# Energy-Efficient Data Collection Maximization for UAV-Assisted Wireless Sensor Networks

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2021 IEEE Wireless Communications and Networking Conference (WCNC) | 978-1-7281-9505-6/20/$31.00 ©2021 IEEE | DOI: 10.1109/WCNC49053.2021.9417258

***Abstract*—The accelerated development of the Internet of Things (IoT) incurs a great demand for data acquired from Wireless Sensor Networks (WSNs), leading to considerable attention on data collection of WSNs in recent years. With the high agility, mobility and flexibility, the Unmanned Aerial Vehicle (UAV) is widely considered as a promising technology for data collection in WSNs. Along with the Orthogonal Frequency Division Multiple Access (OFDMA) technique, the UAV is capable to collect data from multiple sensors simultaneously within its communication range (referred to as the one-to-many data collection scheme), which improves data collection efficiency significantly. In this paper, we focus on the improvement of the data collection efficiency in WSNs under the one-to-many data collection scheme via the trajectory finding of a UAV for data collection. To this end, we first formulate a novel data collection maximization problem in WSNs via deploying an energy-constrained UAV and show the NP-hardness of the problem. We then devise an efficient algorithm for the problem by investigating the impact of UAV hovering locations on the data collection. We finally evaluate the performance of the devised algorithm through experimental simulations. Simulation results demonstrate that the proposed algorithm is promising, and outperforms the other heuristics significantly.**

## I. Introduction

Wireless Sensor Networks (WSNs) play important roles in various applications, including health monitoring [1], ocean monitoring [2] and area coverage [3]. Massive sensory data are continuously generated by sensors, data collection thus is a crucial issue to avoid data loss and data overwritten in WSNs. With high mobility and flexibility, the Unmanned Aerial Vehicle (UAV) has attracted considerable attention for data collection in recent years. By adopting the Orthogonal Frequency Division Multiple Access (OFDMA) technique, the UAV is capable to collect data from multiple sensors within its communication range simultaneously. This data collection scheme is referred to as the *one-to-many data collection scheme*, which can improve the data collection efficiency significantly, compared with the conventional *one-to-one data collection scheme* where the UAV can only collect the sensory data from one sensor at each time. However, the one-to-many data collection scheme also poses challenges. For example, which sensors' data should be collected during a data collection tour, constrained by the battery capacity of the UAV? Considering that there are infinitely many potential hovering locations for the UAV within its monitoring area, which locations should be chosen as its hovering locations and how long the UAV should sojourn at each chosen hovering location? In this paper, we will address the challenges.

Extensive studies on data collection in UAV-enabled WSNs have been conducted in past years. For example, Zhang *et al.* [4] considered the freshness of data collection by deploying the minimum number of UAVs and finding data collection tours for the UAVs, where each tour is constrained by a rigid delay. Gong *et al.* [5] investigated the minimization of the total aviation time of a UAV to collect a certain volume of data from each sensor, where sensors are located on a straight line and only one sensor is served at each time. Liu *et al.* [6] studied the age-optimal trajectory for a UAV to collect data from sensors with different priorities under the one-to-one data collection scheme. Supported by the OFDMA technique, Mozaffari *et al.* [7] focused on optimizing trajectories of multiple UAVs, aiming at minimizing the energy consumption of IoT devices, where data from all sensors are fully collected. Say *et al.* [8] proposed a framework of data collection in a UAV-enabled WSN with the aim to maximize the network throughput, where sensors within the UAV coverage area can transmit their data to the UAV simultaneously, by assigning higher priorities to sensors in hot spots for their data packet uploading. Li *et al.* [9] considered the energy consumption of a UAV on both hovering and traveling, aiming to find an optimal trajectory for the UAV to maximize the volume of data collected, assuming that a set of potential hovering locations for a UAV is given in advance. Chen *et al.* [10] focused on the data collection utility maximization in WSNs via deploying an energy-constrained UAV and efficiently determining the hovering locations of the UAV, where sensory data of sensors can be partially collected at each tour of the UAV. They proposed a $1-\frac{1}{e}$-approximation algorithm for the problem.

Data collection maximization is challenging under the energy constraint on a UAV, where the UAV consumes energy on both hovering and mechanical movement. The identification of hovering locations for the UAV from infinitely many potential ones makes the data collection tour finding more difficult, as different locations correspond to different data collection rates of sensors, which impact significantly on the data collection efficiency. Different from the mentioned works, in this paper, we assume that the UAV consumes energy on both hovering and mechanical movement while data from each sensor should be fully collected. We also consider the fluctuation of data transmission ranges of sensors caused by

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the different Euclidean distance between sensors and the UAV.

The novelties of this study lie in that a novel data collection maximization problem via the deployment of an energy-constrained UAV is formulated, and a promising algorithm for the problem is devised, by jointly considering data transmission rates of sensors and hovering locations of the UAV.

