Joint Energy Replenishment and Operation Scheduling in Wireless Rechargeable Sensor Networks

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***Abstract*—Wireless charging is a promising way to solve the energy constraint problem in sensor networks. While extensive efforts have been made to improve the performance of charging and communication in wireless rechargeable sensor networks (WRSNs), little has been done to address the operation scheduling problem. To fill this void, we propose a joint energy replenishment and scheduling mechanism so as to maximize the network lifetime while making strict sensing guarantees in the WRSN. We first formulate the problem in a general 2D space and prove its NP-Completeness. We then devise an *f*-approximate scheduling mechanism by transforming the classical minimum set cover problem, and develop an optimal energy-replenish strategy based on the energy consumption of nodes returned by the scheduling mechanism. Large-scale simulation results validate our design and show a 39.2% improvement of network lifetime over a baseline method.**

***Keywords*-Rechargeable sensor networks, mobile charger, energy replenishment, scheduling, coverage**

I. INTRODUCTION

Along with the development of wireless energy transfer technology, wireless rechargeable sensor networks (WRSNs) have drawn considerable attention from researchers over the past few years. By exploiting wireless charging techniques, sensor nodes in a WRSN can be replenished by chargers to reduce disposable battery use and extend the operational life of each sensor node. Compared to solar and wind energy harvesting systems, wireless charging offers controllable and predictable energy replenishment for sensor networks. In most application scenarios, mobile chargers carried by autonomous vehicles are considered for recharging already deployed sensors [1]–[5] for the reasons of cost-efficiency and flexibility in dealing with network topology changes. A mobile charger can also be combined with a mobile base station for energy-efficient routing [6] and data gathering [7]–[9].

Like traditional wireless sensor networks (WSNs), rechargeable sensor nodes are deployed to sense environments for various purposes. In most WSN applications including target tracking [10], [11], intrusion detection [12] and environmental monitoring [13], [14], Point of Interest (PoI) or Area of Interest (AoI) needs to be covered to guarantee the quality of sensing. Due to redundant deployment and limited energy supply of nodes, WSNs are duty-cycled to prolong their lifetime. Specifically, duty cycling entails nodes to alternate between sleep and wakeup. When a node sleeps, it turns off most functional components including sensing and communication, which are the most energy-consuming operations.

Operation scheduling of sensor nodes in a WSN while considering the sensing coverage has been studied extensively [10], [15]–[18]. Most of existing work considers a fixed amount of energy aiming to minimize the total energy consumption. However, in a WRSN, sensor operation scheduling becomes more sophisticated since each node's energy balance does not monotonically decrease due to the energy replenishment by charger(s). In traditional sensor networks, network lifetime with a coverage guarantee is subject to *critical* nodes located in the essential sensing area with few nearby neighbors, thus keeping themselves alive for a longer period of time and draining their energy faster than others. However, in a WRSN, the energy of these nodes can be replenished by a charger, thus making them no longer the "bottleneck" nodes. A key problem is, therefore, to design the active/sleep schedule for nodes, and charge them in an energy-balanced manner.

We address the above problem by developing a joint energy replenishment and operation scheduling mechanism that maximizes the network lifetime while providing strict sensing guarantees. Specifically, given the charging capacity of a charger, we want to find the best strategy of operation scheduling and energy partitioning. This way, we mitigate the gap between the heterogeneous energy consumption among nodes and the unbalanced initial energy via energy replenishment, and therefore increase the total energy utility and extend the network lifetime.

This paper makes the following three main contributions.

- To the best of our knowledge, this is the first attempt to maximize the network lifetime by designing joint operation scheduling and energy replenishment in a WRSN. Using both theoretical analysis and extensive simulations, we demonstrate the advantages of this mechanism.
- We formulate the energy replenishment and scheduling (ERS) problem in a general two-dimensional (2D) space with N rechargeable sensor nodes and a mobile charger with given charging capacity. The problem is proved to be NP-Complete, and a heuristic solution with provable sub-optimality (i.e., the ratio of what our solutions achieved to the optimal result) is developed by solving a linear

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packing problem.
- We evaluate the proposed algorithms using extensive simulation and study the impact of multiple environmental factors including the initial energy balances of nodes, the distribution and density of nodes, and the mobile charger's capacity. Several insights are provided, shedding some light on potential improvement.

The rest of the paper is organized as follows. Section II describes the system model and formulates the ERS problem. Section III proves the NP-Completeness of ERS and describes the design of joint energy replenishment and scheduling. Section IV evaluates the performance of the proposed solutions while Section VI discusses related work. Section VII concludes the paper.

II. PROBLEM FORMULATION

We present system models and formulate the Energy Replenishment and Scheduling (ERS) problem in this section.

