# Maximizing Energy Efficiency of Period-Area Coverage with UAVs for Wireless Rechargeable Sensor Networks

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***Abstract*—Wireless Rechargeable Sensor Networks (WRSNs) with perpetual network lifetime have been used in many Internet of Things (IoT) applications, like smart city and precision agriculture. Rechargeable sensors together with Unmanned Aerial Vehicles (UAVs) are collaboratively employed for fulfilling periodic coverage tasks. However, traditional coverage solutions are normally based on static deployment of sensors and not suitable for such coverage requirements. In this paper, we propose a new concept of coverage problem named Period-Area Coverage (PAC) which requires data of the overall area must be collected periodically. We focus on maximizing the energy efficiency of UAVs and propose two heuristic scheduling schemes to balance energy cost. Moreover, we adopt adjustable sensing range to further promote efficiency and develop a charging re-allocation mechanism for UAVs. Test-bed experiments and extensive simulations demonstrate that the proposed schemes can enhance energy efficiency by $18.2\%$ compared to prior arts.**

## I. Introduction

Wireless Rechargeable Sensor Networks (WRSNs) have significantly mitigated the energy limitation of wireless sensor networks through collaborations between mobile chargers (M-Cs) and rechargeable sensors [1]. Lifetime of network can be perpetually prolonged by applying appropriate charging mechanisms and scheduling schemes [2]–[6]. Therefore, WRSNs have been used in a variety of the Internet of Things (IoT) applications, such as precision agriculture and smart city [7], [8]. For example, in a precision agriculture application, static (rechargeable) camera sensors, and mobile camera sensors (*i.e.,* Unmanned Arial Vehicles, UAVs), are collaboratively employed to periodically collect image data and timely monitor the crop growth, plant diseases and insect pests [9]. Data missing may cause catastrophic consequences in such a system , *e.g.,* a local region of crops may suffer from disease or insect pests, leading to widely death, due to the missing detection of the time-critical event. Therefore, a compulsory requirement for this application is to periodically monitor the whole area without any data missing through collaboratively applying static and mobile sensors. Hence, two guarantees should always been satisfied: 1) full and periodical monitoring coverage for the whole area, and 2) normal functionality & survivals for all rechargeable sensors.

We define the concept of Period-Area Coverage problem (PAC) for WRSNs suitable for periodic area coverage applications. It has never been explored before:

**Definition 1 (Period-Area Coverage).** *Given a monitoring area $A$, a number of static rechargeable sensors are deployed for sensing events periodically. A UAV is employed as a mobile sensor & charger to 1) sense vacant regions that are beyond sensors' monitoring scope and 2) replenish energy for sensors. The problem here is how to ensure that any place within $A$ is monitored once in each period $T$.*

Traditional methods overlook the problem of periodically covering an area with both UAVs and sensors in such agriculture monitoring applications. In literature, coverage problems can be summarized into three types: target coverage problem [10], barrier coverage problem [11], [12] and area coverage problem [13]. However, most coverage problems are incident-based, where events can be timely detected through carefully designing sensor deployment scheme. None of them is suitable for the period-area coverage problem.

This paper aims at solving the period-area coverage problem (PAC) by appropriately scheduling event detection placement as well as energy replenishment for this network. However, it is challenging to develop a practical solution due to the following three reasons. First, UAVs provide flexibility of tasks execution; however, it is still difficult to trade off the traveling cost and charging cost for them. Second, energy cost is high in such a complicated coverage problem, and maximizing the energy efficiency increases the difficulty of network performance evaluation. Third, shifting among vacant regions and "hungry" sensors is NP-hard (see our proofs in Section V-A); hence, leveraging complexity and performance of scheduling scheme is crucial.

To overcome these challenges, we aim to maximize energy efficiency when taking data collection period and area coverage as two main constraints (*i.e.,* for guaranteeing PAC).

The main contributions of this paper are summarized below:

- To the best of our knowledge, this is the first work that proposes the concept of period-area coverage, a specific problem suitable for agriculture monitoring applications. We concentrate on maximizing energy efficiency under PAC concern so as to enhance network performance.
- To tackle this problem, we propose a hexagonal decomposition scheduling algorithm to maximize energy efficiency with a lower bound. Moreover, to reduce network dimensionality and computation complexity, a grid-based boustrophedon scheduling method is developed to

sense vacant regions and charge sensors where calculation complexity is effectively reduced.
- To balance energy cost in charging, sensing, and moving, we further propose a charging re-allocation mechanism for UAVs to enhance energy efficiency by promoting charging energy and reducing moving and sensing cost.

We conduct real experiments on a customized test-bed and large-scale simulations to evaluate the performance of the proposed solution. In test-bed experiments, our algorithms have a $0.987$ gap to the optimal results in energy efficiency. In our extensive simulations, we compare our two heuristic algorithms to traditional path scheduling methods: minimum spanning tree (MST) [14] and nearest job next preemption (NJNP) [15] (see Section VII). As energy efficiency maximization is our objective under PAC problem (see Section III-B), we study the impact of sensor numbers, minimum working energy of sensors, and energy capacity of the UAV on energy efficiency. Our algorithms outperform MST and NJNP at least $18.2\%$ and $30.3\%$, respectively.

## II. Related Work

We summarize state-of-the-art research achievements for WRSNs. As period-area coverage is a new concept, we give an overview of related coverage problems in this research field.

### A. Wireless Rechargeable Sensor Networks

In a WRSN, charging models can be classified into two types according to different charging technologies (*e.g.,* magnetic resonant coupling, electro-magnetic radiation): one-to-one model [16], [17] and one-to-many model [18]–[21].