The main contributions of the paper are as follows. We first formulate a novel UAV-enabled data collection maximization problem under the one-to-many data collection scheme and show the NP-hardness of the problem. We then devise an efficient algorithm for the problem, by jointly considering the UAV hovering locations and data transmission rates of sensors. We finally evaluate the performance of the proposed algorithm through extensive experimental simulations. Simulation results demonstrate that the proposed algorithm is promising.

The remainder of this paper is organized as follows. Section II introduces the system model and the problem definition. Section III proposes an efficient heuristic algorithm for the problem, and Section IV evaluates the performance of the proposed algorithm. Section V concludes the paper.

## II. Preliminaries

In this section, we first introduce the system model and the energy consumption model of a UAV. We then define the problem precisely.

### A. System Model

Consider a WSN with a set $\mathcal{V} = \{v_i \mid 1 \leq i \leq N\}$ of homogeneous sensors. Denote by $(x_i, y_i, 0)$ the location of sensor $v_i \in \mathcal{V}$. Assume that each sensor $v_i$ with transmission range $R$ has a volume $D_i$ of sensory data stored locally for later collection, where the data from $v_i$ can be transmitted to a data receiver if the Euclidean distance between $v_i$ and the receiver is no greater than $R$. An OFDMA-applied UAV is adopted to collect sensory data from sensors in the WSN. Guided by a pre-defined data collection schedule, the UAV flies above the monitoring area of the WSN and hovers at certain locations to collect data from multiple sensors simultaneously. It is assumed that the total energy consumption of the UAV per tour is constrained by its energy capacity $\Gamma$, which consists of the energy consumptions on its mechanical movement and hovering with the energy consumption rates $\eta_m$ and $\eta_h$, respectively.

Each data collection tour of the UAV is a closed tour that starts from and ends at a depot, and the UAV will visit the hovering locations in the tour one by one with a specified hovering duration at each hovering location. Assume that $\mathcal{H} = (h_1, h_2, \ldots, h_k, \ldots, h_K)$ is the sequence of $K$ hovering locations (excluding the depot) on the tour, where $h_k$ is the $k$th location. Note that, both $h_0$ and $h_{K+1}$ refer to the depot, which are excluded in $\mathcal{H}$ for the sake of convenience.

Denote by $V(h_k)$ the set of sensors whose data can be collected when the UAV hovers at location $h_k$ with coordinates $(X_k, Y_k, Z_k)$, then

$$V(h_k) = \{v_i \mid (x_i - X_k)^2 + (y_i - Y_k)^2 \leq R^2 - Z_k^2,\ v_i \in \mathcal{V}\}, \tag{1}$$

where $Z_k$ is the hovering altitude of the UAV. In this paper, we assume that the UAV hovers at a fixed altitude $L$ [9] that is no greater than $R$.

Denote by $r_i(h_k)$ the data transmission rate of sensor $v_i$ when the UAV hovers at location $h_k$. Following the Shannon-Hartley formula [11] [12], we have

$$r_i(h_k) = \log\Big(1 + \frac{\sigma_i}{d(v_i, h_k)^\alpha}\Big), \tag{2}$$

where $d(v_i, h_k)$ is the Euclidean distance between sensor $v_i$ and hovering location $h_k$, $\alpha$ is a given path loss exponent with the range between 2 and 6, and $\sigma_i$ is the transmission power of sensor $v_i$.

Due to the limited energy capacity imposed on the UAV, it is intuitively to enlarge its energy spending on hovering to improve the data collection efficiency, we thus assume that the UAV hovers at hovering location $h_k$ for a minimum duration until all data from the sensors in $V(h_k)$ are fully collected [9]. When the UAV hovers at location $h_k$, the set of sensors whose data to be collected is $V(h_k) \setminus \bigcup_{m=1}^{k-1} V(h_m)$, where $h_1, h_2, \ldots, h_{k-1}$ are the hovering locations visited by the UAV so far prior to the visit to location $h_k$.

The hovering duration $t_k$ of the UAV at hovering location $h_k$ thus is calculated as follows.

$$t_k = \max_{v_i \in V(h_k) \setminus \bigcup_{m=1}^{k-1} V(h_m)} \{\frac{D_i}{r_i(h_k)}\}, \tag{3}$$

where $\frac{D_i}{r_i(h_k)}$ is the time duration of the UAV to fully collect data from $v_i$. It can be seen that the value of $t_k$ is determined not only by the data volume of sensors in $V(h_k)$ but also by previous hovering locations visited by the UAV: $h_1, h_2, \ldots, h_{k-1}$. Note that, once the sequence of locations in the tour is given, the value of $t_k$ can be calculated by Eq. (3) directly. The finding of the data collection tour thus is equivalent to determine a sequence of hovering locations for the UAV, i.e., $\mathcal{H} = (h_1, h_2, \ldots, h_k, \ldots, h_K)$.

