A Novel UAV Charging Scheme for Minimizing Coverage Breach in Rechargeable Sensor Networks

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Abstract. In wireless rechargeable sensor networks, one of the most important issues is how and when to recharge the sensor nodes. Existing studies show that not all of the sensors can be properly recharged in time due to the limitation of solar or wind-based charging technologies. As a result, some sensors will be interrupted and cannot function well due to exhaustion of their energy. A recent promising technology is the use of wireless energy transfer technology together with UAV-based wireless charger, which has the opportunity of powering sensors with manageable yet perpetual energy. In this paper, considering not only the remaining energy of the sensors but also the coverage rate of the scenario, we propose a complete coverage and energy knowledge partial charging scheme (Co-EPaCS) to find and plan a charging schedule for the UAV charger in order to minimize the total network coverage breach. Simulation results show that the proposed scheme significantly outperform other methods in terms of coverage rate, energy consumption of all nodes and network lifetime.

Keywords: Wireless rechargeable sensor networks · Wireless energy transfer · Uav-based wireless charger · Coverage

1 Introduction

Wireless sensor networks (WSNs) have been widely deployed to support diverse applications, such as environment monitoring, military surveillance [2,11,23]. Traditional sensor networks usually assume to deploy numerous small nodes each powered by an on-board battery with limited capacity. With such configurations, how to maximize network lifetime yet guaranteeing application requirements, like coverage quality and data transmission rate, has become a critical issue in sensor networks, as well as sensor activity scheduling and energy efficient routing [4,12,20].

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Recently, some have proposed to use rechargeable nodes each equipped with a chargeable battery to sustain a very long, or even perpetual operational time for sensor networks [3]. Many energy replenishment techniques can be used to charge a node by harvesting energy from environmental sources, like sun, wind, etc. [10,14]. However, the cost of equipping each node with such an energy harvesting unit, e.g., a solar panel or windmill, may be too prohibitive. Also energy harvesting may be too dependent on unpredictable environmental conditions, which may degrade single node battery performance. In addition, in order to avoid disasters like collapsed bridges in different countries [19] and bush fires in Australia [18], wireless sensor nodes should be deployed on the bridge to monitor the health of the bridge and to detect early fire in forest. These nodes may have little or no access to the ambient source, which may cause constant interruption of power supply.

Another approach for charging rechargeable nodes is to use the wireless power transfer (WPT) technology [24], where a charger with sufficient energy to get close enough to each individual node and transfer power wirelessly. The wireless power transfer method makes the charging process easy since no complicated mechanical mechanism is required to operate the sensor node. In the literature, many have studied how to use a wheeled mobile charger to charge nodes. Although the mobile charger is assumed to have large energy capacity, its movement also consumes energy. Hence, a key research issue is how to plan a charging route to efficiently charge as many as possible the mostly needed nodes in each single charging tour.

Several charging schemes have been proposed to design efficient charging tours [6,9,13,17,21,22]. For example, He et al. [6] proposed a greedy charging scheme, named Nearest-Job Next with preemption (NJNP), which always selects the nearest requesting node to be charged by the mobile charger first. Analytical results on the number of charging requests served and the charging latency of each sensor node are provided. However, their solution cannot be guaranteed that all of the to-be charged sensors could be charged prior to their energy depletion time. Wang et al. [17] considered a practical model where mobile chargers have limited capacity and their movements consume energy. Their aim is to maximize the recharge profit, the recharged energy less the traveling cost. In addition, the authors also considered the sensor's alive time to avoid node failure before the mobile charger can recharge it. Two algorithms are proposed suitable to the context of the problem. Considering both the traveling time of the mobile charger and the charging time for a node, Ren et al. [13] designed a novel charging scheme. The authors assumed that when charging a node, the node should be fully recharged to its battery capacity. Efficient sensor charging algorithms are proposed so as to charge as many nodes as possible in a given time span. Shih and Yang [22] combined the charging issue with the network coverage quality. Besides using the residual energy for node selection, they also took into account network coverage to prioritize those coverage-critical nodes for the next charging tour. In these schemes, they assume that when charging a node, the node should be fully recharged to its battery capacity. Wu et al. [21] argued that it may not be necessary to fully charge a node each time. Instead, they proposed a partial charging scheme to minimize the depletion of each node by charging a single node with an amount of energy to its some energy level.