With the one-to-one charging model, MCs can only serve one sensor each time; hence, spatial scheduling is essential to prolong network lifetime. In the one-to-many case, MCs can simultaneously provide energy replenishing service for multiple sensors within their charging ranges; thus, a well-designed charging position determination scheme is usually required. Wang *et al.* [22] combined solar energy harvesting with wireless charging for a hybrid wireless sensor network. They equipped cluster heads with solar panels and powered other nodes through mobile chargers. Moreover, mobile data gathering approach is provided for decreasing overall costs. Dai *et al.* [18] proposed a new directional charging mechanism for mobile chargers under the one-to-many charging model. They aimed at maximizing the overall expected charging utility for sensors by determining the positions and orientations of chargers. Coverage problems were also considered in WRSNs [3], in which MCs are employed to achieve k-coverage for targets while ensuring normal functionality of network.

### B. Coverage Problems

Coverage problems in sensor networks are generally classified into three categories: target coverage [10], barrier coverage [11], [12], and area coverage [13], [23].

In target coverage, points of interests are settled first and sensors are then deployed around to monitor events. Chen *et al.* [10] proposed an energy effective movement algorithm (EEMA) to minimize moving distance of sensors to cover all targets. Barrier coverage problems are mainly applied for detection of anomaly where sensing ranges of sensors form a line shape. Kim *et al.* [11] studied the problem of how to organize a hybrid network, which consists of static and mobile sensors, to maximize the lifetime of barrier coverage problem. By combining target coverage and barrier coverage together, Cheng *et al.* [12] defined the concept of target-barrier coverage problem which is suitable for applications in defense surveillance. They focused on how to minimize member numbers required to construct target-barriers in a distributed manner while minimizing the number of required message exchanges. Area coverage problem requires that the union of all sensors' sensing region can cover the whole monitoring area. Sahoo *et al.* [13] concentrated on density of nodes and proposed distributed coverage hole repairing algorithms to accomplish area coverage.

However, most previous works are not suitable for period-area coverage problem, in this work, we develop new scheduling methods which focus on maximizing energy efficiency of UAVs while satisfying coverage requirements.

## III. Preliminaries

In this section, network model, problem statement, and problem analysis are introduced.

### A. Network Model

In a WRSN, $N$ static rechargeable sensors are deployed in a square monitoring area $A$ to periodically collect data. During each period $T$, every sensor delivers their sensory data to the base station (BS). When the remaining energy of a sensor falls below a threshold, a charging request will be initiated and delivered to BS. Upon the reception of the request, a UAV will be employed to replenish energy for sensors. Besides, the UAV also acts as a mobile sensor, and is responsible for sensing vacant regions to remedy drawback of limited sensing coverage posed by static sensors, which is defined as PAC problem. To solve the PAC problem, we face two challenges.

**Problem I (Coverage problem):** Usually, the union of all sensing range of sensors cannot cover the whole area $A$, vacant regions will always exist, which may lead to data missing. Hence, how to remedy such drawback so as to realize complete event monitoring is challenging.

**Problem II (Charging problem):** Once the energy of sensors falls below $E_{min}$ (*i.e.,* the minimum energy that can sustain working), charging requests will be sent from sensors to BS under an on-demand architecture [1]. How to schedule the charging path for UAVs is another concern.

To tackle the above two challenges, a specialized UAV is employed to accomplish coverage and charging missions. In our work, a UAV has two functionalities: i) moving to each vacant region (*i.e.,* interest area that is not covered by sensors) and sensing missing data and ii) replenishing sensors requesting for charge. Hence, our focus is to appropriately schedule UAV's behavior to solve the PAC problem efficiently.

### B. Problem Statement

Without loss of generality, we assume that in a given interest area $A$, one UAV is able to complete sensing and charging tasks. Whenever the scale of network grows, more UAVs will be employed and the scheduling problem can be easily extended from a one-UAV scenario into a multiple-UAV case.

The total energy consumed by the UAV contains sensing energy $E_s$, charging energy $E_c$, and moving energy $E_m$. Then, we define energy utility $\mathcal{U}$ of the UAV as:

$$\mathcal{U} = E_c + E_s + E_m. \tag{1}$$

Our problem is *how to maximize the energy efficiency of a UAV through scheduling while ensuring period-area coverage?* We formulate this problem as below:

$$max \quad \eta = \frac{1}{\mathcal{U}} \sum_{i \in S} C_i. \tag{2}$$

Subject to:

$$\mathcal{U} \leq E, \tag{3}$$

$$\sum_{i \in S} C_i = \lambda E_c, \tag{4}$$

$$E_{min} \leq C_i \leq E_{max}, \tag{5}$$

$$\frac{\sqrt{2}Na}{\upsilon} + \sum_{i=1}^{N} \frac{E_{max}}{\chi} < T, \tag{6}$$

$$A \subseteq A_M \cup A_S. \tag{7}$$

$S$ is denoted as a requesting set, which records all nodes requesting for charge. We define *effective energy* as charged energy for sensors: $\sum_{i \in S} C_i$, which is beneficial for the functionality of a WRSN. Thus, our objective is to maximize the energy efficiency $\eta$, which is calculated as Equation (2).

Equation (3) guarantees that energy utility of the UAV is smaller than its maximum energy capacity $E$ during one period $T$. Due to the energy loss in wireless power transfer of charging [16], we assume that only a fraction of charging energy $\lambda E_c$ can be received by sensors as Equation (4). Equation (5) demonstrates the charged energy constraints for each sensor node.