Denote by $u_k$ the volume of data collected by the UAV at hovering location $h_k$, which can be calculated by accumulating the data stored at sensors in $V(h_k) \setminus \bigcup_{m=1}^{k-1} V(h_m)$, i.e.,

$$u_k = \sum_{v_i \in V(h_k) \setminus \bigcup_{m=1}^{k-1} V(h_m)} D_i. \tag{4}$$

Denote by $U(\mathcal{H})$ the total volume of data collected during tour $\mathcal{H}$, then

$$U(\mathcal{H}) = \sum_{h_k \in \mathcal{H}} u_k. \tag{5}$$

We then define the following operations on a hovering location sequence $(h_1, h_2, \ldots, h_K)$.

- `Append`. Add a new location $p'$ to the end of the sequence, i.e.,

$$(h_1, h_2, \ldots, h_K) + p' = (h_1, h_2, \ldots, h_K, p'). \tag{6}$$

- `Replacement`. Replace a location with index $\alpha$ by a new location $p$, i.e.,

$$(h_1, h_2, \ldots, h_{\alpha-1}, h_\alpha, h_{\alpha+1}, \ldots, h_K)^{h_\alpha \to p} \quad (7)$$
$$= (h_1, h_2, \ldots, h_{\alpha-1}, p, h_{\alpha+1}, \ldots, h_K). \quad (8)$$

- `Pruning`. Remove a location with index $\alpha$ from the sequence, i.e.,

$$(h_1, h_2, \ldots, h_{\alpha-1}, h_\alpha, h_{\alpha+1}, \ldots, h_K) - h_\alpha \quad (9)$$
$$= (h_1, h_2, \ldots, h_{\alpha-1}, h_{\alpha+1}, \ldots, h_K). \quad (10)$$

### *B. The Energy Consumption Model of the UAV*

Denote by $E_h(\mathcal{H})$ the accumulative energy consumption of the UAV on hovering during tour $\mathcal{H}$, which can be expressed as follows.

$$E_h(\mathcal{H}) = \eta_h \cdot \sum_{h_k \in \mathcal{H}} t_k. \quad (11)$$

Recall that $\eta_h$ and $t_k$ are the hovering energy consumption rate of the UAV and the hovering duration at $h_k$, respectively.

Denote by $E_m(\mathcal{H})$ the accumulative energy consumption of the UAV on its mechanical movement during tour $\mathcal{H}$, i.e.,

$$E_m(\mathcal{H}) = \eta_m \cdot \sum_{k=0}^{|\mathcal{H}|} d(h_k, h_{k+1}). \quad (12)$$

Recall that $\eta_m$ and $d(h_k, h_{k+1})$ are the energy consumption rate of the UAV mechanical movement and the Euclidean distance between $h_k$ and $h_{k+1}$, respectively. Note that locations $h_0$ and $h_{|\mathcal{H}|+1}$ represent the same location – the depot.

Denote by $E(\mathcal{H})$ the total energy consumption of the UAV on tour $\mathcal{H}$, then

$$E(\mathcal{H}) = E_h(\mathcal{H}) + E_m(\mathcal{H}), \quad (13)$$

which is constrained by the energy capacity $\Gamma$ of the UAV.

### *C. Problem Definition*

Given a WSN with a set $\mathcal{V} = \{v_i \mid 1 \le i \le N\}$ of homogeneous sensors located on the ground, the *UAV Data Collection Maximization Problem* is to find a closed data collection tour $\mathcal{H}$ for the UAV to maximize the accumulative volume of data collected along the tour, subject to the energy capacity $\Gamma$ on the UAV.

We formalize the problem as follows.

$$Maximize \quad U(\mathcal{H}) \quad (14)$$
$$s.t. \quad (15)$$
$$\mathcal{H} = (h_1,\ h_2, \ldots,\ h_K), \quad (16)$$
$$K \in \mathbb{N}^+, \quad (17)$$
$$E(\mathcal{H}) \le \Gamma, \quad (18)$$
$$\text{Eq. } (1), (2), (3), (4), (5), (11), (12), (13). \quad (19)$$

## III. Algorithm

In this section, we propose an efficient algorithm for the UAV data collection maximization problem.

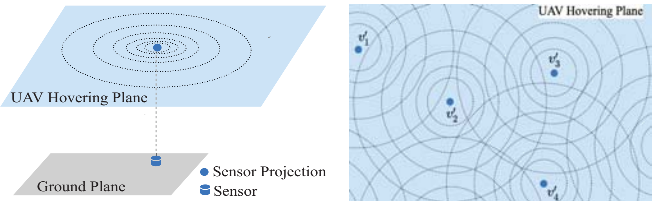


Fig. 1: Potential hovering location identifications: (a) a set of concentric circles centered at the projection of a sensor. (b) The aerial view of the UAV hovering plane discretized by sets of concentric circles.