Since Unmanned Aerial Vehicle (UAV) can move with required speed to cover sensors distributed in a large-scale area that is even inaccessible to human, some have proposed to use UAV instead of wheeled mobile charger to charge nodes [1,9]. The UAV-based wireless power transfer is able to maintain the wireless sensor network as a long-term monitoring system by regularly charge these sensor nodes. UAV charger has better performance and competence due to its fast-moving speed to charge sensor nodes, but similar to the wheeled mobile charger, the key issue of designing a UAV charging tour is to select which nodes to be charged and how to charge them. Johnson et al. [9] studied the use of a UAV as a WPT charger and proposed a single node should be charged to its full battery capacity in each flight. The UAV also needs to recharge its own energy. Previous works redirect the UAV back to the base station which is connected to the power grid [1]. However, such infrastructure could be unavailable in ad-hoc applications such as pollution, forest, bridge monitoring. To this end, a solar energy harvesting base station is required so it can charge the UAV when its energy is depleted. As a result, the network will no longer rely on electricity from the power grid.

In our work, we also study the UAV charging problem. Compared with the previous studies, we consider a scenario where in a remote harsh environment. A base station that uses a large solar panel to harvest energy for charging the UAV which is then responsible for charging sensor nodes is builded. This is motivated from the fact that many sensor networks are deployed in desolated areas without accessing power grids. Although theoretically a rechargeable sensor node will never die as long as it can be recharged in time, it would temporarily loss its functionality if it has depleted its energy while not yet been recharged. As such, network operational quality such as area coverage could be much degraded due to those temporary powered-off nodes.

Some past research only considered the residual energy of the sensor nodes as the only clue to recharge sensors. However, it is obvious that only considering the residual energy of sensors is not enough to avoid the occurrences of coverage holes in the network. In this paper, considering both the residual energy and coverage degree of sensors, we design a complete coverage and energy knowledge partial charging scheme (Co-EPaCS) to find and plan a charging schedule for the UAV so as to minimize network coverage breach. In our work, the network coverage breach is avoided by deploying more nodes equipped with rechargeable batteries. The coverage breach is temporary and it can be self-recovered after the nodes are recharged. We assume that all nodes can work continuously, then a discrete time model is adopt in which the continuous timeline is divided into consecutive slots each with equal length. For each slot, all sensors are in active state and at the beginning of each slot we choose active sensors with remaining energy less than a given threshold to become a candidate. A charging tour plan is then given according to the candidate's priority.

The rest of the paper is organized as follows. Section 2 outlines the problem description to help understand the approach of this paper. Section 3 introduces the proposed charging scheme. Section 4 evaluates the performance of the proposed algorithms and shows the simulation results and Sect. 5 concludes the paper.

2 Problem Description

2.1 Network Model and Assumptions

We consider a sensor network consists of rechargeable nodes that are all randomly deployed in a 2D rectangular field. The set of rechargeable sensors are assumed to be static and homogenous and is denoted by $V_s = \{s_i\}, i = 1, 2, 3, ...n$. Here s_i means a sensor node. Moreover, we consider that each sensor s_i is equipped with Global Positioning System (GPS) and each sensor can communicate with other sensors if the distance between these two sensors is less than a sensor's communication range R_c. A binary coverage model is assumed where the region covered by a sensor node is a disk with radius R_s. Here R_s is the sensing radius of s_i. In other words, each grid point can be considered as covered by s_i with a probability 1 if it is within the sensing radius of s_i and with a probability 0 (uncovered) when it is beyond s_i's sensing range [7,16].

Under such assumptions, the location and energy level of each sensor s_i can be known before the UAV starts its charging task from the base station v_{bs}. Figure 1 illustrates a sample of this work's network model.

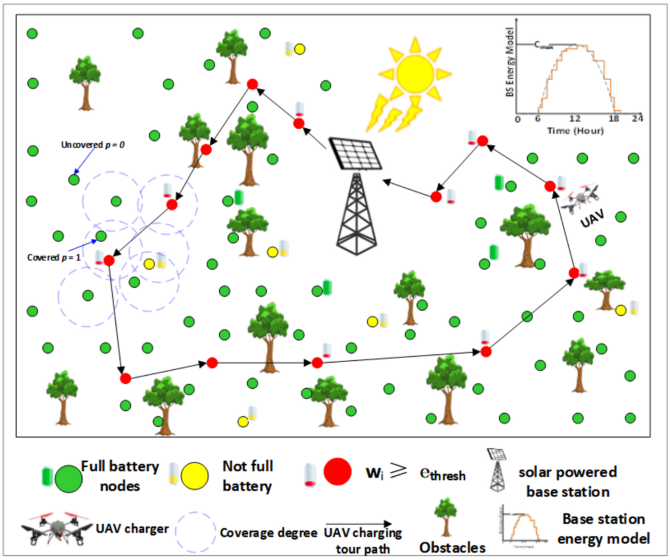


Fig. 1. Network model of the work.