Both Equation (6) and Equation (7) describe the period-area coverage constraints. Here, $\sqrt{2}Na$ denotes the upper bound of moving distance of a $a \times a$ square, and $\upsilon$ denotes moving velocity of the UAV. The charging velocity of sensor $i$ during one period is denoted as $\chi$. Equation (6) ensures that all missions can be accomplished within the period $T$. Equation (7) guarantees area $A$ is fully covered by both sensors and the UAV where $A_M$ and $A_S$ represent the area sensed by the UAV and sensors, respectively.

### C. Problem Analysis

In a WRSN with period-area coverage requirement, we define the maximum charging energy as $E_c^{max}$ and total charged energy for sensors as $\lambda E_c^{max}$. Then, we consider maximizing energy efficiency in two cases:

**Case I:** $E_c^{max} + E_m + E_s \leq E$. In this case, all charging and sensing missions can be achieved within energy capacity $E$. Then, we only focus on minimizing moving energy $E_m^*$ and sensing energy $E_s^*$ to maximize energy efficiency $\eta$.

**Case II:** $E_c^{max} + E_m^* + E_s^* > E$. In this case, with the minimum moving energy and sensing energy, the UAV still cannot charge all sensors to their full capacity. Then, we try to reduce charged energy for sensors to guarantee that $E$ is sufficient in one tour. However, when $E_c^{min} + E_m^* + E_s^* > E$ (*i.e.,* constraint (3)) is not satisfied, a UAV is infeasible to serve such a WRSN. In that case, we need to employ more UAVs, which is outside the scope of this work.

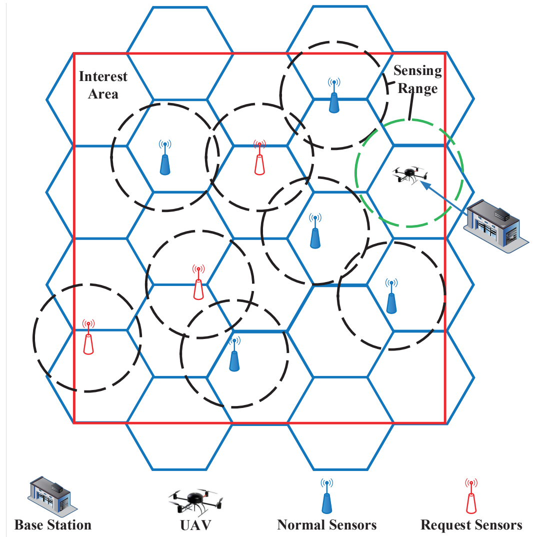


Fig. 1. A diagram of hexagonal decomposition of network.

In brief, to maximize energy efficiency $\eta$ in Equation (2), we have to minimize moving cost and sensing cost. Besides, we also need to re-allocate charging energy $E_c$ to enhance energy efficiency in Case II.

However, it is challenging to minimize $E_m$ and $E_s$, because the UAV has to sense overall interest area by selecting candidate points, which are infinite in such a continuous area. Therefore, how to reduce traveling and sensing cost is quite difficult. As proved in V-A, such a problem is NP-hard, which greatly challenges us.

## IV. Scheduling Scheme

In this section, we first decompose the network into hexagons and employ a UAV with adjustable sensing range to promote monitoring coverage. Then, a hexagon-based covering and charging scheduling method is proposed, and a grid-based boustrophedon algorithm is introduced to reduce scheduling complexity for vacant regions. Finally, a charging re-allocation mechanism is designed to further enhance energy efficiency.

### A. Network Initializations

Due to NP-hardness of the problem (see proofs in Section V-A), we try to heuristically decompose area $A$ into hexagons, which can seamlessly cover an area with the least number of subregions [24]. The edge length of each hexagon is set as the maximum sensing range of sensors. A diagram of decomposed network is shown in Figure 1 where interest area is decomposed into hexagons.

The advantages of hexagonal decomposition are summarized as below:

a) Hexagonal decomposition can form a cellular network which uses the least nodes to cover an area [24]. Correspondingly, a UAV has the least number of sojourning positions, which saves sensing energy $E_s$.

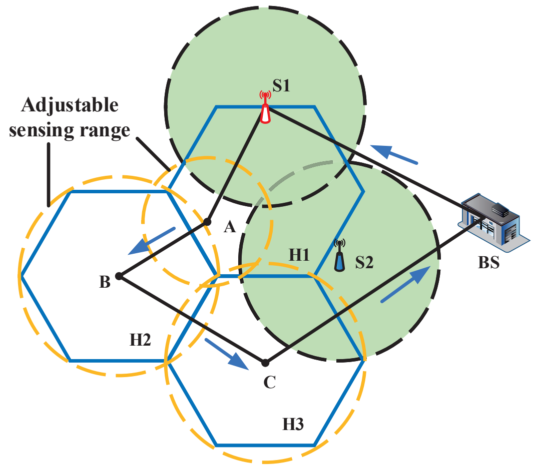


Fig. 2. Sensing with adjustable range when the UAV is scheduling.

b) After hexagonal decomposition, the whole area is divided into finite region pieces, such as hexagons and sensing circles of sensors. The irregular shape of vacant regions become regular, largely reducing the difficultly in determining the sojourning locations for the UAV.

Then the UAV can simply schedule these pieces rather than the whole vacant regions. To schedule a mission tour, the spatial constraint of period-area coverage in Equation (7) can be re-formulated as:

$$\sum_{j=0}^{H} \xi_j = 0, \tag{8}$$

where $H$ denotes the number of hexagons that intersect with area $A$. The sensing state of the $j$th hexagon is represented as $\xi_j$ which can be obtained as:

$$\xi_j = \begin{cases} 0 & \text{Any piece in } j\text{th hexagon is sensed} \\ 1 & \text{Otherwise} \end{cases}. \tag{9}$$

We employ a UAV as a mobile sensor & charger with adjustable sensing range [25] where the maximum sensing range is $R_s$. Since sensing energy is proportional to the number of sensing positions, we can obtain the minimum sensing energy $E_s^*$ through hexagonal decomposition.

