Data Collection of IoT Devices Using an Energy-Constrained UAV

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***Abstract*—In this paper, we study sensing data collection from IoT devices in a wireless sensor network, using an energy-constrained Unmanned Aerial Vehicle (UAV), where the sensory data is stored in IoT devices while the IoT devices may or may not be within the transmission range of each other. We formulate two novel data collection problems to fully or partially collect data from IoT devices using the UAV, by finding a closed tour for the UAV that includes hovering locations and the sojourn duration at each of the hovering locations such that the accumulative volume of data collected is maximized, subject to the energy capacity on the UAV, where the UAV consumes its energy on both hovering and flying from one hovering location to another hovering location. To this end, we first propose a novel data collection framework that enables the UAV to collect the sensory data from multiple IoT devices simultaneously if the IoT devices are within the hovering coverage range of the UAV. We then formulate two data collection maximization problems, and show that both of the problems are NP-hard. We instead devise efficient approximation and heuristic algorithms for the problems. We finally evaluate the performance of the proposed algorithms through experimental simulations. Experimental results demonstrated that the proposed algorithms are promising.**

I. Introduction

Due to its high flexibility, low cost and ease of deployment, Unmanned Aerial Vehicle (UAV) has become a key enabling technology that has received significant attentions recently, which has been widely applied in natural disaster rescuing, good deliveries, crop health assessment, and so on [5]. On the other hand, with the increasing popularity of Internet of Thing devices such as various sensors, wearable sensors, traffic and other monitoring devices, more and more applications of smart homes/smart cities, e-health care, and intelligent transportations built upon IoT devices become part of our daily life. However, most IoT devices (e.g., mobile phones, security cameras, meter collection devices, temperature sensors) usually have very limited energy, computational and storage capacities due to their portable sizes. Sometimes, it is unrealistic to allow these devices to transmit or relay sensing data to a base station through multihop relays, due to the significant transmission energy consumption, and in the worst case, they may not be within the transmission ranges of each other. Thus, it is very challenging to collect sensing data from these IoT devices for processing to better help human decision-making and respond to the monitoring needs.

In this paper, we study the deployment of a UAV for sensory data collection from IoT devices on the ground. Specifically, we consider a sparse sensor network that consists of many IoT devices for sensing their surroundings. Some of the sensors serve as *aggregate sensor nodes* to store their own and neighbors' sensing data. The stored data at an aggregate sensor node will be collected periodically by a UAV for further processing. As the volume of data stored at different aggregate sensor nodes is significantly different, the hovering times of the UAV for data collection at different hovering locations are different, and the amounts of energy consumed by the UAV at different hovering locations are different too. In addition, when the UAV flies from one hovering location to another hovering location, it does also incur energy consumption. Considering that the energy capacity of the UAV is given, this poses great challenges. For example, how to find a closed tour for the UAV including its depot for data collection such that the total volume of data collected by the UAV at different hovering locations in the tour is maximized, subject to its energy capacity. Furthermore, how long the UAV should stay at each hovering location in the tour to ensure all (or partial) data stored at the IoT sensor devices covered by it will be collected. To address the challenges, in this paper we aim to explore a non-trivial trade-off between the amount of energy allocated to hovering and the amount of energy allocated to traveling of the UAV. We will focus on developing efficient approximation and heuristic algorithms for the data collection optimization problems.

The novelties of this work lie in the provisioning of a novel framework of data collection from multiple IoT sensor devices simultaneously, via an energy-constrained UAV. We formulate two data collection maximization problems, and develop efficient approximation and heuristic algorithms for the problems that strive for a fine tradeoff between the energy usages of the UAV on hovering and traveling. To the best of our knowledge, this is the first time that the use of a UAV for collecting data from multiple IoT devices simultaneously is studied, and efficient algorithms for finding a data collection trajectory for the UAV are developed.

The main contributions of this paper are summarized as follows. We study the data collection maximization problem, by deploying an energy-constrained UAV. We first propose a novel data collection framework that enables the UAV to collect sensory data from multiple IoT devices simultaneously. We then formulate two data collection maximization problems based on the proposed data collection framework, and show

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the defined problems are NP-hard. We instead devise efficient approximation and heuristic algorithms for the problems. We finally evaluate the performance of the proposed algorithms through experimental studies. Simulation results reveal that the proposed algorithms are promising.

The rest of the paper is organized as follows. Section II reviews related work. Section III introduces the system model, notions, notations, and problem definitions. Section IV devises an approximation algorithm for the data collection maximization problem without hovering coverage overlapping. Sections V and VI propose efficient heuristic algorithms for the data collection maximization problem and the partial data collection maximization problem with hovering coverage overlapping, respectively. Section VII evaluates the proposed algorithms empirically, and Section VIII concludes the paper.

II. Related Work

The use of mobile charging vehicles or mobile data collection vehicles on the ground for sensor charging and sensory data collection has been widely studied in the past [4], [6], [7], [9], [16], [14], [15]. Most of these studies focused on finding trajectories of charging or data collection for one or multiple mobile vehicles. However, due to various obstacles in real sensor networks including buildings, ponds, rivers, or blocked roads in the monitoring region, mobile vehicles are prevented to travel in the region freely for sensor charging or data collection smoothly. In recent years, there is a growing interest in the employment of UAVs for sensory coverage or data collection for wireless sensor networks, as UAVs have many freedoms for data collection by avoiding the mentioned obstacles by flying over them [10], [8]. For example, Mozaffari *et al.* [10] considered multiple trajectory paths finding for multiple UAVs with the aim to minimize the total transmission energy consumption of IoT devices by uploading their sensory data to the UAVs, where the UAVs are treated as aerial base stations. They proposed a clustering method to cluster IoT devices into different clusters, and they then find trajectories for multiple UAVs that sojourn only at the cluster centers. Liang *et al* [8] considered a coverage quality problem via a UAV. They assumed that the hovering time of the UAV at each hovering location is identical, for which they proposed an approximation algorithm for the coverage quality maximization problem. However, none of the existing works considered a closed tour of data collection for the UAV that the data of multiple IoT devices can be collected at the same time by the UAV. This paper aims to address this issue and to provide efficient approximation and heuristic algorithms for the problem.

III. Preliminaries

In this section, we first introduce the system model, notions, and notations. We then define the problems precisely.

A. System Model

We consider an IoT application scenario, where many IoT devices are deployed in a given region for monitoring purposes, some of the IoT devices (sensors) are chosen as *aggregate sensor nodes* that can store both their own sensing data and their neighbors' sensory data, assuming an IoT device that has not been chosen as an aggregate sensor node can forward its sensory data to one of its neighboring aggregate sensor nodes. In case there are multiple aggregate sensor neighbors, it can choose one of them for the storage of its sensory data. Since aggregate sensor nodes are sparsely distributed, they may or may not be within the communication range of each other. The sensory data collected at each aggregate sensor node thus cannot be transferred to the base station through multi-hop relays, or there are obstacles between the aggregate sensor nodes, e.g., ponds, or buildings that prevent the relays. Furthermore, aggregate sensor nodes are energy-constrained as relaying data will consume considerable amounts of energy. To prolong the lifetimes of aggregate sensor nodes, a UAV is deployed for data collection from the aggregate sensor nodes.