A. Network Model

We consider a WRSN consisting a set S of N rechargeable nodes deployed in a 2D area. Each node $i \in S$ is able to sense events of interest within its sensing range R_i. For example, nodes equipped with vision or ultrasound sensors detect intrusions within a certain range in the field, and nodes deployed in a warehouse environment can track objects and manage inventory. Similar to [12], we assume that the sensing ranges of nodes are open discs centered at nodes with a unique radius, and the union of sensing ranges of all nodes subsumes the region, Ar, needs to be monitored, or *monitoring area*. A set SC of sensor nodes, of which the union of their sensing ranges covers the monitoring area is called a *sensor cover*. Figure 1 illustrates an example of sensor deployment, coupled with the monitoring area. There are four different sensor covers in Figure 1, namely $SC_1 = \{1, 2, 4\}, SC_2 = \{1, 2, 5\}, SC_3 = \{2, 3, 4\}, SC_4 = \{2, 3, 5\}$.

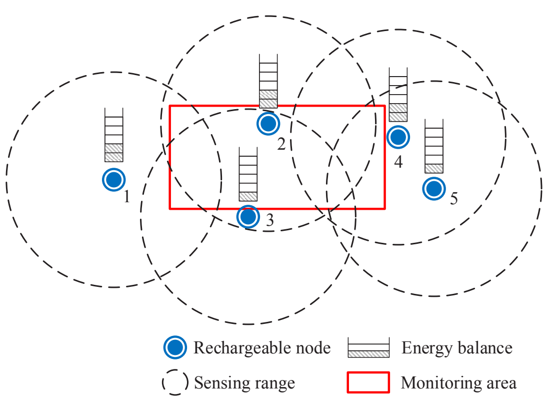


Figure 1. An example of sensor deployment

We assume that positions of nodes are known via some form of WRSN localization techniques, e.g., [19]. Since the main focus of this paper is on environmental sensing and sensors charging, we assume the nodes' communication ranges to be much larger than the sensing ranges.

B. Energy Consumption and Replenishment

Let the initial nodes' energy balances be $E_i^0, i \in \{1, \ldots, N\}$. The operation duration of the WRSN is divided into time slots. To reduce energy consumption, sensor nodes alternate between active and sleep modes. When sensor node i is active, events occurred within R_i could be successfully discovered. Without loss of generality, we can assume the energy consumption during one active time slot is 1. Taking Figure 1 as an example, the initial energy balance of node 1 is 2 (i.e., $E_1^0 = 2$), which allows the node to be active in sensing for 2 time slots.

In order to guarantee the quality of sensing, in this paper, we consider the general scenario that the monitoring area needs to be fully covered, and define the *network lifetime* as follows.

Definition 2.1: (**The network lifetime**). The network lifetime T is the time interval between the first time when the monitoring area is fully covered until the first time when a coverage hole appears.

To replenish energy, a mobile charger with given charging capacity E^c travels through the network to charge sensor nodes wirelessly in its vicinity. While still in the early stage of development and commercial acceptance, wireless charging technology along with the incessant emergence of related products have made industry and research communities optimistic about WRSNs. For example, early this year, Toshiba [20] launched a new wireless charging chip which enables a 5 Watts maximum output power with a 95% maximum power conversion efficiency. Compared to direct-contact charging, wireless charging offers higher availability and simplifies the charging interface which makes it suitable for large-scale sensor networks. Typically, the charger is carried by an autonomous vehicle/robot moving around to charge nodes in operational scenarios, such as warehouse inventory management [21] and structural health monitoring [22]. Even when sensor nodes are deployed in the field, the energy of sensor nodes can be replenish using unmanned aerial vehicles like drones. In this paper, we only focus on the optimization of energy replenish and operation scheduling during one single charging period since the charger may not always be able to get recharged once after it completes the task (e.g., when it is in the field). If the charger travels periodically to replenish nodes, we need to update the initial energy balances of nodes at the beginning of each round. Since sensor networks are able to continuously operate for months/years after charging them fully [23], [24], we assume the charging and moving delay of the charger to be sufficiently small to ignore.

The symbols and notations used in this paper are summarized in Table I.

C. Problem Statement

We formulate the ERS problem as follows:

Definition 2.2: (ERS Problem). Given the monitoring area Ar, a set S of N sensor nodes with initial energy balances $E_i^0, i \in \{1, \ldots, N\}$ and a mobile charger with charging capacity E^c, we want to find the energy partitioning strategy of the charger (i.e., divide E^c and determine the amount of replenished energy at each node $E_i^c, i \in \{1, \ldots, N\}$) and

Table I
NOTATION DEFINITION

Symbol	Meaning
N	Number of nodes
Ar	Monitoring area
SC_i	Sensor cover i
R_i	Sensing range of node i
E_i^0	Initial energy balance of node i
E^c	Charging capacity of the charger
E_i^c	Replenished energy of node i
T	Network lifetime

activation patterns of nodes so as to maximize the network lifetime T.

According to Definition 2.2, we aim to jointly control behaviors of both the charger and sensor nodes to maximize the network lifetime while providing coverage guarantees. On one hand, we activate different sets of nodes during different periods of time to balance the network energy consumption and keep sensing the entire monitoring area. On the other hand, nodes should be charged with distinct amounts of energy in an energy balanced manner. For example, more energy should be replenished to those critical nodes (i.e., those near the data sink) which will drain their limited energy faster.