For easy comprehension, we give an example in Figure 2. The interest area is composed of three connected hexagons (*i.e.,* H1, H2, and H3).

Firstly, after hexagonal decomposition, the UAV can stay at point $B$ and $C$ (*i.e.,* centers of $H2$, and $H3$) to respectively sense region $H2$ and $H3$ with the maximum sensing range $R_s$. As implementing with a smaller sensing radius will lead to less sensing energy cost for the UAV [26], when monitoring region $H1$, instead of configuring with $R_s$, the UAV will configure circumcircle's radius of $H1$ for the sake of energy preservation. Afterwards, we focus on reducing overlapping sensing positions to avoid a vacant region covered by multiple times. Finally, through combining the sensing positions of vacant regions and sensor locations, the shortest Hamiltonian path $BS \rightarrow S1 \rightarrow A \rightarrow B \rightarrow C \rightarrow BS$ is formed.

### *B. Hexagon-based Scheduling*

In this part, we provide detailed scheduling algorithm based on hexagonal network decomposition. A mission queue $Q_M$ is firstly constructed to record the sequence of missions for the UAV. During each period $T$, charging missions will be added into $Q_M$ according to requesting nodes in advance, then sensing mission for vacant regions will be scheduled.

Before scheduling, sensors satisfying the following formula will be regarded as requesting nodes:

$$E_i - \delta_i \leq E_{min}, \tag{10}$$

where $E_i$ is current energy of node $i$, $\delta_i$ is the total energy consumed by node $i$ during $T$. Afterwards, requesting nodes will be added into $Q_M$. If no vacant region exists, the shortest Hamiltonian path will be used to guide the movement for UAV in fulfilling charging missions.

To cover all vacant regions, the UAV will move to circumcircle of every piece (*i.e.,* hexagons and sensor circles). Then, centers of these circumcircles are added into $Q_M$ as sojourning locations. We form the shortest Hamiltonian path starting and ending with BS based on $Q_M$. Moreover, as overlaps may exist in adjacent vacant regions' circumcircle, when the circumcircle of the next vacant piece is influenced by current coverage, the center of the next circumcircle will be replaced in $Q_M$, and the mission path will be adjusted for the remainders. We present details in Algorithm 1.

**Algorithm 1** Hexagon-based Scheduling Algorithm for the UAV (HSA)

**Input:** A mission queue $Q_M$, interest area $A$ and period $T$
**Output:** A shortest path

Decompose interest area $A$ hexagonally
**for** $i = 1 \rightarrow N$ **do**
  **if** $E_i - \delta_i \leq E_{min}$ **then**
    $Q_M \leftarrow i$
  **end if**
**end for**
**for** Each vacant region piece **do**
  Calculate center position of its circumcircle and add it into $Q_M$
**end for**
Form the shortest Hamiltonian path of $Q_M$
**for** Each position in the path **do**
  **if** Center of the next circumcircle changes **then**
    Replace next position with a new center and recompute the remaining path
  **end if**
**end for**
**return** A shortest path

Algorithm 1 proceeds as follows. After creating hexagonal structures in Section IV-A, we firstly add all requesting nodes into mission queue $Q_M$. Then, the circumcircle center of each vacant piece is calculated and appended into $Q_M$, through which we can form the shortest Hamiltonian path. To further adjust the mission path, we focus on overlapping regions among adjacent sensing positions. We replace the next position in current path with new circumcircle center and recompute the remaining path. Since the total serving time of the UAV is within period $T$ (see Equation (6)), Algorithm 1 can guarantee a feasible solution.

After hexagon-based scheduling, we can obtain the minimum moving energy $E_m^*$. Through combining it with sensing

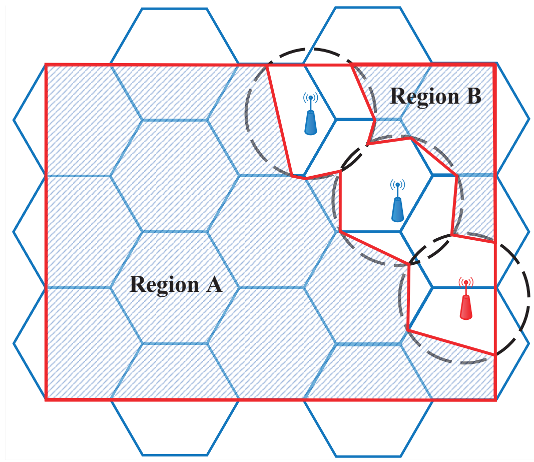


Fig. 3. Vacant regions repartitioned by hexagonal decomposition.

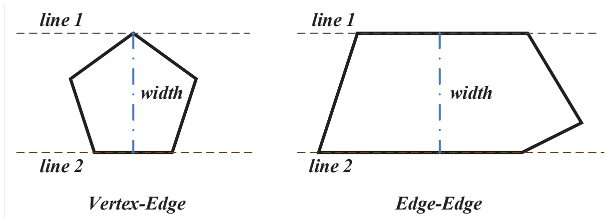


Fig. 4. A diagram of widths in Vertex-Edge and Edge-Edge parallel lines.

energy $E_s^*$, we can maximize energy efficiency in Case I (see Section III-C).