### *A. Algorithm Overview*

The basic idea behind the proposed algorithm is as follows. We first discretize the UAV hovering plane by sets of concentric circles with different radii centered at the projection of each sensor location, where each spot is regarded as a potential hovering location for the UAV. We then find a data collection tour for the UAV in a novel way. That is, based on an initial tour $\mathcal{H}$, each location on $\mathcal{H}$ is iteratively assigned with a substitutive point, and $\mathcal{H}$ is updated by replacing a location with its substitutive point at each iteration. When the number of tour updates exceeds a pre-defined threshold $\theta$, one of the locations on $\mathcal{H}$ will be removed. The algorithm proceeds iteratively until the total energy consumption of the UAV is no greater than its capacity.

### *B. Potential Hovering Location Identifications*

Inspired by the work in [16], in the following we show how to reduce infinitely many potential hovering locations of the UAV to a finite number of potential hovering locations (spots).

For each sensor projection $v'_i$ on the UAV hovering plane, we draw a set of concentric circles centered at $v'_i$ with increasing radii $a_0, a_1, a_2, \ldots, a_M$ with $a_M \le R$ and $a_{M+1} > R$, such that when the UAV hovers on the circumference of the circle with radius $a_m$, the data transmission rate $\log(1 + \frac{\sigma_i}{(\sqrt{a_m{}^2 + L^2})^\alpha})$ calculated by Eq. (2) is equal to

$$\frac{1}{\Phi^m} \cdot \log(1 + \sigma_i), \quad (20)$$

where $\Phi$ $(0 < \Phi < 1)$ is a constant between 0 and 1, and $\log(1 + \sigma_i)$ is the data transmission rate of sensor $v_i$ with a unit Euclidean distance away from the UAV. As a result, the data transmission rate between any two conjunctive circles with radii $a_m$ and $a_{m+1}$ is bounded between $\frac{1}{\Phi^m} \cdot \log(1 + \sigma_i)$ and $\frac{1}{\Phi^{m+1}} \cdot \log(1 + \sigma_i)$ respectively, where the values of $\{a_0, a_1, a_2, ..., a_M\}$ can be calculated by the expression (20).

Consequently, the 2-D hovering plane of the UAV is partitioned into a set of small-sized spots by arcs of the circles, as shown in Fig. 1(b). We refer to each of the separated spots as a potential hovering location for the UAV, and denote by $\mathcal{P}$ the set of potential hovering locations whose cardinality is bounded, which will be shown later.

### C. Data Collection Tour Scheduling

We find the data collection tour for the UAV by finding a sequence of hovering locations in $\mathcal{P}$.

Given a partial tour $\mathcal{H}$, we define the *Expanding Ratio* $\rho^E(p_j)$ as the ratio of the increment of collected data volume to the increment of the hovering energy cost, by adding $p_j$ into $\mathcal{H}$ as the last hovering location, i.e.,

$$\rho^E(p_j) = \frac{U(\mathcal{H}+p_j) - U(\mathcal{H})}{E_h(\mathcal{H}+p_j) - E_h(\mathcal{H})}. \tag{21}$$

Define the *Pruning Ratio* as the ratio of the decrement of the collected data volume to the decrement of the total energy consumption of the UAV, by removing $h_\alpha$ from the tour, i.e.,

$$\rho^P(h_\alpha) = \frac{U(\mathcal{H}) - U(\mathcal{H}-h_\alpha)}{E(\mathcal{H}) - E(\mathcal{H}-h_\alpha)}. \tag{22}$$

The algorithm proceeds as follows.

**Tour Initialization:** Start from an empty tour $\mathcal{H}$, we iteratively expand $\mathcal{H}$ by selecting an unvisited location $p_{j^+} \in \mathcal{P} \setminus \mathcal{P}(\mathcal{H})$ with the maximum $\rho^E(p_{j^+})$, and adding it on $\mathcal{H}$ as the last visited location, i.e.,

$$j^+ = \text{argmax}_{p_j \in \mathcal{P}\setminus\mathcal{P}(\mathcal{H})} \rho^E(p_j), \tag{23}$$

where $\mathcal{P}(\mathcal{H})$ denotes the set of hovering locations on $\mathcal{H}$. The tour expanding continues until the total hovering energy $E_h(\mathcal{H})$ exceeds the energy capacity $\Gamma$ of the UAV.

Tour $\mathcal{H}$ then contains a sequence of visited locations. We then consider another tour $\mathcal{H}^{TSP}$, which is defined as the tour with exactly same visited locations as $\mathcal{H}$ but with a minimum closed tour to visit them. It can be seen that $U(\mathcal{H}^{TSP}) = U(\mathcal{H})$ since $\mathcal{P}(\mathcal{H}^{TSP}) = \mathcal{P}(\mathcal{H})$, and $E_m(\mathcal{H}^{TSP}) \le E_m(\mathcal{H})$ according to the definition of $\mathcal{H}^{TSP}$. However, as we mentioned before that different visiting orders of a set of visited locations may result in different hovering duration at each location by Eq. (3), it is uncertain whether $E_h(\mathcal{H}^{TSP}) < E_h(\mathcal{H})$. In the case where $E_h(\mathcal{H}^{TSP}) < E_h(\mathcal{H})$, we replace $\mathcal{H}$ by $\mathcal{H}^{TSP}$ and continue adding new locations to $\mathcal{H}$ by Eq. (23), until both $E_h(\mathcal{H}^{TSP})$ and $E_h(\mathcal{H})$ are greater than $\Gamma$. It then proceeds to the operation of `Substitution Selection and Tour Update` as follows.