Table II
ONE FEASIBLE SOLUTION OF FIGURE 1

Node	Activation pattern			Energy balance	
	$1st$ slot	$2nd$ slot	$3rd$ slot	Initial	Charged
1	ON	ON	OFF	2	0
2	ON	ON	ON	2	1
3	OFF	OFF	ON	1	0
4	ON	ON	OFF	2	0
5	OFF	OFF	ON	1	0

Again, let's consider the scenario shown in Figure 1 where all four sensor covers contain Node 2. Considering a simple case where $E_1^0 = 2, E_2^0 = 2, E_3^0 = 1, E_4^0 = 2, E_5^0 = 1$ and $E^c = 1$, it is easy to find that the optimal solution of the ERS problem is to replenish the only 1 unit energy to Node 2 with the corresponding maximized network lifetime $T = 3$. One feasible solution is shown in Table II.

III. ALGORITHM DESIGN

We first prove the NP-Completeness of the ERS problem and then design an algorithm with provable suboptimality.

A. NP-Complete Proof

We first define the decision version of the ERS problem and then prove it is NP-Complete.

Definition 3.1: Decision version of the ERS problem: Given initial energy balance $E_i^0, i \in \{1, \ldots, N\}$ and charging capacity E^C, does there exist an energy-allocation strategy with the corresponding activation patterns of nodes such that the network lifetime is longer than T?

Theorem 3.1: The ERS problem is NP-Complete.

Proof: We first prove ERS is an NP problem. Given a specific energy-allocation strategy and E_i^0, we get the total amount of energy of each node. According to Theorem 1 in [12], the sensor set SC is a sensor cover if and only if it covers every intersection point of sensing borders of nodes located inside the monitoring area. Therefore, we can enumerate all intersection points IP and build a matrix D_{ij} which specifies whether the intersection point IP_i is covered by node j in $O(n^3)$ time. Then, given a family of set covers $SC_1, \ldots, SC_k$ which covers all intersection points and the corresponding working duration $t_1, \ldots, t_k$, we can verify in polynomial time whether (1) the energy consumption of each node is feasible and (2) $t_1 + \ldots + t_k \le T$.

To prove further that the ERS problem is NP-hard, we reduce a known NP-hard problem, the Maximum Set Cover (MSC) problem [13], to ERS in polynomial time.

Definition 3.2: Maximum Set Cover (MSC) Problem: Given a collection $C = \{S_i\}$ of subsets of a finite set R, find a family of set covers $S_1, \ldots, S_p \in C$ with weights $t_1, \ldots, t_p \in [0, 1]$ such that, to maximize $\sum_{i=1}^{p} t_i$ and for each element s in C, s appears in $S_1, \ldots, S_p$ with a total weight of at most 1.

Let the initial energy balance $E_i^0 = 1, i \in \{1, \ldots, N\}$ and charging capacity $E^C = 0$, then the ERS problem contains a known NP-hard problem, namely the MSC problem, as a special case. That is, there is an implicit reduction, from each instance of the MSC problem to itself, relabeling it as an instance of the unrestricted ERS problem. As the ERS problem is also in NP, it is NP-complete. ■

Since the coverage of limited intersection points of sensing borders of nodes located inside the monitoring area guarantees full coverage of the entire monitoring area, we will henceforth focus on the design of joint sensor scheduling and energy replenishment with the point coverage constraint. Specifically, we enumerate the intersection point sets IP and build the matrix D_{ij} before proceeding with algorithm design.

Next we describe the algorithms to solve the ERS problem. The basic idea is to seek and replenish more energy to the energy-critical nodes. In the first step, we devise a sensor scheduling mechanism by only considering the initial energy balance and then proceed to calculate the optimal charging energy of each node. This way, we decouple the original problem and achieve a provable performance guarantee.

B. Sensor Scheduling

At the beginning of design, we transform the original ERS problem to a linear programming (LP). Mathematically, if we can enumerate all sensor covers $SC = \{sc_1, \ldots, sc_{n_c}\}$ where n_c is the number of sensor covers, then the ERS problem can be cast to the following linear programming problem:

$$
\begin{aligned}
Maximize \quad & \sum_{j=1}^{n_c} t_j \\
s.t. \quad & \sum_{j=1}^{n_c} C_{ij} t_j \le E_i^0 + E_i^c \qquad (1)\\
& \sum_{i=1}^{N} E_i^c \le E^C
\end{aligned}
$$

In Eq. (1), C_{ij} is an $N \times n_c$ matrix where binary number $c_{ij} = 1$ means that node i is active in sensor cover sc_j. Two constraints lie in this problem. The first guarantees that the total energy consumption of each node should be no more than the summation of the initial energy balance and charged energy while the second one means the total amount of the replenished energy of all nodes should be no more than the capacity of the charger.[1]

In order to find energy-critical nodes and provide guidelines for energy replenishment, we take into account the initial energy of nodes and propose the sensor scheduling algorithm. Letting $E_i^c = 0$, we find that the ERS problem is a packing LP. However, C_{ij} cannot be directly obtained as the number of sensor covers grows exponentially with the number of sensors. To deal with this problem, we adopt the Garg-Könemann algorithm [25] which is originally proposed to solve multicommodity flows and fractional packing problems. The Garg-Könemann algorithm guarantees that a packing LP of this kind

$$\begin{aligned} &Maximize \ \{c^T x | Ax \leq b, x \geq 0\} \\ &\qquad A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^{m \times 1}, c \in \mathbb{R}^{n \times 1} \end{aligned} \tag{2}$$

is implicitly given by b and column j of A whose length

$$l_y(j) = \sum_i \frac{A(i,j)y(i)}{c(j)} \tag{3}$$

is minimum, where y is the dual variable of the original packing LP.