### C. Grid-based Scheduling

Scheduling for vacant pieces based on hexagonal decomposition can reduce moving energy for the UAV, however, a large number of pieces will increase the computational complexity. Thus, we propose a grid-based scheduling method to deal with such a problem.

Based on intersections of above sensing circles and hexagons, we can obtain a series of polygonal regions instead of previous vacant regions by merging every adjacent intersections of pieces in sensors' sensing circle (see Figure 3). For example, region $A$ and region $B$ are both polygons with larger areas than practical vacant regions. In each single region, we then apply a grid-based boustrophedon algorithm to schedule. Lastly, a start point and an end point are obtained in each region for further cross-regional scheduling.

To deal with each polygon, we utilize the characteristic of boustrophedon method. We then intend to cover the area with the least number of turns as UAVs' energy consumption are mainly spent on turning [27]. We hereby propose the concept of width of convex polygon for minimizing the number of turns, which is described below.

**Definition 2 (Convex Polygon Width).** *The width of a convex polygon is defined as the minimum distance between a pair of parallel lines of support, which only appears in the form of Vertex-Edge type or Edge-Edge type (see Figure 4).*

With the boustrophedon moving mechanism, turning of the UAV can be minimized by moving in the direction perpendicular to the width. Thus, we minimize the total width of a polygon (convex or concave) as below:

$$min \quad \sum_{k=1}^{m} W_k, \tag{11}$$

where each subregion $k$ is a convex polygon, $m$ denotes the number of subregions and $W_k$ represents the width of the $k$th subregion. Since decomposing a concave region into multiple convex polygons with the minimum width is NP-hard [28], we adopt a greedy method to form subregions for a complete polygon region. Then, we put these subregions together and calculate the shortest path from a start point to an end point for each region. At last, regions can be represented by groups of two linked points for easier computation.

The whole process of the grid-based boustrophedon algorithm is presented in Algorithm 2.

**Algorithm 2** Grid-based Boustrophedon Scheduling Algorithm (GBSA)

**Input:** Vacant regions, maximum sensing range $R_s$, mission queue $Q_M$ and period $T$
**Output:** A grid-based boustrophedon path

```
1:  Add charging mission of request sensors into Q_M
2:  Expand each vacant region into a polygon by hexagonal
    decomposition results
3:  for Each polygon P do
4:    while P is concave do
5:      Obtain the set of concave vertex S_V
6:      for Each i ∈ S_V do
7:        Form two polygons by drawing a line that passes
          i and parallels to an edge
8:      end for
9:      Select two polygons with the minimum sum of width
        and decompose them recursively
10:   end while
11:   Form a boustrophedon path with the maximum sensing
      range R_s of each subregion (convex polygon)
12:   Merge each subregion in P into the shortest path
13:   Obtain a start point P_a and an end point P_b
14:   Add the segment (P_a, P_b) into Q_M
15: end for
16: Schedule Q_M into the shortest Hamiltonian path within
    T
17: return A new mission path
```

Algorithm 2 proceeds as follows. At first, polygons are obtained by expanding vacant regions. Then, multiple convex subregions are produced by minimizing the sum of width. Afterwards, a boustrophedon path is applied with the maximum sensing range $R_s$ (Line 3-11). Then, the shortest path with a start point and an end point is gained by merging subregions and each polygon can be regarded as a segment (Line 12-13). Finally, a mission path will be returned, which is calculated from segments and requesting sensors.

To reduce the complexity of large-scale hexagon-based scheduling algorithm, we obtain a shortest boustrophedon path where $E_m^*$ is minimized after grid-based scheduling algorithm. Therefore, the problem of maximizing energy efficiency by minimizing moving energy and sensing energy is solved by our two proposed algorithms.

### D. Charging Re-allocation Mechanism

As mentioned in Case II (see Section III-C), when energy capacity $E$ of the UAV is insufficient for fully charging all requesting sensors under optimal values of $E_m^*$ and $E_s^*$ (*i.e.,* $E_c^{max}+E_m^*+E_s^* > E$), we will re-allocate charged energy for sensors. Thus, we propose a charging re-allocation mechanism to further enhance energy efficiency of the UAV.

Based on the minimum working energy $E_{min}$ of sensors, the minimum charging energy of the UAV is calculated as:

$$E_c^{min} = \frac{1}{\lambda}\sum_{i \in S}(E_{min} - E_i + \delta_i). \tag{12}$$

Here, we consider both current energy and energy consumption of each sensor during one period $T$ to give the lower bound of charging energy.

To maximize energy efficiency, we should take full advantage of charging energy of the UAV. Thus, we give a charging re-allocation mechanism to determine how much energy should be charged for each requesting sensor.

Algorithm 3 is described as below. We first try to charge all sensors in requesting set $S$ by applying minimum moving energy and sensing energy for the UAV. If energy utility $\mathcal{U}$ is smaller than $E$, each sensor can be fully charged. However, when the energy capacity is not sufficient for full charge, we should compute the maximum charging energy to achieve energy efficiency maximization. Moreover, minimum charged energy should always be satisfied to ensure operation of sensors (Line 5-6). To allocate charging energy for sensors, we consider both periodic energy consumption and maximum charged energy of requesting sensors. Sensors with a higher energy consumption $\delta_i$ will be allocated more energy. However, if a sensor is allocated much energy than its capacity, redundant energy will be re-allocated to sensors whose energy are not full (Line 11-13). The charging re-allocation process ends when charging energy is completely allocated.

**Algorithm 3** Charging Re-allocation Mechanism

**Input:** Current energy $E_i$, energy consumption $\delta_i$, and minimum working energy $E_{min}$ of requesting sensors, minimum moving energy $E_m^*$ and sensing energy $E_s^*$, requesting set $S$.