In Fig. 1, we can see that the sensors are randomly deployed in a rectangular field located in a remote area, a single UAV charger UAV_c is employed to perform the charging task to the sensor nodes. The UAV's power source is from a solar powered base station located in the field. The arrow depicts the charging path of the UAV, which starts from the base station v_{bs} and must return back to v_{bs}. The sensors' energy level are differentiated in three colors. The green color represents full battery, the yellow color represents not full battery and the red color represents a sensor node's battery is less than or equal to a pre-defined energy threshold. It means these nodes need to be charged immediately before they exhaust their energy. When performing a charging tour task, the UAV will start flying from v_{bs} and must return back to v_{bs} after finishing its charging tour task to recharge itself or rest for the next charging tour. Each sensor node s_i is powered by a rechargeable battery of limited energy, and it consumes energy when performing sensing, data processing, data transmissions and receptions. The UAV_c flies at a constant speed v within the deployment field and replenishes the energy supply to a sensor s_i with a fixed charging rate r. The UAV_c energy consumption while flying is e_f, while hovering is e_h and while transferring energy to a sensor s_i is e_t during a charging tour. The total energy consumption of the UAV_c for traveling and charging should not exceed its battery capacity E_{UAV}, as shown in (1), where t_{charging} is the charging time.

$$(t \times e_f) + (t \times e_h) + ((r \times e_t) \times t_{\text{charging}}) < E_{\text{UAV}} \tag{1}$$

We adopt an approximate one-day energy charging model for the base station [8], which uses a quadratic curve to model the solar energy harvested in the daytime, while in the night, the harvested energy is zero.

2.2 Partial Recharging Model

Let B_i denote the total battery capacity of a sensor s_i and E_i denotes the amount of energy of a sensor s_i before charging, to partially charge s_i, we use a unit charging strategy. We use $\triangle_i$ to denote an amount of energy needed to be replenished to s_i at each charging tour. Thus, the amount of energy needed to charge to a sensor s_i to its full capacity is $\triangle_i = B_i - E_i$. In our work, we assume that the energy charge to s_i at each time is a value in $\{\frac{\triangle_i}{2}, \frac{\triangle_i}{3} ..., \frac{\triangle_i}{k}\}$ where k is an integer. The minimum amount of energy charged per charging tour is $\triangle_{\min} = \min\{\triangle_i\}$. We also assume that the UAV can charge each sensor node with a fixed number of charging times no more than K per tour, where K is the number of possible charging to a sensor s_i per tour and it is a given non-negative constant integer. Since the UAV has limited energy capacity, it is hard to cover too much sensor nodes in a single flight tour. As a result, a sensor can only be charged once in a charging tour. Therefore, we set $K = 1$. Moreover, we adopt a discrete time model where the total time of each tour T, is divided into consecutive slots $\tau_q, q = 1, 2, ...$ each with equal length.

2.3 Problem Definition

To define the problem clearly, we us an undirected metric graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ to represent the rechargeable sensor network. Here vertex set $\mathcal{V} = \{s_i, v_{\text{bs}}\}$. Elements in $\mathcal{V}$ are connected through edges in $\mathcal{E}$, which are possible UAV flight paths. The UAV is able to travel along edges and stop at some nodes to charge them. Given a set of to-be-charged sensors V_c, we let $TOUR \triangleq P((v_{\text{bs}}, 0) \rightarrow (s_1, e_1) \rightarrow (s_2, e_2) \rightarrow ... \rightarrow (s_j, e_j) ... \rightarrow (v_{\text{bs}}, 0))$ be the charging tour for the UAV charger UAV_c. Here $s_j \in V_c$, e_j is the amount of energy charged to sensor s_j. The total energy consumed by UAV_c cannot exceed its energy capacity E_{UAV}, in addition, the total amount of energy being charged to a node s_i by UAV_c per tour should not be greater than its energy demand $B_i - E_i$. Let $Z_j = 1$ if a target TAG_j in the region can be covered by at least one sensor, $Z_j = 0$ otherwise, the total time coverage breach occurs during a slot τ_q can be defined as $\sum_j t_j(1 - Z_j)$. Here t_j is the duration TAG_j can not be covered by at least one sensor.