**Substitution Selection and Tour Update:** For the partial tour $\mathcal{H}$ delivered so far, we have that $E_h(\mathcal{H}) > \Gamma$ and thus $E(\mathcal{H}) > \Gamma$. In this step, we reduce the mechanical movement energy consumption $E_m(\mathcal{H})$, while mitigating the decrement on the volume of the collected data.

Within each iteration, we find a substitutive location $h'_k$ for each visited location $h_k$ on tour $\mathcal{H}$ in the following ways. As shown in Fig. 2, let $h_{k-1}$ and $h_{k+1}$ on $\mathcal{H}$ be the two focal points (where $h_0$ and $h_{K+1}$ are the location of the depot), then we can obtain an ellipse $\mathcal{E}(h_k)$ with $h_k$ sitting on the circumference. Note that $\mathcal{E}(h_k)$ is unique since with two focal points and a point on the circumference, only one ellipse can be obtained. Denote by $\mathcal{P}(\mathcal{E}(h_k))$ the subset of potential hovering locations in $\mathcal{P}$ inside $\mathcal{E}(h_k)$ (excluding locations on the circumference), and $\mathcal{P}'(\mathcal{E}(h_k))$ the subset of unvisited potential hovering locations of $\mathcal{P}(\mathcal{E}(h_k))$, i.e.,

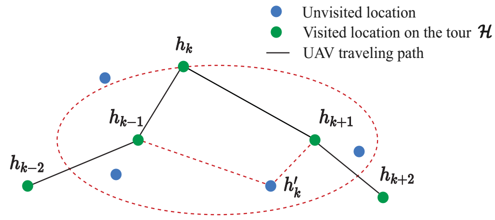


Fig. 2: With focal points $h_{k-1}$ and $h_{k+1}$, an ellipse $\mathcal{E}(h_k)$ can be obtained by letting $h_k$ sit on its circumference. $h'_k$ is the chosen substitutive location for $h_k$, which is inside $\mathcal{E}(h_k)$ and is unvisited by the UAV.

$\mathcal{P}'(\mathcal{E}(h_k)) = \mathcal{P}(\mathcal{E}(h_k)) \setminus (\mathcal{P}(\mathcal{H}) \cap \mathcal{P}(\mathcal{E}(h_k)))$. We then find an unvisited potential hovering location $p_{j'} \in \mathcal{P}'(\mathcal{E}(h_k))$ that satisfies

$$j' = \text{argmin}_{p_j \in \mathcal{P}'(\mathcal{E}(h_k))} U(\mathcal{H}) - U(\mathcal{H}^{h_k \to p_j}). \tag{24}$$

Then, $h'_k = p_{j'}$ is the substitutive location for $h_k$.

With a substitutive location for each location on $\mathcal{H}$, we then update the tour as follows.

We select the hovering location $h_{k^*}$ on $\mathcal{H}$ which satisfies

$$k^* = \text{argmin}_{h_k \in \mathcal{H}} U(\mathcal{H}) - U(\mathcal{H}^{h_k \to h'_k}). \tag{25}$$

We replace $h_{k^*}$ by $h'_{k^*}$ on $\mathcal{H}$, and replace $\mathcal{H}$ by $\mathcal{H}^{TSP}$ if $E(\mathcal{H}^{TSP}) < E(\mathcal{H})$.

When the tour $\mathcal{H}$ is updated at each iteration, the mechanical movement energy consumption $E_m(\mathcal{H})$ declines, which will be proved later. The algorithm terminates when the total energy consumption $E(\mathcal{H})$ is no greater than $\Gamma$.

However, there is an extreme case where $E(\mathcal{H})$ is not converging, since the replacement with a substitutive location may enlarge $E_h(\mathcal{H})$ and $E(\mathcal{H})$. To deal with this case, we introduce a threshold $\theta$, such that when the number of tour updates exceeds $\theta$, it proceeds to the following `Tour Pruning` operation to further reduce $E(\mathcal{H})$.

**Tour Pruning:** When the number of tour updates exceeds a predefined threshold $\theta$, we choose a hovering location $h_{k^-}$ on $\mathcal{H}$ with the minimum $\rho^P$ ratio, i.e.,

$$k^- = \text{argmin}_{h_k \in \mathcal{P}(\mathcal{H})} \rho^P(h_k). \tag{26}$$

We then remove $h_k$ from the tour and replace tour $\mathcal{H}$ by $\mathcal{H}^{TSP}$ if $E(\mathcal{H}^{TSP}) < E(\mathcal{H})$. It proceeds to the previous step – `Substitution Selection and Tour Update` if $E(\mathcal{H}) > \Gamma$; otherwise, the algorithm terminates.