Instead of enumerating all sensor covers to build C_{ij}, we only have to find the minimum length column $a(y) = \min_j l_y(j)$. Further, if we let the weight of each column of C_{ij} (i.e., a sensor cover) be proportional to $y(i)$ in Eq. (3) (e.g., $w(i) = y(i)$), to find the minimum length column is the same as finding the minimum weight set cover of the original problem. Detailed Garg-Könemann algorithm with f-approximate minimum weight set cover is presented in Algorithm 1. In Section III-C, based on the energy consumption of nodes returned by the scheduling mechanism, we propose the optimal energy replenish strategy.

In Algorithm 1, given the initial energy balances of nodes, we first initialize parameters δ, D, the dual variable y and weight w. Since $D := {E^0}^T y$, in line 7 we have $D = N\delta$. In the main loop, we first find the sensor cover with minimum weight through the f-approximate algorithm F and then calculate p which is the index of the row with the minimum $\frac{b(p)}{C_j(p)}$. We then iteratively update y, w and D. Algorithm 1 terminates when $D \geq 1$ and outputs a set of $k, k \leq n_c$ column $\{C_j\}$ each supplied with the corresponding working duration $t_j = \frac{t_j}{\log_{1+\epsilon} \frac{1+\epsilon}{\delta}}$. Thus, the network lifetime $T_0 = \sum t_j$, which is approximated within a factor of $(1+\epsilon)f$, for any $\epsilon > 0$. Detailed proof of the suboptimality of the Garg-Könemann algorithm can be found in [16].

We devise the f-approximate algorithm F based on the classical minimum set cover algorithm. Algorithm 2 repeatedly

[1] More generally, we can multiply a vector of diverse energy consumption rates of nodes by C_{ij} to relax the assumption of uniform energy consumption in Section II-B.

Algorithm 1 *Garg-Könemann algorithm*

1: **Input**: Initial energy balance vector $E^0 \in \mathbb{R}^{N \times 1}$, a fixed parameter ϵ and an f-approximate algorithm F for the problem of finding the minimum weight set cover
2: $\delta = (1+\epsilon)((1+\epsilon)N)^{-1/\epsilon}$
3: **for** $i = 1$; $i \leq N$; $i++$ **do**
4: $\quad y(i) = \frac{\delta}{E_i^0}$
5: $\quad w(i) = y(i)$
6: **end for**
7: $D = N\delta$
8: $j = 1$
9: **while** $D < 1$ **do**
10: $\quad$ Find the minimum weight set cover C_j using the f-approximate algorithm F
11: $\quad p = \arg\min_p \frac{E_p^0}{C_j(p)}$
12: $\quad t_j = \frac{E_p^0}{C_j(p)}$
13: $\quad j = j + 1$
14: $\quad$ **for** $i = 1$; $i \leq N$; $i++$ **do**
15: $\quad\quad y(i) = y(i)(1 + \epsilon C_j(i) t_j / E_i^0)$
16: $\quad\quad w(i) = y(i)$
17: $\quad\quad D = {E^0}^T y$
18: $\quad$ **end for**
19: **end while**
20: $t_j = \frac{t_j}{\log_{1+\epsilon} \frac{1+\epsilon}{\delta}}$
21: **return** $\{C_j, t_j\}$

chooses a set defined by D_j that minimizes the weight w_i divided by the number of elements in the set but not covered by chosen sets. It terminates and returns the chosen sets $\mathcal{C}$ when they form a sensor cover. Let H_k denote $\sum_{i=1}^{k} \frac{1}{i}$, where k is the largest set size, then it is easy to prove that the weight of the resultant sensor cover is at most H_k times the minimum weight of any sensor cover. Therefore, using Algorithm1, the network lifetime T_0 can be approximated within a factor of $\rho_0 = (1+\epsilon)(1 + 2\ln N)$, for any $\epsilon > 0$.

Algorithm 2 *f-approximate algorithm F*

Input: IP, $D_{ij} \in \mathbb{R}^{N \times |IP|}$ and $w \in \mathbb{R}^{1 \times N}$
$U = IP$
$\mathcal{C} = \emptyset$
while $U \neq \emptyset$ **do**
$\quad$ Select D_j that minimize $\frac{\sum_i \{w_i | D_{ij} = 1\}}{\{i | D_{ij} = 1\} \cap U}$
$\quad U = U - \{i | D_{ij} = 1\}$
$\quad \mathcal{C} = \mathcal{C} \cup \{i | D_{ij} = 1\}$
end while
return $\mathcal{C}$

C. Optimal Energy Replenishment

So far, we proposed a sub-optimal sensor scheduling mechanism considering the initial energy of all nodes. With a given amount of energy E^0 and locations of nodes, Algorithm 1 calculates sets of sensor cover C_j with the corresponding working duration t_j. In addition, the total energy consumption of each node obtained through Algorithm 1 serves as a good indicator of energy-criticality. Specifically, nodes with plenty of energy and whose sensing area is covered less by other nodes will be scheduled to sense for a longer period of time, thus having a higher energy demand.