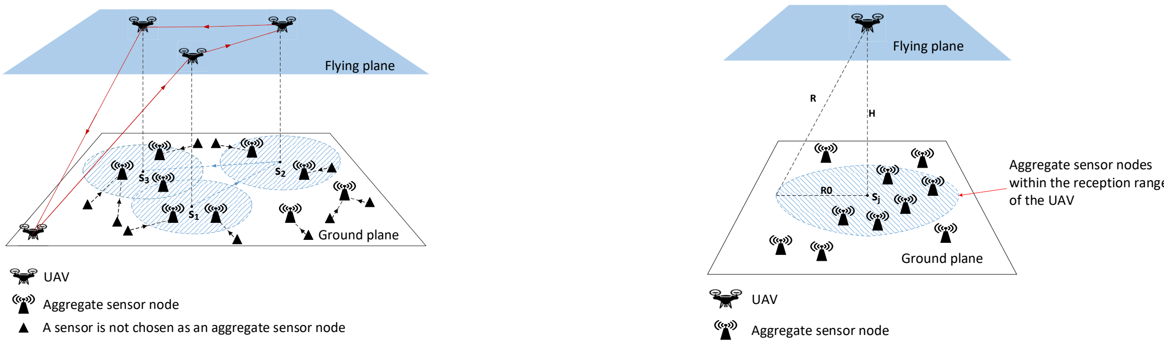
We assume that the UAV is at a depot d initially and powered by a limited energy battery $\mathcal{E}$. The UAV consumes energy at hovering locations for data collection from aggregate sensor nodes in its hovering coverage range and traveling (flying) from one hovering location to another hovering location. For the sake of convenience, in the rest of this paper we term the aggregate sensor nodes as IoT devices or sensor nodes exchangeably if no confusion arises. The aggregate sensor nodes in a monitoring region form a sparse sensor network $G = (V \cup \{d\}, E)$, where V is the set of aggregate sensor nodes, and there is an edge $e \in E$ between each pair of aggregate sensor nodes. The depot of the UAV is d, in which the UAV will be recharged and its collected data will be downloaded for further processing.

To ensure that the UAV can return depot d per tour, its data collection tour must be a closed tour including depot d. The duration of a tour of the UAV will be determined by the tour length and the volume of data stored in the IoT devices covered by the UAV at hovering locations in the tour. Assume that the UAV takes T time units to finish its tour, in which T_h and T_t are the amounts of time spent on hovering and traveling respectively, then $T = T_h + T_t$ and the total amount of energy consumed by the UAV in the tour must meet that $T_h \cdot \eta_h + T_t \cdot \eta_t \leq \mathcal{E}$, where η_h and η_t are the energy consumption rates of the UAV on hovering and traveling, respectively.

B. Data Collection of IoT Devices Using a UAV

We assume that each aggregate sensor node $v_i \in V$ in a monitoring region is labeled by coordinates $(x_i, y_i, 0)$. Denote by (x', y', H) the coordinates of a hovering location of the UAV, where H is the flying altitude of the UAV, which is no greater than the transmission range R of each aggregate sensor node. Let B be the transmission bandwidth of any aggregate sensor node. An aggregate sensor node $v \in V$ can upload its stored data to the UAV with bandwidth B if the UAV is within its transmission range R. The hovering altitude H of the UAV for data collection thus is no greater than R, i.e., $H \leq R$.

Following the data collection model, if all IoT devices are within the reception range of the UAV, then their transmitted



(a) An IoT sensor network (b) A hovering location for the UAV

Fig. 1. An example of data collection in an IoT sensor network G via a UAV.

data can be collected by the UAV, assuming that the IoT devices use different channels to transmit their data through adopting the orthogonal frequency division multiple access (OFDMA) technique [10]. We assume that the reception range of the UAV is a ball centralized at its hovering location, this ball is projected to the ground at which the IoT devices are located to form a circle with the same radius as the one of the ball, the data stored at these aggregate sensor nodes within this projected circle can be collected by the UAV when it hovers at the center of the ball.

It is well known that there are infinite potential hovering locations for the UAV in the sky. To make the problem tractable, we here assume that the hovering locations of the UAV are finite, by partitioning the hovering region into finite numbers of equal squares with edge length $\delta > 0$, and the UAV can only hover at the square centers for data collection. For a given data collection period T, assume that the volume of data stored at each aggregate sensor node $v \in V$ is D_v, which consists of its own sensory data and the data forwarded by its neighboring IoT devices that are not aggregate sensor nodes. Fig. 1(a) is an illustrative example of data collection in an aggregate sensor network G with a UAV.

We assume that the monitoring region by IoT devices is partitioned into M squares: $s_1, s_2, \ldots, s_M$, and the UAV performs data collection at the centers of these squares $s_j = (x_j, y_j, H)$ as its hovering locations, let $C(s_j)$ be the set of aggregate sensor nodes whose distances to the projected location $(x_j, y_j, 0)$ of s_j in the ground are no greater than the hovering coverage range R_0 of the UAV, i.e., the data in an aggregate sensor node $v_i \in V$ with coordinates $(x_i, y_i, 0)$ can be collected by the UAV if v_i is within the ball of the UAV centered at hovering location s_j, i.e., $\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \le R_0$ and $R_0 = \sqrt{R^2 - H^2}$ (see Fig. 1 (b)). Notice that the data transmission time of an aggregate sensor node from the ground to the UAV usually is determined by their distance, the volume of data the node contains, and the transmission bandwidth of the node. Given two aggregate sensor nodes in the coverage circle of the UAV at different locations, it is well known that their transmission time and bandwidth will be different even if they have the same amounts of data to be transmitted. However, such differences are negligible if the UAV altitude H is relatively low (not too high). For the sake of discussion simplicity, in this paper we assume that all sensors within the hovering coverage range of the UAV have the same data transmission rates B or transmission bandwidths.

The hovering (sojourn) duration of the UAV for data collection at hovering location s_j is

$$t(s_j) = \max_{v_i \in V}\{\frac{D_{v_i}}{B} \mid \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \le R_0\}, \quad (1)$$

the total volume of data collected at location s_j is

$$P(s_j) = \sum_{v_i \in V}\{D_{v_i} \mid \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \le R_0\}, \quad (2)$$

and the total amount of energy consumed by the UAV at s_j on data collection is

$$w_1(s_j) = t(s_j) \cdot \eta_h. \quad (3)$$

C. Problem Definitions

In this paper we define two data collection maximization problems using a single UAV, under the assumption of whether the data at each sensor can be collected once or multiple times as follows.

Definition 1: Given an aggregate sensor network $G(V \cup \{d\}, E)$ and a UAV with energy capacity $\mathcal{E}$, each aggregate sensor node $v \in V$ has a volume D_v of data for collection, *the data collection maximization problem* using the UAV for collecting data is to find a closed tour for the UAV such that the accumulative volume of data collected by it in the closed tour is maximized, subject to the energy capacity $\mathcal{E}$ of the UAV, assuming that the data stored at each IoT device covered by the UAV at its hovering location will be fully collected.