The problem is to find a charging tour $TOUR$ for UAV_c to charge the nodes in V_c from the network $\mathcal{G}$ so that the network coverage breach is minimized. Since the value of the total coverage breach is related to the total time, we can use breach rate instead as the coverage performance criteria. The problem can be formulated as follows.

$$\mathcal{G} \Rightarrow \{V_c, TOUR\} \Big|_{\arg\min \sum_q \frac{\sum_j t_j(1-Z_j)}{\tau_q}} \tag{2}$$

3 Complete Coverage and Energy Knowledge Partial Charging Scheme (Co-EPaCS)

In this section, we will explain how the complete coverage and energy knowledge partial charging scheme (Co-EPaCS) works. There are two steps in our scheme, the first one is to find a subset of sensors to charge and to decide when to start a charging tour, the second one is to plan a charging tour for the UAV and recharging of sensors.

3.1 Finding a Subset of Sensors to Charge and Deciding When to Start a Charging Tour

The first stage of Co-EPaCS is to find a subset of sensors V_c to charge and to decide when to launch a charging tour for the UAV. In our work, once V_c is found, the base station v_{bs} will not receive any charging requests from other sensors in V_s before the UAV finishes its current charging task. Choosing an appropriate time to begin the charging tour depicts a design challenge that can significantly affects the solution performance in terms of energy consumption, thus we designed a pre-defined energy threshold, denoted by e_{thresh} that triggers the launching time of a charging tour. The pseudo-codes for the first step of Co-EPaCS are given in Algorithm 1. In line 1, the weights, denoted by w_i which combines both remaining energy E_i and coverage sets CS_i for each sensor s_i, aiming to avoid or delay existence of a coverage hole, is calculated. The design of the weights w_i is shown in (3). T_i^{CS} denotes the total number of cover sets for a sensor s_i. It means when a sensor s_i is about to exhaust its energy, its sensing range can be covered by T_i^{CS} sets of sensors. Apparently, the larger T_i^{CS} is, the less possibility coverage breach occurs.

Algorithm 1 Finding a subset of sensors to charge and deciding when to start a charging tour

Require:
Sensor nodes V_s, cover sets CS_i, sensor residual energy E_i, sensor battery capacity B_i, charging rate r, sensor energy consumption rate θ.

Ensure:
Subset of sensors to charge V_c and energy threshold e_{thresh}

1: $w_i \leftarrow \left\lfloor \frac{(B_i - E_i)+(r \times e_t)}{B_i} \right\rfloor \times \frac{1}{T_i^{\mathrm{CS}}+1}$
2: $l_w \leftarrow w_i$
3: $l_u \leftarrow \emptyset$
4: **for** $i \leftarrow 1$ to length $(l_w) - 1$ **do**
5:     $e_{\mathrm{thresh}} \leftarrow \left\lfloor \frac{(B_i - \theta)+(r \times e_t)}{B_i} \right\rfloor \times \frac{1}{\lfloor AVG_C \rfloor}$
6:     **if** $l_w \geq e_{\mathrm{thresh}}$ **then**
7:         $l_u \leftarrow s_i + i^{\mathrm{th}}$ node in l_w
8:         UAV start to charge all the sensor nodes in l_u
9:     **else**
10:         $l_u \leftarrow \emptyset$
11:         UAV start to charge all the sensor nodes in l_w
12:     **end if**
13: **end for**
14: **return** V_c
15: **return** e_{thresh}

$$w_i = \left\lfloor \frac{(B_i - E_i) + (r \times e_t)}{B_i} \right\rfloor \times \frac{1}{T_i^{\mathrm{CS}} + 1} \tag{3}$$

In line 2, the calculated weights w_i in (3) are sorted in a list denoted by l_w accordingly. An empty list of urgent nodes denoted by l_u is shown in line 3. Here, the urgent nodes are defined as the nodes that exceeds the energy threshold e_{thresh} and its energy battery will exhaust very soon. In line 5, the energy threshold e_{thresh} is calculated according to (4) which is derived from (3). Here θ is the energy consumption of a sensor s_i.

$$e_{\mathrm{thresh}} = \left\lfloor \frac{(B_i - \theta) + (r \times e_t)}{B_i} \right\rfloor \times \frac{1}{\lfloor AVG_C \rfloor} \tag{4}$$