As a result, $\mathcal{H}$ is the data collection tour of the UAV. The detailed algorithm for finding $\mathcal{H}$ is shown in `Algorithm` 1.

### D. Algorithm Analysis

The rest is dedicated to the theoretical analysis of the proposed algorithm. We first show the NP-hardness of the UAV data collection maximization problem. We then prove that the set of potential hovering locations separated by concentric circles is finite. We finally show that the energy consumption

**Algorithm 1** Algorithm for the UAV data collection maximization problem

**Input:** A set $\mathcal{V} = \{v_i \mid 1 \leq i \leq N\}$ of sensors; data volume $D_i$ of $v_i$; data transmission range $R$; the energy capacity $\Gamma$ for the UAV per tour.
**Output:** A data collection tour $\mathcal{H}$ for the UAV.

Discretize the UAV hovering plane by sets of concentric circles with different radii based on Eq. (20), and form the potential hovering location set $\mathcal{P}$;
$\mathcal{H} \leftarrow \emptyset$; $K \leftarrow 0$; $\mathcal{F} \leftarrow \mathcal{P}$;
**while** $E_h(\mathcal{H}) \leq \Gamma$ **and** $|\mathcal{F}| > 0$ **do**
  $j^+ \leftarrow \text{argmax}_{p_j \in \mathcal{P} \setminus \mathcal{P}(\mathcal{H})} \rho^E(p_j)$;
  $K \leftarrow K + 1$; $h_K \leftarrow p_{j^+}$; $\mathcal{H} \leftarrow \mathcal{H} + h_K$, $\mathcal{F} \leftarrow \mathcal{F} \setminus \{p_{j^+}\}$;
  **if** $E_h(\mathcal{H}) > \Gamma$ **and** $E_h(\mathcal{H}) > E_h(\mathcal{H}^{TSP})$ **then**
    $\mathcal{H} \leftarrow \mathcal{H}^{TSP}$;
**while** $E(\mathcal{H}) > \Gamma$ **do**
  $r \leftarrow 0$; /* number of iterations*/
  **while** $r \leq \theta$ **do**
    **for** $k \leftarrow 1$ to $K$ **do**
      Draw an ellipse $\mathcal{E}(h_k)$ with focal points $h_{k-1}$ and $h_{k+1}$, with $h_k$ on the circumference;
      $j' \leftarrow \text{argmin}_{p_j \in \mathcal{P}'(\mathcal{E}(h_k))} U(\mathcal{H}) - U(\mathcal{H}^{h_k \to p_j})$;
      $h'_k \leftarrow p_{j'}$;
    $k^* \leftarrow \text{argmin}_{h_k \in \mathcal{H}} U(\mathcal{H}) - U(\mathcal{H}^{h_k \to h'_k})$;
    $\mathcal{H} \leftarrow \mathcal{H}^{h_{k^*} \to h'_{k^*}}$; $r \leftarrow r + 1$;
    **if** $E(\mathcal{H}) > E(\mathcal{H}^{TSP})$ **then**
      $\mathcal{H} \leftarrow \mathcal{H}^{TSP}$;
    **if** $E(\mathcal{H}) \leq \Gamma$ **then**
      **return** $\mathcal{H}$
  $k^- \leftarrow \text{argmin}_{h_k \in \mathcal{P}(\mathcal{H})} \rho^P(h_k)$;
  $\mathcal{H} \leftarrow \mathcal{H} - h_{k^-}$;
  **if** $E(\mathcal{H}) > E(\mathcal{H}^{TSP})$ **then**
    $\mathcal{H} \leftarrow \mathcal{H}^{TSP}$;
**return** $\mathcal{H}$

on mechanical movement $E_m(\mathcal{H})$ of the UAV decreases, by replacing a visited location on $\mathcal{H}$ with its substitutive location.

*Theorem 1:* The UAV data collection maximization problem is NP-hard.

**Proof** We show the claim by a reduction from an NP-hard Robust $k$-Center (*RKC*) problem [13] [14], which is using $k$ identical disks with radius $r$ to cover at least $p$ points of a given point set $V$ in a 2-D plane, where $k$, $p$ and $r$ are given. Denote by $I_R$ and $I_U$ the instances of the RKC and the UAV data collection maximization problem, respectively. The number of disks of $I_R$ corresponds to the UAV energy capacity in $I_U$, i.e., $\Gamma = k$ and we further set $\eta_h = 1$ and $\eta_m = 0$ (neglecting the energy consumption of the UAV on mechanical movement). Denote by $V_R$ and $V_U$ the point set in $I_R$, and the sensor set in $I_U$ respectively, where for each vertex $v_i = (x_i, y_i)$ and $v_i \in V_R$, there exists a sensor $v'_i \in V_U$ with location $(x_i, y_i, 0)$ and the volume $D_i = 1$ of data stored locally. For the data transmission rate in Eq. (2), it has $\sigma_i = 1$ and $\alpha = 0$, such that for any $v_i$ and $h_k$, we have $r_i(h_k) = 1$. As a result, the hovering duration of the UAV at any visited location would be exactly 1 time unit. The transmission range of each sensor is $R = \sqrt{L^2 + r^2}$, where $r$ is the radius of disks of $I_R$, and $L$ is the hovering altitude of the UAV. It can be seen that a solution to $I_U$ returns a solution to $I_R$, and the reduction is polynomial. The theorem then follows. □