We will deal with the data collection maximization problem under two different settings. That is, whether the hovering coverage ranges of the UAV at any two different hovering locations are allowed to be overlapping. We thus have two cases for the problem: the data collection maximization problem *with and without hovering coverage overlapping*.

Sometimes, the UAV may not need to collect all data stored at an IoT device at its hovering location, this may help the UAV to save energy for collecting more data from

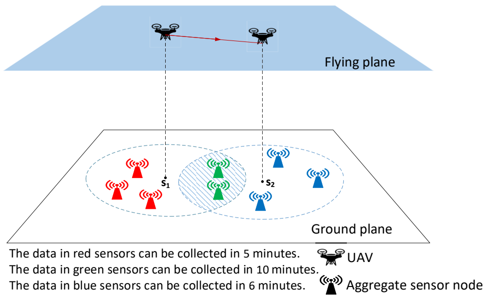


Fig. 2. An illustration of the partial data collection in an IoT sensor network G via a UAV.

other IoT devices at other hovering locations. We here use an example (see Fig. 2) to illustrate this scenario. Assume that the UAV can stop at two hovering locations s_1 and s_2 with hovering coverage overlapping. We further assume that it takes 10 minutes and 6 minutes to collect all data when it is located at s_1 and s_2, respectively. If it is allowed to collect partial data from the IoT devices when it is located at s_1 and s_2, for example, it takes 5 minutes to collect partial data at s_1 and 6 minutes to collect partial data at s_2. The same amount of data will be collected from both hovering locations in the end. However, its total amount of energy consumed on full data collection at these two locations is $(10+6)\eta_h$ energy units, while the total energy consumption on the partial data collection at the two locations is $(5+6)\eta_h$ energy units, thereby saving energy of the UAV. Motivated by this example, given a positive integer $K \geq 1$, we can partition the sojourn duration $t(s_j)$ of the UAV for data collection at each hovering location s_j into K equal sojourn durations: $t(s_j)/K,\ 2 \cdot t(s_j)/K,\ \ldots,\ K \cdot t(s_j)/K$, respectively. In other words, for each hovering location $s_j \in S$, there are K corresponding *virtual hovering locations* $s_{j,1}, s_{j,2}, \ldots, s_{j,K}$ with sojourn durations being $t(s_j)/K,\ 2 \cdot t(s_j)/K,\ \ldots,\ K \cdot t(s_j)/K$. The maximum amount of data collected at the virtual hovering location $s_{j,k}$ with the sojourn duration $k \cdot t(s_j)/K$ is

$$P(s_{j,k}) = \sum_{v \in C(s_j)} \{\frac{B \cdot k \cdot t(s_j)}{K} \mid \frac{D_v}{B} \geq k \cdot t(s_j)/K\} + \sum_{v' \in C(s_j)} \{D_{v'} \mid \frac{D_{v'}}{B} < k \cdot t(s_j)/K\}, \quad (4)$$

where $C(s_j)$ is the set of IoT devices within the coverage range of the UAV at hovering location s_j, and the IoT devices in $C(s_j)$ are further partitioned into two subsets: their data transmission time is no less than $k \cdot t(s_j)/K$ and their transmission time is strictly less than $k \cdot t(s_j)/K$ with $1 \leq k \leq K$.

$$t(s_{j,k}) = k \cdot t(s_j)/K. \quad (5)$$

That is, the amount of data collected by the UAV at each hovering location s_j can be from the partial volume of data to the full volume of data, i.e., $P(s_{j,1}) \leq P(s_{j,2}) \leq \ldots \leq P(s_{j,K})$ with $t(s_{j,1}) < t(s_{j,2}) < \ldots < t(s_{j,K})$. We formulate this partial data collection via a UAV as follows.

Definition 2: Given an aggregate sensor network $G(V \cup \{d\}, E)$ and a UAV with energy capacity $\mathcal{E}$ located at a depot d initially, each IoT device $v \in V$ has a volume D_v of data for collection, *the partial data collection maximization problem* in G is to find a closed tour including depot d of the UAV such that the accumulative volume of data collected by the UAV in the tour is maximized, subject to the energy capacity $\mathcal{E}$ of the UAV, assuming that the UAV is allowed to collect partial data at each hovering location.

D. NP-hardness of the Defined Problems

It can be seen that the data collection maximization problem is a special case of the partial data collection maximization problem when $K = 1$. Unfortunately, both problems are NP-hard, which are stated by the following theorem.

Theorem 1: Both the data collection maximization problem and the partial data collection maximization problem in an aggregate sensor network $G(V \cup \{d\}, E)$ are NP-hard.

Proof: We show that the data collection maximization problem without hovering coverage overlapping is NP-hard, by a reduction from a well-known NP-hard problem - the orienteering problem. We consider a special case of the data collection maximization problem where the potential hovering location of the UAV is on top of each aggregate sensor node, and there is not any energy consumption on data collection at each hovering location. We further assume that there is not any hovering coverage overlapping between any two hovering locations. Even for this special data collection maximization problem, we show that the problem is equivalent to an orienteering problem in G as follows.

Given a node- and edge-weighted undirected graph $G(V, E)$, in which each node $v \in V$ has a positive award $p(v) = D_v$ and each edge $(u, v) \in E$ has a positive integral length $l(u, v)\eta_t$, and a given integral length L, the orienteering problem is to find a closed tour in G including a specified node (the depot d) such that the total award collected from the nodes in the closed tour is maximized, subject to the tour length no greater than L [2], [1], [13].

We reduce the orienteering problem in G to this special data collection maximization problem as follows. The award collected at each hovering location $s_j \in S$ (the coordinates of s_j are (x_j, y_j, H) assuming that the coordinates of $v_j \in V$ is $(x_j, y_j, 0)$) is $P(s_j) = D_{v_j}$, $L = \lceil \frac{\mathcal{E}}{\eta_t} \rceil$, and the hovering energy consumption at each potential hovering location $s_j \in S$ ($S = V$ by the assumption) is zero. As the orienteering problem is NP-hard [13], the data collection maximization problem is NP-hard.

The data collection maximization problem is a special case of the partial data collection maximization problem when $K = 1$, the latter is NP-hard, too. ■

IV. Approximation algorithm for the data collection maximization problem without hovering coverage overlapping

In this section, we first deal with the problem without hovering coverage overlapping, by proposing an approximation algorithm, under the assumption that the hovering locations within each square are indistinguishable, or the differences of data collected by the UAV when it is located at any locations within a square can be ignored. We then analyze the time complexity of the proposed algorithm.

A. Overview of the Approximation Algorithm

The basic idea behind the proposed algorithm is to reduce the problem to *the orienteering problem* [13], an approximate solution to the latter in turn returns an approximate solution to the former. However, the challenge of such a reduction lies in that the amounts of hovering energy consumed of the UAV at different hovering locations are different. We aim to find a closed tour including depot d for the UAV such that the accumulative volume of data collected by the UAV at the hovering locations in the tour is maximized, while its total amount of energy consumed on hovering and traveling is no greater than its energy capacity $\mathcal{E}$. We tackle this challenge by constructing an auxiliary graph and assigning each edge with an energy weight in the auxiliary graph for both hovering at the endpoints of the edge and traveling along the edge as follows.