Let b^c be the vector of energy consumption of nodes and b^r be he vector of remaining energy of nodes when $t = \sum t_j$, respectively, then the optimization problem of energy replenishment can be written as

$$\begin{aligned} Maximize \quad & \min_i \frac{E_i^c + b_i^r}{b_i^c} \\ s.t. \quad & \sum_{i=1}^{N} E_i^c \leq E^C \\ & E_i^c \geq 0, \forall i \in \{1, \ldots, N\}. \end{aligned} \tag{4}$$

In Eq. (4), we need to calculate the amount of energy replenishment $E_i^c, i \in \{1, \ldots, N\}$ of each node based on the energy consumption ratio returned by Algorithm 1. To solve this optimization problem, we add an additional variable $e = \min_i \frac{E_i^c + b_i^r}{b_i^c}$ and rewrite Eq. (4) as

$$\begin{aligned} Maximize \quad & e \\ s.t. \quad & \frac{E_i^c + b_i^r}{b_i^c} \geq e, \forall i \in \{1, \ldots, N\} \\ & \sum_{i=1}^{N} E_i^c \leq E^C \\ & E_i^c \geq 0, \forall i \in \{1, \ldots, N\} \end{aligned} \tag{5}$$

Hence, Eq. (4) can be expressed in canonical form as

$$\begin{aligned} Maximize \quad & c^T X \\ s.t. \quad & AX \leq b \\ & X \geq 0 \end{aligned} \tag{6}$$

where the vector of variables $X = [E_1^c, \ldots, E_N^c, e]^T$, vectors of coefficients $c = [0, 0, \ldots, 0, 1]^T$ and $b = [\frac{b_1^r}{b_1^c}, \ldots, \frac{b_N^r}{b_N^c}, E^C]^T$ are $(N+1) \times 1$ vectors and the matrix of coefficients

$$A = \begin{pmatrix} -\frac{1}{b_1^c} & 0 & \ldots & 0 & 1 \\ 0 & -\frac{1}{b_2^c} & \ldots & 0 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \ldots & -\frac{1}{b_N^c} & 1 \\ 1 & 1 & \ldots & 1 & 0 \end{pmatrix} \in \mathbb{R}^{(N+1)^2} \tag{7}$$

Since c, b, A are known vectors, the optimal strategy of energy distribution E^c can be directly obtained with the corresponding network lifetime $T = (e+1)T_0$.

Theorem 3.2: The calculated network lifetime can be approximated within a factor of $\rho_1 = \frac{\rho_0 \sum_i E_i^0}{|\mathcal{C}| \min_i E_i^0}$, where $|\mathcal{C}|$ is the minimum set size of a sensor cover.

Proof: Let the optimal network lifetime with/without energy replenishment be T_0^* and T^*, respectively. Considering the fact that all available energy is evenly distributed among the sensor cover with minimum set size, the upper-bound of the network lifetime can be obtained as:

$$T^* \leq \frac{\sum_i E_i^0 + E^C}{|\mathcal{C}|}. \tag{8}$$

According to the energy replenishment algorithm,

$$\begin{aligned} T &= (e+1)T_0 \geq (\frac{E^C}{\sum b^c} + 1)T_0 \\ &\geq (\frac{E^C}{\sum_i E_i^0} + 1)T_0 \geq \frac{\sum_i E_i^0 + E^C}{\sum_i E_i^0} \frac{T_0^*}{\rho_0} \end{aligned} \tag{9}$$

Therefore, combining Eqs. (8) and 9, we have

$$\begin{aligned} \rho_1 = \frac{T^*}{T} &\leq \frac{\sum_i E_i^0 + E^C}{|\mathcal{C}|} / \frac{(\sum_i E_i^0 + E^C)T_0^*}{\rho_0 \sum_i E_i^0} \\ &= \frac{\rho_0 \sum_i E_i^0}{|\mathcal{C}| T_0^*} \leq \frac{\rho_0 \sum_i E_i^0}{|\mathcal{C}| \min_i E_i^0} \end{aligned} \tag{10}$$

■

Theorem 3.2 proves that the suboptimality of the algorithm of the ERS problem is relevant to both network topology and the initial energy balances of nodes. Particularly, if $E_i^0 = E_j^0, i \neq j \in \{1, \ldots, N\}$, ρ_1 can be further simplified as $\rho_1 = \frac{\rho_0 N}{|\mathcal{C}|}$.

IV. EVALUATION

We evaluate algorithm performance via large-scale simulations. We first describe simulation settings and then compare the performance of the proposed algorithm with a baseline method in Section IV-B. In Section IV-C, we provide the simulation results under different network densities. In Sections IV-D and IV-E, we also study the impact of various charging capacities and initial energy levels of nodes.