*Theorem 2:* The number of potential hovering locations in $\mathcal{P}$ is at most $|\mathcal{V}|^2 M^2 - |\mathcal{V}|M + 2$, where $\mathcal{V}$ is the set of sensors, $M$ is the number of circles centered at each sensor projection.

**Proof** According to Eq.(20) that $\log(1 + \frac{\sigma_i}{(\sqrt{a_m{}^2 + L^2})^\alpha}) = \frac{1}{\Phi^m} \cdot \log(1 + \sigma_i)$, we can calculate $a_1, a_2, a_3, \ldots$ by setting $m = 1, 2, 3, \ldots$ respectively, where we can find a constant $M$ satisfying $a_M \leq R$ and $a_{M+1} > R$. Then, $M$ is the number of circles centered at each sensor. Since the number of sensors on the WSN is $|\mathcal{V}|$, the number of circles on the UAV hovering plane is $|\mathcal{V}| \cdot M$. By [15] and [16], the number of regions separated by these circles, which are also referred to as potential hovering locations for the UAV, is at most $|\mathcal{V}|^2 M^2 - |\mathcal{V}|M + 2$. □

*Theorem 3:* $E_m(\mathcal{H})$ decreases by replacing a visited location $h_{k^*}$ with its substitutive location $h'_{k^*}$.

**Proof** As shown in Fig. 2, $h'_{k^*}$ is within $\mathcal{E}(h_{k^*})$. According to the property of ellipses $\mathcal{E}(h_{k^*})$, for any two points $p_1$, $p_2$ on the circumference, there is $d(h_{k^*-1}, p_1) + d(p_1, h_{k^*+1}) = d(h_{k^*-1}, p_2) + d(p_2, h_{k^*+1})$, where $h_{k^*-1}$ and $h_{k^*+1}$ are focal points of $\mathcal{E}(h_{k^*})$. Since $h_{k^*}$ is on the circumference of $\mathcal{E}(h_{k^*})$ and $h'_{k^*}$ is within the circumference of $\mathcal{E}(h_{k^*})$, we have that $d(h_{k^*-1}, h'_{k^*}) + d(h'_{k^*}, h_{k^*+1}) < d(h_{k^*-1}, h_{k^*}) + d(h_{k^*}, h_{k^*+1})$. Due to the fact that $h'_{k^*}$ is selected from unvisited locations, the other visited locations on $\mathcal{H}$ will not be affected. The theorem then follows. □

## IV. Performance Evaluation

In this section, we evaluate the performance of the proposed algorithm by experimental simulations. We also investigate the impacts of parameters on the algorithm performance.

### A. Experimental Environment Settings

We consider a WSN deployed within $1,000 \times 1,000$ square meters, where sensors are randomly distributed [17]. The data transmission range and the transmission power of each sensor are set as 21 $m$ and 330 $mW$ [12] respectively. The data volume $D_i$ of each sensor $v_i$ is randomly drawn from $(0,\ 1024]$ $MB$. We deploy one UAV for the data collection, hovering at an altitude 5 m [12]. The energy capacity of the UAV is set as $5 \times 10^5$ $J$, and the energy consumption rates on traveling and hovering are 10 $J/m$ and 150 $J/s$, respectively [9]. The threshold $\theta$ of numbers of iterations in the proposed algorithm is set as $5,000$. Unless otherwise specified, these parameters will be adopted in the default setting. As the UAV data collection maximization problem is a new problem, existing algorithms in the literature are

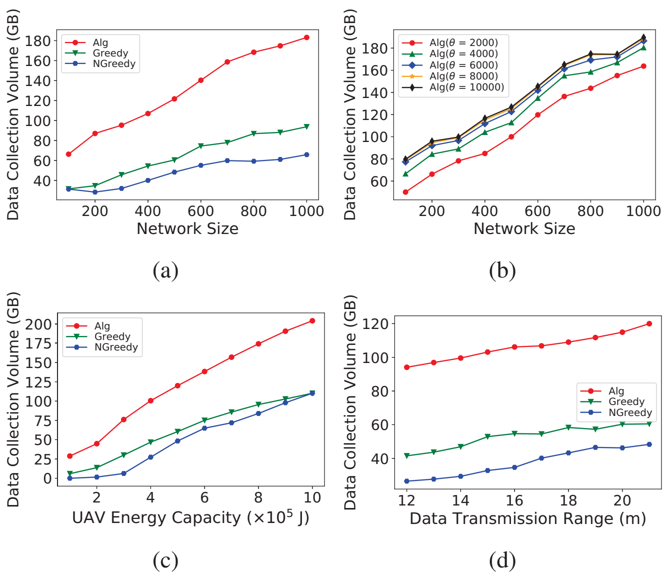


Fig. 3: Performance of `Alg`, `Greedy` and `NGreedy`.

unlikely to be adopted directly, we here propose the following benchmark heuristics to evaluate the performance of the proposed algorithm.