Since there are infinite numbers of potential hovering locations for the UAV, to enable the problem to be tractable, we partition the hovering region (or the IoT device deployment region) into a number of squares with edge length $\delta > 0$. We assume that the volume differences of the data collected by the UAV at different hovering locations in each square are negligible if the value of δ is sufficiently small. We further assume that the center of each square is a potential hovering location for the UAV when it is in the square.

Assume that the entire hovering region of the UAV is partitioned into M squares. Denote by $S = \{s_1, s_2, \ldots, s_M\} \cup \{d\}$ the set of the squares. Notice that M is a linear function of the number of aggregate sensor nodes in V. For example, assume that the coverage range of the UAV at a hovering location is a circle with radius R_0, then, the number of its potential hovering locations for collecting data from an IoT device $v \in V$ will be no greater than $\lceil \frac{\pi \cdot R_0^2}{\delta^2} \rceil$ in terms of the number of squares covering v. Thus, the maximum number of squares in S is no greater than $\sum_{v \in V} \lceil \frac{\pi \cdot R_0^2}{\delta^2} \rceil \le (\frac{\pi R_0^2}{\delta^2} + 1) \cdot |V|$ as both R_0 and δ usually are constants. It must be mentioned that a square may or may not contain any IoT devices. In the rest of our discussion, we assume that the measurement unit of the UAV movement in its hovering region is the edge length δ of each square. Or the coordinates of potential hovering locations in each square are indistinguishable.

Having partitioned the hovering region of the UAV into M squares, we now construct a node and edge weighted, undirected graph $G_s = (S, E_s;\ p(\cdot), w_1(\cdot), w_2(\cdot, \cdot))$ as follows. S is the set of potential hovering locations of the UAV, and E_s is the set of edges that the UAV hovering from one hovering location to another hovering location. The functions related to nodes and edges in G_s are defined as follows. $p: S \mapsto \mathbb{R}^{\ge 0}$ is the award function, $w_1: S \mapsto \mathbb{R}^{>0}$ is the hovering energy consumption function, and $w_2: E_s \mapsto \mathbb{R}^{\ge 0}$ is the energy consumption function on both hovering and traveling. There is an edge $(s_i, s_j) \in E_s$ between each pair of nodes s_i and s_j in S.

For each potential hovering location $s_j \in S$, the award (the amount of data collected) $p(s_j)$ is

$$p(s_j) = \sum_{v_i \in C(s_j)} D_{v_i}, \tag{6}$$

where $C(s_j)$ is the set of IoT devices in the data coverage range of the UAV when it is at hovering location s_j, i.e., $C(s_j) = \{v_i \mid v_i \in V \ \&\ \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \le R_0\}$, assuming that the UAV is at location $s_j = (x_j, y_j, H)$. If $C(s_j) = \emptyset$, then $p(s_j) = 0$, $t(s_j) = 0$ and $w_1(s_j) = 0$. D_{v_i} is the volume of data stored at sensor node v_i that is a function of the monitoring duration T and the sensing data generation rates of neighboring sensors of v within the period.

The hovering duration $t(s_j)$ of the UAV at location s_j for collecting data from the sensors in $C(s_j)$ is

$$t(s_j) = \max_{v_i \in C(s_j)} \{\frac{D_{v_i}}{B}\}, \tag{7}$$

where B is the transmission bandwidth of an aggregate sensor node (an IoT device).

The amount of energy consumed by the UAV on data collection at location s_j thus is

$$w_1(s_j) = t(s_j) \cdot \eta_h. \tag{8}$$

We assign a weight $w_2(s_j, s_k)$ to each edge $(s_j, s_k) \in E_s$ as follows.

$$w_2(s_j, s_k) = \frac{w_1(s_j) + w_1(s_k)}{2} + l(s_j, s_k) \cdot \eta_t \tag{9}$$

where the first term in the right hand side of Eq. (9) is half the sum of the amounts of hovering energy consumed by the UAV for data collection at locations s_j and s_k, respectively, the second term is the amount of traveling energy consumption of the UAV along edge (s_j, s_k), and $l(s_j, s_k)$ is the Euclidean distance between locations s_j and s_k.

B. Algorithm

Having constructed the auxiliary graph $G_s(S, E_s;\ p(\cdot), w_1(\cdot), w_2(\cdot, \cdot))$, the orienteering problem in G_s is to find a closed tour including depot d such that the total award collected from the hovering locations in the tour is maximized, subject to that the tour length (measured in terms of energy) is no greater than the energy capacity $\mathcal{E}$ of the UAV. It can be seen that a solution to this orienteering problem in G_s returns a solution to the data collection maximization problem in G without hovering coverage overlapping. Thus, an approximate solution to the former gives an approximate solution to the latter. The detailed algorithm is given in `Algorithm` 1.

Algorithm 1 Approximation algorithm for the data collection maximization problem without hovering coverage overlapping

Input: An aggregate sensor network $G = (V, E)$ with a set V of aggregate sensor nodes, a UAV with energy capacity $\mathcal{E}$ at depot d, and each node $v \in V$ has data volume D_v, and a given constant $\delta > 0$ but $\delta \leq R_0$.

Output: Find a closed tour including the depot d for the UAV such that the volume of data collected from all aggregate sensor nodes covered by the UAV at hovering locations in the tour is maximized, subject to the energy capacity of the UAV.

1: Partition the monitoring region into M squares $s_1, s_2, \ldots, s_M$ with the edge length of each square being δ; let $S = \{d, s_1, s_2, \ldots, s_M\}$;
2: Compute $t(s_j)$, $p(s_j)$, and $w_1(s_j)$ for each $s_j \in S$ with $1 \leq j \leq M$;
3: Construct an auxiliary graph $G_s = (S \cup \{d'\}, E_s \cup \{(v, d') \mid (v, d) \in E_s\}; p(\cdot), w_1(\cdot), w_2(\cdot, \cdot))$, where d' is a dummy depot;
4: Find a simple path P in G_s between the depot d and the dumpy depot d' such that the total award collected in the path is maximized (as there is no coverage overlapping between any two hovering locations by the assumption), subject to the energy capacity $\mathcal{E}$ of the UAV, by the approximation algorithm for the orienteering problem in metric graphs [1];
5: **return** A closed tour C derived from P for the UAV, which contains the hovering locations and the sojourn time at each of the hovering locations.

C. Algorithm Analysis

In the following, we first show that the auxiliary graph G_s is a metric graph as the given approximation algorithm is only applicable to metric graphs. We then analyze the time complexity of the proposed approximation algorithm. Notice that this is an approximation algorithm under the assumption that there are no distinctions among the hovering locations within each square; otherwise, the problem is intractable due to infinite numbers of hovering locations even for a small square area. The solution is truly an approximate solution to the problem when the value of δ is sufficiently small, or approaches zero.

Lemma 1: The auxiliary graph G_s is a metric graph.