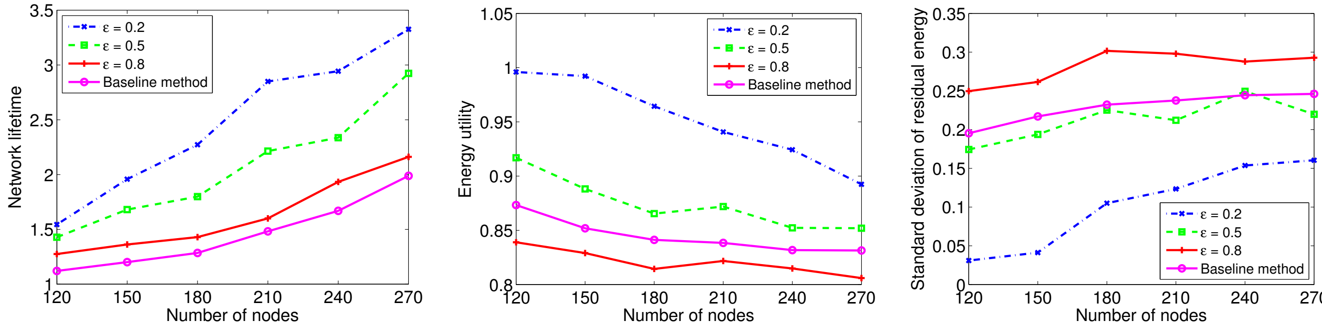
A. Simulation Settings

In all simulations, we use uniform distribution of nodes with at least one sensor cover. The initial energy of nodes is randomly generated that follows the uniform distribution between 0 and 2. The charging capacity of the charger is set to the total amount of the initial energy of all nodes. Default simulation parameters are listed in Table III.

Table III
DEFAULT SIMULATION PARAMETERS

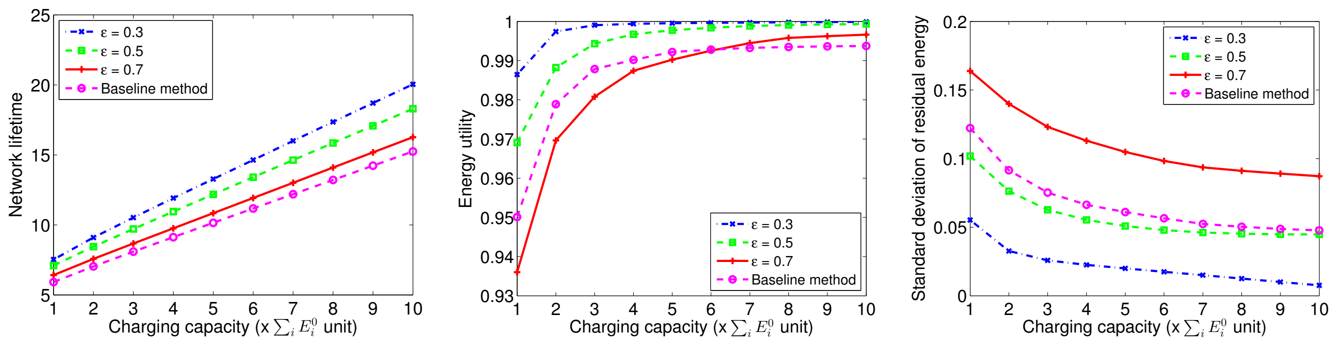
Parameters	Description
Field Area	1000×1000 (Grid Unit)
Node Distribution	Uniform Distribution
Number of Nodes	$N = 500$
Sensing Range of Each Node	100
Initial Energy Level of Nodes	$E_i^0 \in U[0, 2]$ (Unit), $\forall i \in [1, N]$
Charging Capacity	$\sum_i E_i^0$
Random Seed	100 runs

We adopt the *network lifetime* and the *energy utility* as two metrics to evaluate the performance of the proposed joint energy replenishment and operation scheduling. The network lifetime is the time interval between the first full cover of the monitoring area and the first occurrence of a coverage hole (as defined in Definition 2.1), and the energy utility is the ratio of the total energy consumption to the overall amount of available energy in the network (i.e., summation of the initial energy and the capacity of the charger). The energy utility not only indicates energy-efficiency but also reflects the



(a) Network lifetime (b) Energy utility (c) Standard deviation of residual energy

Figure 2. Performance with different numbers of nodes



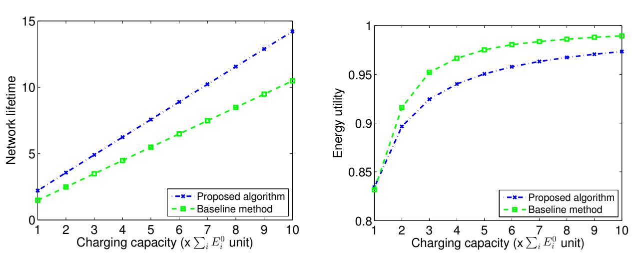
(a) Network lifetime (b) Energy utility (c) Standard deviation of residual energy

Figure 3. Performance with different charging capacities

energy provisioning performance in terms of the adaptability to diverse network settings. In addition, we calculate the standard deviation of residual energy of nodes (when a coverage hole occurs) to demonstrate the network's energy balance.