- *Greedy*. The projection of each sensor on the UAV hovering plane is regarded as a potential hovering location for the UAV. It starts with an empty tour $\mathcal{H}$ and iteratively selects a hovering location $p_{max}$ with the maximum $U(\mathcal{H}+p_{max})-U(\mathcal{H})$. Then $p_{max}$ is added to $\mathcal{H}$ as the last visited location if $E(\mathcal{H}+p_{max})<\Gamma$. This procedure continues until $E(\mathcal{H}+p_{max})>\Gamma$.
- *NGreedy*. The projection of each sensor on the UAV hovering plane is regarded as a potential hovering location for the UAV. The UAV firstly visits a location $p_{max_1}$ with the maximum $U(\mathcal{H}+p_{max_1})-U(\mathcal{H})$. It then visits a location $p_{max_2}$ from the neighbors of $p_{max_1}$ (potential hovering locations no larger than 50 meters away from $p_{max_1}$), with the maximum $U(\mathcal{H}+p_{max_2})-U(\mathcal{H})$ among neighbors of $p_{max_1}$. The procedure continues until $p_{max_m}$ is found with $E(\mathcal{H}+p_{max_m})>\Gamma$.

Each value in figures is the mean result by applying each mentioned algorithm to 50 network instances with the same size. The running time of all the mentioned experimental simulations is obtained from a desktop with 2.7 GHz Intel Core i7 CPU and 16 GB RAM.

### B. Performance Evaluation of Different Algorithms

We investigate the performance of the proposed algorithm (denoted by `Alg`) against algorithms `Greedy` and `NGreedy`, by varying the number of sensors from 100 to $1,000$. Fig. 3(a) demonstrates that the performance of `Alg` significantly outperforms the other two heuristics, where the volume of the data collected by `Alg` is approximately $200\%$ of the one collected by `Greedy`, and $300\%$ of the one collected by `NGreedy`. It can be seen that, the volume of collected data by all mentioned algorithms is proportional to the number of sensors in the network.

### C. Impacts of Parameters on the Performance of Algorithms

The rest is to investigate the impact of the iteration threshold $\theta$ on the performance of `Alg`, the UAV energy capacity and the data transmission range on the performance of the mentioned algorithms.

We first investigate the impacts of $\theta$, which is the maximum number of iterations in `Substitution Selection and Tour Update` (in step 10 of `Algorithm 1`). We compare the performance of `Alg` with $\theta = 2,000,\ 4,000,\ 6,000,\ 8,000,\ 10,000$ respectively, by varying the number of sensors from 100 to $1,000$. Fig. 3(b) depicts that the volume of collected data increases in any size of the network by increasing the value of $\theta$ from $2,000$ to $6,000$, but it remains constant when $\theta$ varies from $6,000$ to $10,000$.

We then investigate the impacts of the energy capacity $\Gamma$ of the UAV and the data transmission range $R$ on the performance of the mentioned algorithms, by increasing the energy capacity from $1\times10^5 J$ to $10\times10^5 J$ and the data transmission range from 12 $m$ to 21 $m$ respectively, with 500 sensors randomly deployed in the network. Fig. 3(c) depicts that the volume of the data collected by the mentioned algorithms grows rapidly against the energy capacity of the UAV, as the UAV can visit more locations and collect data from more sensors at each visited location. Fig. 3(d) plots that the volume of the data collected by different algorithms increases against the data transmission ranges, since a larger data transmission range allows data from more sensors to be collected simultaneously. It can be seen that the data collection volume of `Alg` is proportional to the iteration threshold $\theta$, the UAV energy capacity and data transmission ranges of sensors.

## V. Conclusion

In this paper, we studied the data collection maximization problem in a UAV-enabled WSN under the one-to-many data collection scheme, where there are infinitely many hovering locations for the UAV, and the UAV consumes energy on both hovering and mechanical movement. We first formulated a novel UAV data collection maximization problem. We then devised an efficient algorithm for the problem by jointly considering the UAV hovering locations and data transmission rates of sensors. We finally evaluated the proposed algorithm through experimental simulations. Simulation results demonstrate that the proposed algorithm is promising and outperforms the other benchmarks significantly.

**Acknowledgement:** It is acknowledged that the work by Mengyu Chen, Weifa Liang and Jing Li was supported by the Australian Research Council Discovery Projects: No. DP200101985 and No. DP210103002 respectively.

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