Proof: Since there is an edge for each pair of nodes in G_s, we show that the edge weights in G_s meet the triangle inequality. For the three edges formed by any three nodes s_j, s_k, and s_l in S, we have

$$\begin{aligned}
& w_2(s_j, s_k) + w_2(s_k, s_l) \\
&= (\frac{w_1(s_j) + w_1(s_k)}{2} + l(s_j, s_k) \cdot \eta_t) + \\
&\quad (\frac{w_1(s_k) + w_1(s_l)}{2} + l(s_k, s_l) \cdot \eta_t) \\
&= \frac{w_1(s_j) + w_1(s_l)}{2} + w_1(s_k) + (l(s_j, s_k) + l(s_k, s_l)) \cdot \eta_t \\
&\geq \frac{w_1(s_j) + w_1(s_l)}{2} + w_1(s_k) + l(s_j . s_l) \cdot \eta_t \\
&\geq \frac{w_1(s_j) + w_1(s_l)}{2} + l(s_j, s_k) \cdot \eta_t \\
&= w_2(s_j, s_l).
\end{aligned} \tag{10}$$

Thus, G_s is a metric graph. ∎

Theorem 2: Given an aggregate sensor network $G(V, E)$ with each node $v \in V$ having a data volume D_v for collection, and a UAV with energy capacity $\mathcal{E}$ and its depot d, assuming that the moving unit of the UAV is measured by a value of $\delta > 0$ and its coverage range at each hovering location is a circle with radius R_0, there is a 3-approximation algorithm for the data collection maximization problem in G without hovering coverage overlapping, assuming that the difference of the distances among the locations within each square is negligible. The algorithm takes $O(T_{ort}(\frac{\pi \cdot R_0^2}{\delta^2} \cdot |V|, \ \frac{\pi^2 \cdot R_0^4}{\delta^4} \cdot |V|^2))$ time, where $T_{ort}(|V'|, \ |E'|)$ is the time complexity of the approximation algorithm of Bansal *et al.* [1] for the orienteering problem in a graph with $|V'|$ nodes and $|E'|$ edges.

Proof: We first show that the solution obtained by `Algorithm 1` is feasible. It is obvious that the closed tour C is a simple closed tour including the depot d. We show that the total energy consumption of the UAV on the closed tour C is no greater than $\mathcal{E}$. As the total length of C is no greater than $\mathcal{E}$, the energy consumption of the UAV on C (hovering at nodes and traveling on edges) is the weighted sum of the edges in C, which is no greater than its energy capacity. Furthermore, for each hovering location s_j in C, assume that s_i and s_k are its two neighboring hovering locations in C, then the hovering energy consumption $w(s_j)$ of the UAV at location s_j is distributed to its two incident edges (s_i, s_j) and (s_j, s_k) as part of their weights, i.e., the energy weights of the two edges are $w_2(s_i, s_j) = \frac{w_1(s_i)+w_1(s_j)}{2} + l(s_i, s_j) \cdot \eta_t$ and $w_2(s_j, s_k) = \frac{w_1(s_j)+w_1(s_k)}{2} + l(s_j, s_k) \cdot \eta_t$, respectively. Thus, the UAV has sufficient energy at each hovering location s_j to collect the data from the IoT devices in $C(s_j)$.

We then analyze the time complexity of the proposed algorithm, `Algorithm 1`. It can be seen that G_s contains $|S| = O(\frac{\pi \cdot R_0^2}{\delta^2} \cdot |V|)$ nodes and $|E_s| = O(|S|^2) = O(\frac{\pi^2 \cdot R_0^4}{\delta^4} \cdot |V|^2)$ edges. Finding a 3-approximate solution (a closed tour C) for the orienteering problem in G_s starting at node d takes $O(T_{ort}(\frac{\pi \cdot R_0^2}{\delta^2} \cdot |V|, \ \frac{\pi^2 \cdot R_0^4}{\delta^4} \cdot |V|^2))$ time, by the approximation algorithm due to Bansal *et al.* [1], assuming that the distances of hovering locations within each square are negligible, where $T_{ort}(|V'|, |E'|)$ is the time complexity of the approximation algorithm of Bansal *et al.* [1] for the orienteering problem in a graph with $|V'|$ nodes and $|E'|$ edges. ∎

V. Heuristic Algorithm for the Data Collection Maximization Problem with Hovering Coverage Overlapping

In this section we deal with the data collection maximization problem with hovering coverage overlapping, by proposing an efficient heuristic algorithm.

A. Algorithm

The basic idea behind the proposed algorithm is to find the closed tour for the UAV iteratively. The closed tour consists of the depot only initially. Within each iteration, a new hovering location is added to the tour. For the sake of convenience, we assume that a partially closed tour that consists of hovering locations $s_0, s_1, \ldots, s_{j-1}$ has been constructed. Let $S_{j-1} = \{s_0, s_1, s_2, \ldots, s_{j-1}\}$ be the set of hovering locations for the UAV so far and $s_0 = d$, which also implies that the sum of energy consumptions on these j hovering locations and traveling along the closed tour $TSP(S_{j-1})$ is no more than $\mathcal{E}$, where

$TSP(S_{j-1})$ is the length of the closed tour induced by all nodes in set S_{j-1}, which is obtained by applying Christofides's algorithm for the Travelling Salesman Problem [3]. Recall that the coordinates of location s_j are (x_j, y_j, H), and $C(s_j) = \{v_i \mid v_i \in V \ \& \ \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \leq R_0\}$ is set of IoT devices covered by the UAV at hovering location s_j, i.e., each IoT device in $C(s_j)$ is able to transmit its data to the UAV when the UAV is located at s_j. The rest is to determine the next hovering location s_j as follows.

The volume $P'(s_j)$ of data collected by the UAV when it is located at s_j is

$$P'(s_j) = \sum\{D_v \mid v \in C(s_j) \setminus \cup_{j'=0}^{j-1} C(s_{j'})\}, \qquad (11)$$

i.e., if the data of an aggregate sensor node has been collected in any of the previous $j-1$ hovering locations of the UAV, it will not contribute any award towards the optimization objective anymore.

The hovering duration $t'(s_j)$ of the UAV for data collection at hovering location s_j is

$$t'(s_j) = \max_{s_j \in S \setminus S_{j-1}} \{\frac{D_v}{B} \mid v \in C(s_j) \setminus \cup_{l=0}^{j-1} C(s_l)\}. \qquad (12)$$

Denote by the ratio $\rho(s_j)$ of the volume of data collected to the total amount of energy consumed by the UAV on hovering, and traveling to and from location s_j as follows.

$$\rho(s_j) = \frac{P'(s_j)}{t'(s_j) \cdot \eta_h + (TSP(S_j) - TSP(S_{j-1})) \cdot \eta_t}$$
$$\text{if} \sum_{s_{j'} \in S_{j-1} \cup \{s_j\}} t'(s_{j'}) \cdot \eta_h + TSP(S_j) \cdot \eta_t \leq \mathcal{E}, \qquad (13)$$

where $S_j = S_{j-1} \cup \{s_j\}$. Notice that $\sum_{s_{j'} \in S_{j-1}} t'(s_{j'}) \cdot \eta_h + TSP(S_{j-1}) \cdot \eta_t \leq \mathcal{E}$ always holds, as S_{j-1} is a feasible solution to the problem, following the assumption.