B. Baseline Comparison

Since at present there is no algorithm available for joint energy provisioning and operation scheduling, we introduce a greedy algorithm as the baseline for comparison. Specifically, we charge all nodes in the network to the same energy level and adopt the suboptimal sensor scheduling algorithm proposed in [12].



(a) Network lifetime (b) Energy utility

Figure 4. Comparison with the baseline method

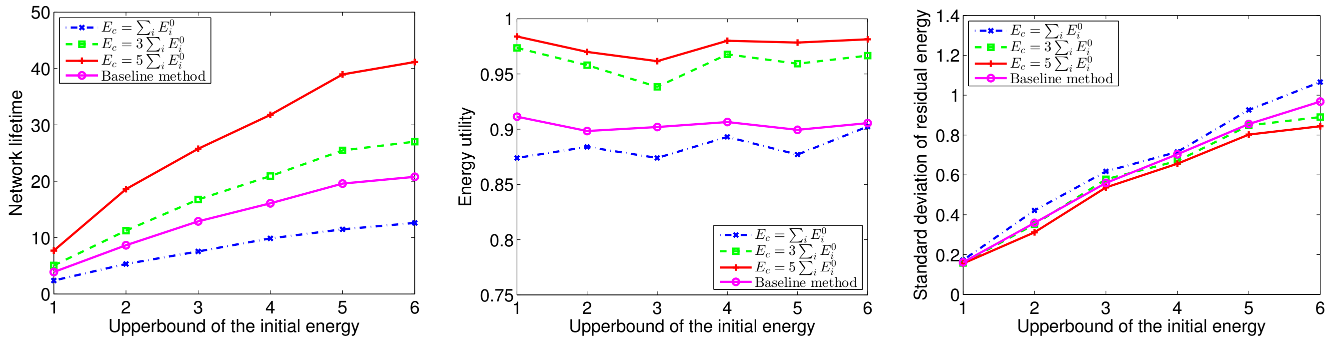
Figure 4 shows that the proposed joint energy replenishment and operation scheduling algorithm outperforms the baseline method in both network lifetime and energy utility. For example, the average gain in the network lifetime by the proposed algorithm is 39.2%, demonstrating the effectiveness of our algorithm. In what follows, we will further examine the network performance under different systems settings.

C. Performance with Different Numbers of Nodes

We evaluate the network lifetime while varying the number of nodes. Figure 2(a) shows that the network lifetime increases as the number of nodes grows. For example, the network lifetime is prolonged by 90.67% (2.944 vs. 1.544) when the number of nodes grows from 120 to 240 with $\epsilon = 0.2$. This is because the number of sensor covers grows when the sensor deployment becomes denser. In such a case, more nodes with plenty of energy can replace the nodes with insufficient energy to cover the monitoring area, thus prolonging the network lifetime. On the contrary, the energy utility in Figure 2(b) decreases with the increasing density of the network since the total amount of remaining energy on all nodes increases. This can be verified further in Figure 2(c), where the standard deviation of residual energy grows with a rising number of nodes. In all three figures, a smaller ϵ leads to a better performance, validating the theoretical analysis. Particularly, in all scenarios, the network lifetime of the proposed algorithm is longer than the baseline result.

D. Impact of Charging Capacities

As one of the key system parameters, the charger's capacity has a great influence on the network performance. Figure 3(a)



(a) Network lifetime (b) Energy utility (c) Standard deviation of residual energy

Figure 5. Performance with different initial energy levels

shows the network lifetime with charging capacities ranging from $E_c = \sum_i E_i^0$ to $E_c = 10\sum_i E_i^0$. We can tell from the figure that the network lifetime grows linearly with increasing charging capacity. Take the case of $\epsilon = 0.5$ as an example to find that the network lifetime grows from 12.2 to 18.3 when the charging capacity is doubled from $5\sum_i E_i^0$ to $10\sum_i E_i^0$.

From Figure 3(b), we can see that the energy utility grows with rising charging capacity. The mobile charger is shown to make most of the initial energy balance and "distribute" energy across the network intelligently. The larger charging capacity, the better balanced the energy distribution is. As a result, in Figure 3(c), the standard deviation of residual energy at the end of the life of the network becomes smaller when E_c gets larger. In addition, since the sensor scheduling mechanism is approximated by the factor of $1 + \epsilon$, our algorithm with a smaller ϵ achieves a better performance in terms of the energy utility and the standard deviation of residual energy. Like in Figure 2, the proposed algorithm outperforms the baseline algorithm in terms of the network lifetime.

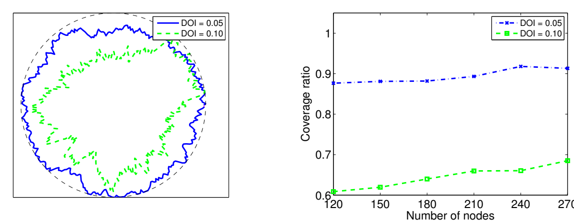
E. Impact of Initial Energy Levels

We also study the impact of nodes' initial energy levels. Specifically, we consider uniformly distributed initial energy levels with different upper-bounds, and plot the network performance while varying the charging capacity.