**Output:** Feasibility of charging re-allocated mechanism for requesting sensors.

1: Compute $E_c^{max} = \frac{1}{\lambda}\sum_{i \in S}(E_{max} - E_i + \delta_i)$ and $E_c^{min} = \frac{1}{\lambda}\sum_{i \in S}(E_{min} - E_i + \delta_i)$.
2: **if** $E_c^{max} + E_m^* + E_s^* \leq E$ **then**
3:     Fully charge for each requesting sensor in $S$.
4: **end if**
5: **if** $E_c^{min} + E_m^* + E_s^* > E$ **then**
6:     **return** false
7: **end if**
8: Compute charging energy to be allocated $E_c = E - E_m^* - E_s^*$.
9: Charge each sensor to $E_{min}$ and $E_c \leftarrow E_c - \frac{E_c^{min}}{\lambda}$.
10: **while** $E_c \neq 0$ **do**
11:     Allocate energy $\frac{\delta_i \lambda E_c}{\sum_{i \in S}\delta_i}$ to each sensor $i$ in $S$.
12:     **if** There exists sensor whose charged energy exceeds $E_{max}$ **then**
13:         Update $E_c$ by summing redundant energy and delete sensors with $E_{max}$ energy from $S$.
14:     **end if**
15: **end while**
16: **return** true

## V. Characteristic Analysis

In this section, we prove the NP-hardness of the energy efficiency maximization problem under PAC constraints and discuss the lower bound of hexagon-based scheduling method.

### A. NP-hardness Proof

To maximize the energy efficiency in Equation (2), we focus on minimizing the moving cost of the UAV (see Section III-C). Specially, if area $A$ can be fully covered by only sensors, the UAV can simply execute path scheduling among requesting sensors. This can be regarded as a traveling salesman problem (TSP) [29], which is NP-hard explicitly.

When vacant regions exist, they will be added into UAV's tour. For ease of simplicity, we take a single region as an example. To prove the NP-hardness, we utilize a simple decomposed grid graph to substitute for our network.

**Theorem 1.** The problem of maximizing energy efficiency of a UAV under PAC constraints is NP-hard.

**Proof.** We make use of the reduction from Hamiltonian Circuit in Planar Bipartite Graphs with Maximum Degree 3 Problem [30] to hamiltonian circuit in grid graphs.

Given a planar bipartite graph $G$ with $n$ vertices and a maximum degree of 3, we define a grid graph $G'$ with $m$ vertices where $m = O(n)$, such that $G'$ has the shortest path if and only if $G$ has the shortest one. Then we define a region $R$ which is formed by placing squares (whose edge length equals to maximum sensing range) at the vertices of $G'$.

Obviously, the existence of a tour with $m$ vertices in $G'$ implies the existence of a UAV tour of $m$. That means the region $R$ is partitioned into a non-overlapping path. Traveling through a path corresponds to traveling through the corresponding grid vertices. Therefore, a UAV tour with a length of $m$ indicates a tour with a length of at most $m$ in the grid graph. ■

### B. Approximation Analysis

To analyze the characteristic of energy efficiency of UAV, we concentrate on the sensing energy and moving energy that caused by hexagonal decomposition networks. We consider a unit square with edge length 1 as an interest area $A$, where a coverage rate $\epsilon$ $(0 < \epsilon < 1)$ is given for sensors. Thus, we can obtain a lower bound of hexagon-based scheduling algorithm below.

**Theorem 2.** The hexagon-based scheduling algorithm maximizes energy efficiency with a $(C_1 - (1-\epsilon)^{-1}C_2)^{\frac{1}{2}}$ approximation where $C_1 = \frac{2}{2-\sqrt{3}NR_s^2}$, and $C_2 = \frac{2\pi NR_s^2}{2-\sqrt{3}NR_s^2}$.

**Proof.** First, we calculate the approximate sensing area $\tilde{X}$ as:

$$\tilde{X} = 1 - \frac{\pi NR_s^2}{1-\epsilon}. \tag{13}$$

Here, $\tilde{X}$ represents the practical sensing area where overlaps exist with coverage rate $\epsilon$. While the optimal sensing area is calculated by area coverage with no overlaps, which is computed as:

$$X^* = 1 - \frac{\sqrt{3}NR_s^2}{2}. \quad (14)$$

Without loss of generality, sensing energy dissipation coefficient is denoted as $\alpha$ and the approximate total energy consumed by sensing can be represented by $\alpha\tilde{X}$. To further deal with the moving cost, a deterministic upper bound of the shortest path traversing $|Q_M|$ nodes is derived as $\sqrt{2(|Q_M|-2)\tilde{X}}$ [3] for a square sensing field with area $\tilde{X}$.

We formulate the optimal energy efficiency with only sensing missions as below:

$$\eta^* = \frac{\alpha X^*}{\alpha X^* + \sqrt{2(|Q_M|-2)X^*}}. \quad (15)$$

Hence, we have:

$$\begin{aligned}\frac{\tilde{\eta}}{\eta^*} &= \frac{\alpha\tilde{X}X^* + \tilde{X}\sqrt{2(|Q_M|-2)X^*}}{\alpha\tilde{X}X^* + X^*\sqrt{2(|Q_M|-2)\tilde{X}}} \\ &= \frac{\sqrt{2(|Q_M|-2)}X^{*-\frac{1}{2}} + \alpha}{\sqrt{2(|Q_M|-2)}\tilde{X}^{-\frac{1}{2}} + \alpha} \\ &> \frac{\sqrt{2(|Q_M|-2)}X^{*-\frac{1}{2}}}{\sqrt{2(|Q_M|-2)}\tilde{X}^{-\frac{1}{2}}} \\ &= \sqrt{\frac{\tilde{X}}{X^*}}.\end{aligned} \quad (16)$$

Combine Equation (13) and Equation (14), a lower bound of energy efficiency is obtained as:

$$\tilde{\eta} > (C_1 - (1-\epsilon)^{-1}C_2)^{\frac{1}{2}}\eta^*, \quad (17)$$

where $C_1$ and $C_2$ are constants. $C_1 = \frac{2}{2-\sqrt{3}NR_s^2}$ and $C_2 = \frac{2\pi NR_s^2}{2-\sqrt{3}NR_s^2}$. ■

Through analyzing the approximation ratio of hexagon-based scheduling algorithm, we can bound the optimal energy efficiency according to Equation (17).