The hovering location s_j is chosen as the next hovering location of the UAV if its ratio $\rho(s_j)$ is the maximum one among all potential hovering locations in $S \setminus S_{j-1}$, and the total energy consumption of the UAV in the closed tour including s_j is no greater than its energy capacity. This procedure of adding hovering locations continues until no more hovering locations can be added to the closed tour without violating the energy capacity of the UAV.

The detailed algorithm is given in `Algorithm` 2.

Algorithm 2 A heuristic algorithm for the data collection maximization problem with hovering coverage overlapping

Input: An aggregate sensor network $G = (V, E)$ with a set V of aggregate sensor nodes, a UAV with energy capacity $\mathcal{E}$ at depot d, and each node $v \in V$ has data volume D_v, and a given constant $\delta > 0$.

Output: Find a closed tour including depot d for the UAV such that the volume of data collected from all aggregate sensor nodes covered by it at its hovering locations in the tour is maximized, subject to the energy capacity of the UAV.

Partition the monitoring region into M squares $s_0, s_1, \ldots, s_M$, let $S = \{s_0, s_1, \ldots, s_M, d'\}$;
Construct the closed tour for the UAV iteratively, $S_0 = \{d\}$ initially;
$j \leftarrow 1$;
while $\sum_{s_{j'} \in S_{j-1}} t'(s_{j'}) \cdot \eta_h + TSP(S_{j-1}) \cdot \eta_t < \mathcal{E}$ **do**
  choose the next hovering location $s_j \in S \setminus S_{j-1}$ such that the ratio $\rho(s_j)$ is the maximum one, i.e., $s_j = \text{argmax}_{s_{j'} \in S \setminus S_{j-1}} \{\frac{P'(s_{j'})}{t'(s_{j'}) \cdot \eta_h + (TSP(S_j) - TSP(S_{j-1})) \cdot \eta_t} \mid \sum_{s_{j'} \in S_{j-1} \cup \{s_j\}} t'(s_{j'}) \cdot \eta_h + TSP(S_j) \cdot \eta_t \leq \mathcal{E}\}$;
  $S_j \leftarrow S_{j-1} \cup \{s_j\}$;
  $j \leftarrow j + 1$;
end while;
return the closed tour with the hovering location sequence $s_0, s_1, \ldots, s_j$.

B. Analysis of the Proposed Algorithm

In the following, we analyze the time complexity of the proposed algorithm, `Algorithm` 2.

Theorem 3: Given an aggregate sensor network $G(V, E)$ with each node $v \in V$ having a data volume D_v for collection, and a UAV with energy capacity $\mathcal{E}$ and its depot d, assuming that the moving unit of the UAV is measured by $\delta > 0$ and its coverage range at each hovering location is a circle with radius R_0, there is an efficient heuristic algorithm, `Algorithm` 2, for the data collection maximization problem in G with hovering coverage overlapping, assuming that the differences of the distances among potential hovering locations in each square are negligible. The algorithm takes $O(\frac{\pi^4 \cdot R_0^8}{\delta^8} \cdot |V|^4)$ time.

Proof: `Algorithm` 2 proceeds iteratively, and the number of iterations is bounded by $|S| = M$. Within iteration j with $1 \leq j \leq M$, identifying the next hovering location s_j is performed through the calculations of $\rho(s_j)$ for all $s_j \in S \setminus S_{j-1}$. This takes $O(|S \setminus S_{j-1}| \cdot |V| + |S_j|^3) = O(M \cdot |V| + M^3)$ time, due to the fact that the calculation of $TSP(S_j)$ takes $O(|S_j|^3)$ time by Christofides' algorithm [3]. The proposed algorithm thus takes $O(M^2 \cdot |V| + M^4) = O(\frac{\pi^4 \cdot R_0^8}{\delta^8} \cdot |V|^4)$ time. Notice that in practice, the values of both δ and R_0 are constants, the time complexity of `Algorithm` 2 thus is $O(|V|^4)$. ∎

VI. An Algorithm for the Partial Data Collection Maximization Problem

In this section, we consider the partial data collection maximization problem by devising an efficient algorithm for it. It can be seen that there are hovering coverage overlapping among UAVs at the K virtual hovering locations derived from each potential hovering location. We tackle the partial data collection maximization problem, by adopting a similar technique for the data collection maximization problem with hovering coverage overlapping in the previous section.

A. Algorithm

We show how to modify `Algorithm` 2 for this purpose. Specifically, we treat each virtual hovering location derived from each potential (real) hovering location as a potential hovering location of the UAV as we did for `Algorithm` 2. However, (i) we only allow one virtual hovering location from each potential hovering location to be included in the closed tour as the tour must be a simple closed tour. If two virtual hovering locations s_{j,k_1} and s_{j,k_2} derived from the same hovering location s_k are chosen to be included in the closed tour with $1 \leq k_1 < k_2 \leq K$, then only location s_{j,k_2}

will be included while location s_{j,k_1} will be discarded. Notice that the amount of data that was supposed to be collected by the UAV at location s_{j,k_1} for the sojourn duration $t'(s_{j,k_1})$ will be collected by the UAV at location s_{j,k_2}, since the UAV at s_{j,k_2} takes a longer sojourn duration $t'(s_{j,k_2}) > t'(s_{j,k_1})$ than it is at location s_{j,k_1}. And there will be no increase on the traveling energy consumption, but there will result in the extra amount of $(k_2 - k_1) \cdot t'(s_j) \cdot \eta_h / K$ of hovering energy consumed for the extra amount of data collection. (ii) It is also noted that the volume of data in each sensor $v \in V$ may be collected by the UAV at multiple hovering locations if the data in v has not been fully collected yet. We here use an example to illustrate this situation. Assume that the duration of collecting all data from a sensor v is $t(v) = D_v/B$ time units. We further assume that v is covered by the UAV at three different hovering locations s_{j_1} s_{j_2} and s_{j_3} with sojourn times t_1, t_2 and t_3, respectively, i.e., $v \in C(s_{j_1})$, $v \in C(s_{j_2})$, and $v \in C(s_{j_3})$. If $t(v) \geq t'(s_{j_1}) + t'(s_{j_2}) + t'(s_{j_3}) = t_1 + t_2 + t_3$, then the rest of data stored at sensor v can still be collected by the UAV at these three hovering locations. Therefore, the residual data volume and the hovering duration at some to-be-considered virtual hovering locations must be recalculated after a virtual hovering location s_j is added to the closed tour, since the data of some aggregate sensor nodes in $C(s_j)$ are contained by these potential virtual hovering locations and their data have been partially collected in the previous hovering locations already. The detailed algorithm is given in `Algorithm` 3.

Algorithm 3 A heuristic algorithm for the partial data collection maximization problem

Input: A sensor network $G = (V, E)$ with a set V of aggregate sensor nodes, a UAV with energy capacity $\mathcal{E}$ at depot d, and each node $v \in V$ has data volume D_v, and a given constant $\delta > 0$.