Like in Figure 3(a), the network lifetime grows in Figure 5(a) as the upper-bound of the initial energy or the charging capacity increases, simply owing to the fact that the total amount of the network's energy becomes greater. However, the energy utility remains relatively stable even in case of varying amounts of initial energy. For example, when $E_c = \sum_i E_i^0$, the fluctuation of energy utility is less than 1.6% (0.89 ± 0.014) in Figure 5(b). This is because the charging capacity enhanced with the initial energy compensates the unbalanced energy during provisioning. Since the range of the nodes' initial energy levels becomes larger, the standard deviation of residual energy increases in Figure 5(c).

V. Discussion

In Section II, we assumed the sensing ranges of nodes are open discs. Since this assumption may not always hold in real sensor deployments, we have evaluated the effects of non-isotropic sensing ranges as shown in Figure 6. Note that how to design robust algorithms to minimize such effects is orthogonal to what we addressed in this paper, hence leaving it as our future work.



(a) DOI (b) Coverage ratio

Figure 6. Impact of non-isotropic sensing range

To study the impact of non-isotropic sensing ranges, Degree Of Irregularity (DOI) model in [26] is used as an example (as shown in Figure 6(a)). Figure 6(b) shows imperfect sensor coverage with different DOIs. This figure shows that coverage ratios in two cases are below 1, meaning that sensor covers cannot guarantee full coverage of the monitoring area when DOI$\neq 0$. However, the average actual coverage ratio among all sensor covers increases with the number of nodes. This is because the monitoring area is more likely to be covered when the node density becomes higher.

VI. Related Work

To put our work in a comparative perspective, we discuss work related to sensor scheduling and energy replenishment.

Early work studied the sensor scheduling problem for the purpose of sensors deployment [27], communication collision avoidance [28] and network lifetime maximization with coverage guarantees [12], [13], [15], [16]. Cardei *et al.* [13] proved that the maximum set cover problem with given targets is NP-Complete by reducing it to 3-SAT. They then provided two heuristics using both Integer Programming and relaxation techniques in Linear Programming. To maximize the network lifetime, Berman *et al.* [16] first gave a provably good algorithm with performance ratio $1 + \ln n$, where n is the number of sensor nodes. To design a schedule with full coverage of an area, Kasbekar *et al.* [12] proposed the intersection point concept which transforms the area coverage problem to a point coverage problem and provided a distributed algorithm with an approximation factor $O(\ln n)$. More recently, Ding *et al.* [15] presented a polynomial-time constant-approximation algorithm to solve the maximum lifetime coverage problem based on the idea of Prime-Dual-Method. Algorithms proposed in this paper rely on the results of this work, which nevertheless focused on fixed amount of initial energy without considering energy replenishment.

Efforts have been made to solve the energy replenishment problem in WRSNs, but they focus on different scenarios under certain assumptions. A real deployment of WRSN monitoring temperature and humidity in a zoo was demonstrated in [29] using the Wireless Power Platform from FireFly Power Technologies. He *et al.* [30] studied how to deploy static chargers so that static or mobile rechargeable tags may receive sufficient power to keep their continuous operation. [31] studies the network utility maximization problem in static-routing rechargeable sensor networks with link and battery capacity constraints. Fu *et al.* [32] planned an optimal movement strategy of the charger, such that the time to charge all nodes' onboard energy storages above a threshold is minimized. Shi *et al.* [33] investigated the problem of periodically charging sensors inside the network to maximize the ratio of charger's vacation time to a cycle. A joint routing and charging scheme was proposed in [6]. However, it maximizes network lifetime through an energy-efficient routing protocol design, whereas our work aims to guarantee the sensing performance of the network. Dai *et al.* [34] proposed a near-optimal charging and scheduling scheme for stochastic event capture. They assumed a mobile charger to travel periodically with a fixed traveling period in order to maximize the quality of monitoring of stochastic events, which are also *identifiable*. However, in this paper, we focus on the maximization of network lifetime with a given capacity of the charger.

VII. Conclusion

In this paper, we have made the first attempt to formulate and solve the problem of jointly replenishing energy and designing operation scheduling in a wireless rechargeable sensor network. We first proved this problem to be NP-complete, and then developed a suboptimal algorithm with provable suboptimality. To verify our design, we performed an indepth evaluation of its performance via large-scale simulations, demonstrating an average of 39.2% improvement of network lifetime over the baseline method.

Despite the significant improvement of network lifetime with the proposed design, there are several practical issues and limitations that are worth further investigation. For example, the assumption of isotropic sensing ranges and exactly known locations of nodes may not always hold. Joint design of energy replenishing and operation scheduling with multiple mobile chargers is also an interesting subject to explore.

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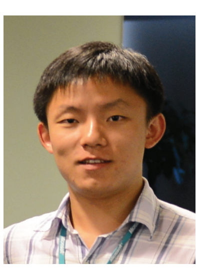

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