## VI. Test-bed Experiments

To demonstrate the effectiveness of the proposed schemes and feasibility for agricultural applications, a test-bed experiment imitating an agricultural monitoring application (*i.e.,* monitoring crop growth) is conducted [31].

In the experiment, five camera sensors (Type OV7670) built with Powercast by RF charging (P2110 Powerharvester Receiver converts RF into DC power) and a UAV equipped with a camera (Type MT9V034) and a TX91501 transmitter (sending out RF signals on 915MHz) are deployed to collect image data, as shown in Figure 5.

We enclose a $10m \times 10m$ area region and deploy five fixed camera sensors for static monitoring. Then, a UAV is employed as a supplemental mobile camera sensor. Besides, we construct a traveling tour for the UAV based on hexagon-based structure (see Figure 6).

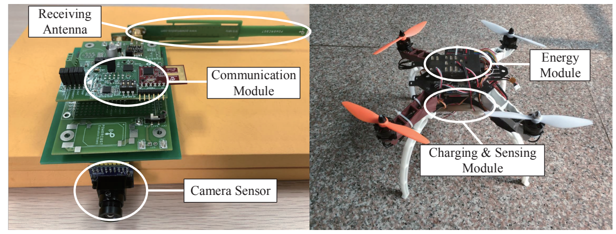


Fig. 5. A diagram of practical rechargeable sensors and a UAV.

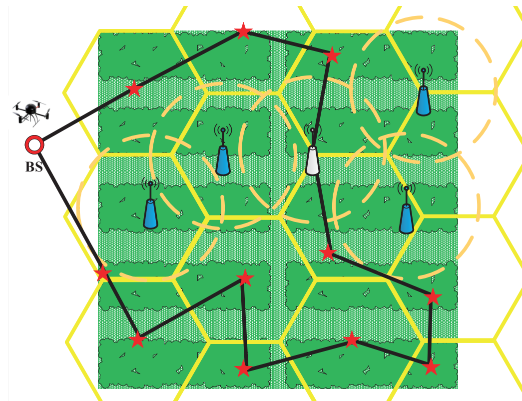


Fig. 6. A scheduling path in an interest area with grasses and shrubs.

The flying height of the UAV is determined by both charging distance and resolution requirement. Thus, we give the maximum height of the UAV as:

$$h_{max} = max\{R_C, \frac{I}{2R_d tan(\frac{\theta}{2})}\}, \quad (18)$$

where $R_C$ denotes the effective charging radius, and $R_d$ represents the required spatial resolution. Image resolution is denoted as $I$ and $\theta$ is the angle of view (AOV) which is defined as the angular extent imaged by the camera.

We compare the energy efficiency of the UAV obtained by two algorithms with the theoretical optimal results and verify the correctness of the approximate ratio given in Section V-B. As shown in Figure 7, we set diverse data collecting periods $1h - 6h$ to observe the energy efficiency in each line. We have $\epsilon = 0.1$ by measuring coverage area of sensors and calculate a 0.987 approximate ratio of hexagon-based scheduling algorithm (HSA) in Equation (17) which is verified by our test-bed experiments perfectly. Besides, GBSA can reach 94.4% energy efficiency compared to the optimal value. This is because HSA and GBSA are both based on hexagonal decomposition where HSA has a shortest path among sensors and vacant regions, GBSA forms a boustrophedon path to reduce complexity.

## VII. Simulation Analysis

In this section, large-scale simulations are conducted to evaluate the performance of the proposed schemes.

### A. Simulation Setup

As listed in Table I, $50 - 100$ sensors are deployed in a $100m \times 100m$ square area. A UAV responsible for sensing and charging missions is employed. The energy capacity of a sensor and the UAV is $2KJ$ and $50 - 100KJ$, respectively.


Fig. 7. Comparison of HSA, GBSA, and optimal value of energy efficiency in test-bed experiments.

Sensors consume $200J/h - 300J/h$ energy per hour for network operation and the minimum working energy for sensors is $100J - 150J$. The working period of the UAV is 10 hours, within which data collecting and energy replenishing missions are accomplished. When traveling, its speed ranges from $3m/s$ to $8m/s$.

As no previous works have ever focused on serving WRSNs with PAC constraints, we select two classic distance-based methods as baselines: MST [14] and NJNP [15]. In MST, the shortest line between sensors and vacant regions is primarily selected in each iteration. In NJNP, a mission with the closest spatial distance will be served firstly.

TABLE I
SIMULATION SETUP

| Parameters | Values |
|---|---|
| Network area | $100m \times 100m$ |
| Number of nodes | $50 - 100$ |
| Energy consumption rate of nodes | $200J/h - 300J/h$ |
| Velocity of the UAV | $3m/s - 8m/s$ |
| Energy capacity of nodes | $2KJ$ |
| Energy capacity of the UAV | $50KJ - 100KJ$ |
| Minimum working energy of nodes | $100J - 150J$ |
| Data collecting period | $10h$ |
| Scheduling scheme | HSA, GBSA, MST, NJNP |

### B. Performance Comparison

In this part, we first compare two proposed scheduling algorithms under different data collecting periods. Then, we compare our algorithms with MST and NJNP in terms of number of sensors, minimum working energy of sensors, energy capacity of the UAV, and moving velocity of the UAV.