Output: Find a closed tour for the UAV including depot d such that the volume of data collected from aggregate sensor nodes within the hovering locations in the tour is maximized, subject to the energy capacity of the UAV.

Partition the monitoring region into M squares $s_0, s_1, \ldots, s_M$;
$S' \leftarrow \cup_{k=1}^{K} \{s_{j,k} \mid s_j \in S\}$;
Construct the closed tour for the UAV, $S'_0 = \{d\}$ initially;
$j \leftarrow 1$;
while $\sum_{s'_j \in S'_{j-1}} t'(s_{j'}) \cdot \eta_h + TSP(S'_{j-1}) \cdot \eta_t < \mathcal{E}$ **do**
  Choose a location $s_{j,k} \in S' \setminus S'_{i-1}$ such that the ratio $\rho(s_{j,k})$ is the maximum one, i.e., $s_{j,k} = \text{argmax}_{s_{j',k} \in S' \setminus S'_{j-1}} \{ \frac{P'(s_{j',k})}{t'(s_{j',k}) \cdot \eta_h + (TSP(S'_j) - TSP(S'_{j-1})) \cdot \eta_t} \mid \sum_{s_{j',k} \in S'_{j-1} \cup \{s_{j',k}\}} t'(s_{j',k}) \cdot \eta_h + TSP(S_j) \cdot \eta_t < \mathcal{E} \}$;
  $S'_j \leftarrow S'_{j-1} \cup \{s_{j,k}\} \setminus \{s_{j,k'} \mid 1 \leq k' < k\}$;
  $S' \leftarrow S' \setminus \{s_{j,k'} \mid 1 \leq k' \leq k\}$; /* as only one virtual hovering location from each hovering location is added to the tour */
  if $\exists k' : s_{j,k'} \in S'_{k-1}$ with $k' < k$ **then**
    $S'_j \leftarrow S'_{j-1} \setminus \{s_{j,k'}\}$;
    Calculate the data volume $D_v^{(j)}$ of each sensor $v \in C(s_{j,k})$;
    Calculate $P'(s_{j',k'})$ and $t'(s_{j',k'})$ for each potential location $s_{j',k'} \in S' \setminus S'_j$ if $C(s_{j',k'}) \cap C(s_{j,k}) \neq \emptyset$;
  end if;
  $j \leftarrow j + 1$;
end while;
return the closed tour that consists of the hovering location sequence $s_0, s_1, \ldots, s_j$ can be derived from S'_j.

B. Analysis of the Proposed Algorithm

The rest is dedicated to the correctness and time complexity analyses of the proposed algorithm. We first show that the amount of data that is supposed to be collected by the UAV at s_{j,k_1} will be collected by the UAV at s_{j,k_2} if $k_1 < k_2$ by the following lemma.

Lemma 2: For a given hovering location s_j, if one of its virtual hovering locations s_{j,k_1} is included in the closed tour and its another virtual hovering location s_{j,k_2} is chosen to be added to the tour, then we have $k_2 > k_1$ and s_{j,k_1} will be removed from the closed tour by the proposed algorithm, `Algorithm` 3. By doing so will not reduce the amount of data collected when the UAV at hovering location s_j, and the correctness of the proposed algorithm holds.

Proof: We note that for each hovering location, there is at most one of its virtual hovering locations included in the closed tour. Following `Algorithm` 3, if at most one virtual hovering location derived from each potential hovering location in S is included in the closed tour, the solution is feasible. Otherwise, assume that we add a virtual hovering location s_{j,k_1} of s_j at iteration i_1 of the algorithm into the closed tour already. We now add another virtual location s_{j,k_2} of s_j at iteration i_2 to the closed tour with $1 \leq i_1 < i_2 \leq |S|$. To make sure that at most one virtual hovering location for each hovering location is added to the closed tour, we remove s_{j,k_1} from the tour and add s_{j,k_2} to the tour, and all the other virtual hovering locations $s_{j,k'}$ of s_j with $k' < k_2$ will be removed from S for further consideration by the algorithm. Despite that the volume of data collected and sojourn durations at each hovering location from iterations $i_1 + 1$ to $i_2 - 1$ could be changed due to the removal of s_{j,k_1} from the closed tour, we will not update these hovering locations and their sojourn durations as the residual volume of data at each IoT device in $C(s_{j,k_1})$ (iteration i_1) in fact is larger than when the virtual hovering location s_{j,k_1} is included in the tour. The volume of all data that was supposed to be collected by the UAV at location s_{j,k_1} with a sojourn duration $k_1 \cdot t(s_j)/K$ will be later collected by the UAV at location s_{j,k_2} (iteration i_2) with a sojourn duration $k_2 \cdot t(s_j)/K$. Thus, the total volume of data collected from the closed tour by the removal of s_{j,k_1} from it does not change. ■

We then have the following theorem.

Theorem 4: Given an aggregate sensor network $G(V, E)$ with each node $v \in V$ having a data volume D_v for collection, and a UAV with energy capacity $\mathcal{E}$ and its depot d, assuming that the moving unit of the UAV is measured by $\delta > 0$ and its coverage range at each hovering location is a circle with radius R_0, there is a heuristic algorithm, `Algorithm` 3, for the partial data collection maximization problem in G, assuming that the differences of the distances among potential hovering locations in each square are negligible. The algorithm takes $O(\frac{\pi^4 \cdot R_0^8}{\delta^8} \cdot K^4 \cdot |V|^4)$ time, where K is a given integer with $K \geq 1$.

Proof: The correctness of the solution delivered by `Algorithm` 3 is shown by Lemma 2, omitted. The time complexity analysis of Algorithm 3 is similar to the one in the proof body of Theorem 3, and the only difference lies in the fact that we now have $M' = K \cdot M$ virtual squares instead of M squares in Theorem 3, omitted. ∎

VII. Performance Evaluation

In this section, we evaluate the performance of the proposed algorithms for the full (or partial) data collection maximization problems through experimental simulations. We also investigate the impact of important parameters on the algorithm performance.

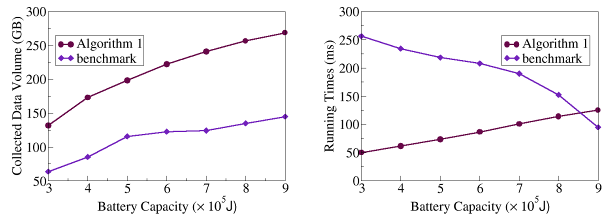
A. Experimental Settings

We consider a sensor network that consists of 500 aggregate sensor nodes randomly deployed in a 1,000 × 1,000 square meters. The data volume of each aggregate sensor node is randomly drawn in the range from 100 MB to 1,000 MB. Without loss of generality, we assume that the hovering coverage range R_0 of each aggregate sensor node is 50 $meters$ and its transmission bandwidth is 150 MB/s [12]. We assume that a UAV is initially deployed at a depot d. The UAV has energy capacity $\mathcal{E} = 3 \times 10^5$ $joules$ at constant flying speed 10 m/s. The energy consumption rates of the UAV on traveling and hovering are $\eta_t = 100$ J/s and $\eta_h = 150$ J/s, respectively [11]. The value in each figure is the mean of the results out of 15 network instances of the same size. The running time of an algorithm is obtained based on a machine with 3.6 GHz Intel i7 single-core CPU and 16 GB RAM. Unless otherwise specified, these parameters will be adopted in the default setting.

