocol in wireless sensor networks employing UAV," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Istanbul, Turkey, Apr. 2014, pp. 2342–2347.

[20] X. Ma, R. Kacimi, and R. Dhaou, "Fairness-aware UAV-assisted data collection in mobile wireless sensor networks," in *Proc. Int. Wireless Commun. Mobile Comput. Conf.*, Paphos, Cyprus, Sep. 2016, pp. 995–1001.

[21] S. Say, H. Inata, J. Liu, and S. Shimamoto, "Priority-based data gathering framework in UAV-assisted wireless sensor networks," *IEEE Sensors J.*, vol. 16, no. 14, pp. 5785–5794, Jul. 2016.

[22] M. B. Ghorbel, D. Rodriguez-Duarte, H. Ghazzai, M. J. Hossain, and H. Menouar, "Energy efficient data collection for wireless sensors using drones," in *Proc. IEEE 87th Veh. Technol. Conf.*, Porto, Portugal, Jun. 2018, pp. 1–5.

[23] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Drone small cells in the clouds: Design, deployment and performance analysis," in *Proc. IEEE Global Commun. Conf.*, San Diego, CA, USA, Dec. 2015. Q2

[24] J. V. Dries Hulens and T. Goedeme, "How to choose the best embedded processing platform for onboard UAV image processing," in *Proc. Int. Joint Conf. Comput. Vis., Imag. Comput. Graph. Theory Appl.*, Berlin, Germany, Mar. 2015.

[25] G. Wesolowsky, "The Weber problem: History and perspectives," *Address Sci.*, no. 1, pp. 5–23, 1993.

[26] E. Weiszfeld and F. Plastria, "On the point for which the sum of the distances to n given points is minimum," *Ann. Operations Res.*, vol. 167, no. 1, pp. 7–41, 2009. [Online]. Available: http://dx.doi.org/10.1007/s10479-008-0352-z

[27] L. A. Kazakovtsev, "Algorithm for constrained Weber problem with feasible region bounded by arcs," *Facta Universitatis, Ser, Math. Inform.*, vol. 28, no. 3, pp. 271–284, 2013.

[28] N. Christofides and Carnegie-Mellon University Pittsburgh PA Management Sciences Research Group, "Worst-case analysis of a new heuristic for the travelling salesman problem," Defense Technical Information Center, Fort Belvoir, VA, USA, Tech. Rep. ADA025602, 1976. [Online]. Available: https://books.google.ca/books?id=2A7eygAACAAJ Q3

[29] G. Auer *et al.*, "D2.3 v2: Energy efficiency analysis of the reference systems, areas of improvements and target breakdown," Energy Aware Radio Network Technologies, Tech. Rep. INFSO-ICT-247733, Jan. 2011. Q4

[30] J. Isaacs and J. Hespanha, "Dubins traveling salesman problem with neighborhoods: A graph-based approach," *Algorithms*, vol. 6, no. 1, p. 84–99, Feb. 2013. [Online]. Available: http://dx.doi.org/10.3390/a6010084


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