*1) HSA vs. GBSA:* At first, energy efficiency of the UAV and charging time for sensors are compared in Figure 8. In Figure 8(a), energy efficiency in hexagon-based scheduling algorithm is near $98\%$ and always stays higher than that of grid-based scheduling algorithm, which indicates that hexagon-based scheduling algorithm matches the objective better.

With respect to charging time, it decreases gradually as time goes. The reason is that, more requesting sensors will emerge, leading to more moving time (see Figure 8(b)). Statistically, the charging time in hexagon-based scheduling is about $60\%$ higher than the other, resulting from the shorter path it derives.

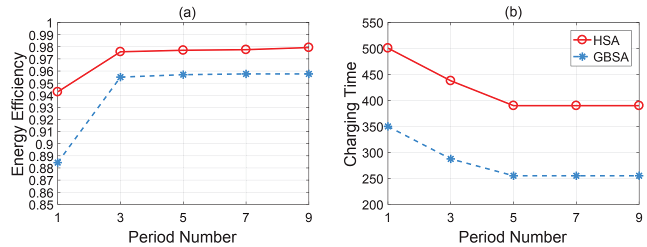


Fig. 8. Performance comparison between HSA and GBSA in energy efficiency, and charging time.

*2) Impact of Sensor Number:* We set the number of sensors in our network from 50 to 100 as shown in Figure 10. All algorithms have a rising trend as the number of sensors increases and our algorithms (*i.e.,* HSA and GBSA) have the highest energy efficiency than others. Moreover, the efficiency increases slowly as the number of sensors rises, and the reason is that, more requesting sensors need more charged energy than moving energy of the UAV, which causes a slow rise.

*3) Impact of Minimum Working Energy of Sensors:* As shown in Figure 11, our algorithms outperform MST and NJNP at least $18.2\%$ and $30.2\%$, respectively. The energy efficiency increases as $E_{min}$ rises in all four lines. This is because when the minimum working energy of sensors is high, more sensors will be added into requesting set and the total charged energy for sensors will increase. Hence, the energy efficiency is promoted eventually.

*4) Impact of Energy Capacity of the UAV:* As shown in Figure 12, four algorithms increase and gradually become stable as the energy capacity of the UAV ranges from $50KJ$ to $100KJ$. HSA outperforms NJNP at most $26.6\%$ when $E = 70KJ$. The reason is that, HSA forms the shortest Hamiltonian cycle based on requesting sensors and vacant regions, which leads to the least moving energy which thus maximizes energy efficiency. However, NJNP only selects the nearest sensor or vacant region to serve locally, which causes great moving cost.

*5) Impact of Moving Velocity of the UAV:* The moving velocity of the UAV directly influences the value of period $T$ (see Equation (6)), which ensures all requesting sensors can be charged at least $E_{min}$ energy for keeping operational. As shown in Figure 13, the minimum period in four algorithms decreases as the moving velocity of the UAV rises from $3m/s$ to $8m/s$. This is because when the UAV moves fast, the traveling time will be shortened and servicing time will be reduced. We set the moving velocity of the UAV as $5m/s$ and the minimum periods in four algorithms are smaller than $10h$, obviously.

## VIII. CONCLUSIONS

In this paper, we developed a new concept of period-area coverage problem (PAC) in WRSNs and proposed two heuristical scheduling algorithms to maximize energy efficiency with UAVs. We proved an approximate ratio of the hexagon-based scheduling method and then introduced a grid-based boustrophedon method to reduce scheduling complexity by scheduling fewer missions. Moreover, a charging re-allocation mechanism

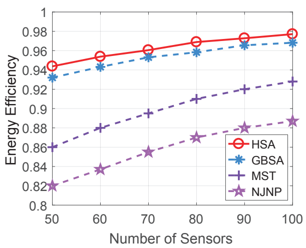


Fig. 10. Energy efficiency vs. Number of sensors

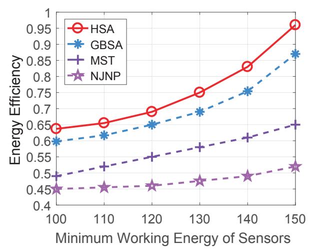


Fig. 11. Energy efficiency vs. Minimum working energy of sensors

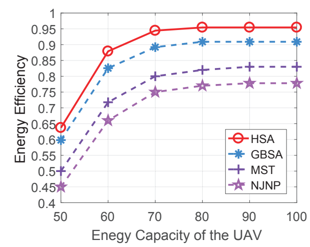


Fig. 12. Energy efficiency vs. Energy capacity of the UAV

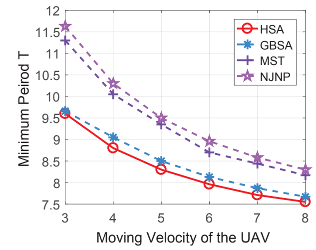


Fig. 13. Minimum Period $T$ vs. Moving velocity of the UAV

was designed for further promoting energy efficiency. Through theoretical analysis, test-bed experiments, and simulations, we demonstrated that our scheme can effectively maximize energy efficiency and achieve a promising period-area coverage with UAVs for WRSNs.

In the future work, we will focus on exploring real-time scheduling methods to solve such coverage problem.

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