To evaluate the performance of the proposed algorithms for the data collection maximization problems, we here introduce a heuristic benchmark which proceeds iteratively. It starts finding a closed tour C that includes all aggregate sensor nodes and the depot by the Christofides algorithm. If the total amount of energy consumed in C is no greater than the energy capacity of a UAV, done. Otherwise, a node in the tour is chosen if its removal will result in the minimum loss of data volume per unit energy consumption. This procedure continues until the total energy consumption of the resulting closed tour is no greater than $\mathcal{E}$.

B. Performance Evaluation of Different Algorithms for the Problem Without Hovering Coverage Overlapping

We first investigate the performance of different algorithms for the data collection maximization problem without hovering coverage overlapping. As shown in Fig.3(a), the collected data volumes by both algorithms increase as the UAV has more energy capacity. It can be seen that Algorithm 1 outperforms the benchmark algorithm. For example, when $\mathcal{E} = 3 \times 10^5$ $joules$, the collected data volume by the former is around twice the amount of the one by the benchmark algorithm, and the gap of then collected data volume between them becomes larger and larger, with the growth on the energy capacity $\mathcal{E}$. Fig. 3(b) plots the time curves of the two mentioned algorithms, from which it can be seen that the running time of Algorithm 1 increases with the growth of the UAV energy capacity, while the running time of the benchmark algorithm decreases with the growth of the UAV energy capacity, this is because fewer nodes will be pruned from the initial TSP tour, since more energy can be consumed for the tour.



(a) Collected data volume by different algorithms (b) The running time of different algorithms

Fig. 3. Performance of different algorithms for the Data collection maximization problem without hovering coverage overlapping.

C. Performance Evaluation of Algorithms for the Problem With Hovering Coverage Overlapping

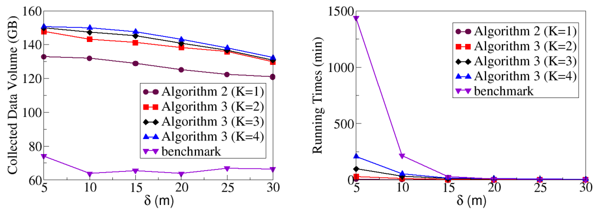
We then study the performance of Algorithm 2 and Algorithm 3 for the data collection maximization problem with hovering coverage overlapping against the benchmark algorithm. It can be seen from Fig.4(a) that both algorithms outperform the benchmark algorithm significantly. Furthermore, Algorithm 3 is superior to Algorithm 2, as the latter is a special case of the former when $K = 1$. Particularly, when $\delta = 5$ meters, the collected data volumes by Algorithm 2 and Algorithm 3 ($K = 2$) are 132.8 GB and 147.7 GB, respectively, which are higher than the benchmark algorithm (74.14 GB) by 79.12% and 99%, respectively.

We also study the performance of Algorithm 3 by varying the partitioning K of the sojourn duration at each hovering location. It can be seen from Fig. 4(a) that a larger K will result in more data collected per tour, this is due to more accurate planning for data collection per unit energy consumption. For instance, the collected data volume increases from 147.7 GB to 150.7 GB when K increases from 2 to 4. Fig. 4(b) indicates that Algorithm 3 takes a longer running time than that of Algorithm 2 with the growth of K due to the problem size increase. For example, the running time of Algorithm 3 is about 54.1 minutes when $K = 4$, which is around 50 times of the running time 1.61 minutes of Algorithm 2 when $K = 1$.

D. Parameter Impacts on the Performance of the Proposed Algorithms for the Problem With Hovering Coverage Overlapping

In the following we study the impact of parameters δ, $\mathcal{E}$ and $|V|$ on the performance of Algorithm 2 and Algorithm 3.

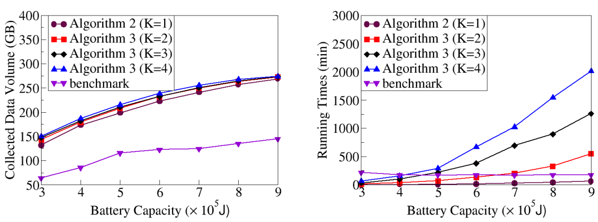
We start with the impact of δ on the performance of the two mentioned algorithms. It can be seen from Fig. 4 that with the increase of δ, for a fixed number $K \geq 1$ of partitioning of the sojourn duration at each hovering location, the total volume of data collected per tour reduces, so do the running times of



(a) Collected data volume by different algorithms (b) The running time of different algorithms

Fig. 4. Performance of different algorithms by varying the value of δ from 5 $meters$ to 30 $meters$ when $|V| = 500$.

the two algorithms, because the number of potential hovering locations for the UAV becomes smaller, and less data will be collected. E.g., when $K = 4$, it can be seen from Fig.4(a) `Algorithm` 3 when $\delta = 5$ meters is about 13.9% higher than that by itself when $\delta = 30$ meters. Therefore, when δ is sufficiently small, the total volume of data collected by the UAV is maximized. Fig. 4(b) depicts the running times of the two mentioned algorithms.



(a) Collected data volume by different algorithms (b) The running time of different algorithms

Fig. 5. Performance of different algorithms by varying the UAV's battery capacity so that the longest flying time varying from 3×10^5 $joules$ to 9×10^5 $joules$.

We then investigate the impact of the energy capacity $\mathcal{E}$ of the UAV on the performance of different algorithms, by varying it from 3×10^5 $Joules$ to 9×10^5 $Joules$ while fixing the value of δ at 10 meters. Fig. 5(a) illustrates that the collected data volume goes up with the increase in the energy capacity of the UAV, since the UAV can visit more hovering locations with longer hovering durations to collect more data from its hovering locations. For example, when $K = 4$, the collected data increased by 82% with the increase of the energy capacity of the UAV from 3×10^5 Joules to 9×10^5 Joules. Fig. 5(b) demonstrates the impact of the battery capacity of UAV on the running time of the algorithm. A larger battery capacity implies that `Algorithm` 2 and `Algorithm` 3 can visit more hovering locations, hence increasing the running time of the algorithm. On the other hand, with more energy supplies for the UAV, the benchmark algorithm will remove fewer nodes from the found closed tour C initially, which leads to shorter running time. Therefore, `Algorithm` 3 takes more running time while the benchmark algorithm takes less running time, with the growth of the energy capacity of the UAV.

VIII. Conclusions

In this paper, we studied data collection for IoT applications, using an energy-constrained UAV. We first proposed a novel data collection framework that enables the UAV to collect sensory data from multiple IoT devices simultaneously. We then formulated two data collection maximization problems that allow the UAV to fully or partially collect sensory data from IoT devices at each hovering location, and showed that both the problems are NP-hard. Instead, we devised efficient approximation and heuristic algorithms for the problems. We finally evaluated the performance of the proposed algorithms through simulations. Simulation results demonstrate that the proposed algorithms are promising.

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