We use $\lfloor AVG_C \rfloor$ as the average number of cover sets for all the sensors. When a senor s_i's total number of cover sets T_i^{CS} is smaller than $\lfloor AVG_C \rfloor$, this sensor is likely to be considered have a coverage hole. As shown in line 6 to 13, if a sensor s_i's weight w_i in the weights list l_w is greater than the pre-defined energy threshold e_{thresh}, s_i will be added to the urgent nodes list l_u, the UAV will begin its charging tour and start to charge all the sensors V_c in l_u immediately, else it will start to charge all the sensors V_s in l_w.

3.2 Planning UAV Charging Tour and Charging the Sensors

The second step of Co-EPaCS is planning a charging tour for the UAV and charging the sensors, as shown in Algorithm 2. Here we use a *for loop* to compute which sensors should be charged, how much energy UAV_c needs to fly to the sensors, recharge them and fly back to the base station v_{bs} without exceeding its battery capacity E_{UAV}. Assuming a subset of sensors V_c in the urgent list l_u is computed according to Algorithm 1, if UAV_c's current energy level $\triangle E_{\mathrm{UAV}}$ is greater than a pre-defined minimum energy level $\triangle E_{\mathrm{UAV\,min}}$, UAV_c will first calculate how much energy it will consume to fly to the sensors in V_c to recharge them and then fly back to the base station v_{bs} before starting the charging tour. For each sensor s_i in V_c, the distance between UAV_c and s_i is computed, denoted as $dist_i$. For the most urgent sensor s_d that needs charging, if $dist_d$ is less than the distance UAV_c's remaining energy can take, which denoted as $dist_{\triangle E_{\mathrm{UAV}}}$, UAV_c will immediately fly to s_d and perform the charging task. If $dist_d \geq dist_{\triangle E_{\mathrm{UAV}}}$, we need to find another sensor from V_c where UAV_c's remaining energy can reach, then UAV_c will fly to this sensor to recharge it. Note that once UAV_c flies to a new destination sensor, its coordinate will be updated. However, if there is no sensor where UAV_c's remaining energy can reach, UAV_c will fly back to v_{bs} to recharge itself. As shown in line 25 to 34, if the current weight w_i of a sensor to be charged in the urgent list l_u is greater than the pre-defined energy threshold e_{thresh}, that sensor will exhaust its energy soon and needs to be charged immediately. The amount of energy e_j to be charged to those sensors is $\lfloor \frac{B_i - E_i}{2} \rfloor$. The UAV will start its tour from sensor s_i with the highest weights w_i in the urgent nodes list l_u then flies to the sensor s_i with the second highest weight, and so forth else if the urgent list l_u is empty, the UAV_c charges the sensors in the weights list l_w in the same order else it flies back to the base station. Although this path planning is not the most energy-efficient, it ensures that the sensor who will exhaust its energy soon will be charged first to avoid coverage hole and prolongs the lifetime of the sensor network.

4 Performance Evaluation

4.1 Parameter Settings

We consider a sensor network consisting of 240 sensor nodes randomly deployed within a $1,000\,\mathrm{m} \times 1,000\,\mathrm{m}^2$ area. The sensing range R_s of a node is 121 m. The UAV and the base station are both co-located in the center of the field. The base station's solar energy maximum charging rate $C_{\max}$ is set to $0.1 - 0.6$. The energy capacity of the UAV is $E_{\mathrm{UAV}} = 300\,\mathrm{kJ}$. The battery (NiMH battery 1.2 V/2.5 Ah) capacity of each sensor $s_i \in V_s$ is $B_i = 10.8\,\mathrm{kJ}$ [15]. The residual energy of each sensors are generated in the range of 20%–60% of 10.8 kJ. The UAV_c travels at a constant speed of $v = 7.33\,\mathrm{m/s}$. The energy consumption rate for flying is

$e_f = 121.9\,\text{W}$, for hovering is $e_h = 92.28\,\text{W}$ and for energy transferring is $e_t = 20\,\text{W}$. The charging rate r is 0.2. The energy consumption rate θ of each sensor s_i is 1.625 mW. A node is Urgent when its energy level reaches threshold $e_{\text{thresh}} = 0.1$. The energy charging efficient rate of the UAV to a sensor is 4 J/s.

Algorithm 2 Planning UAV Charging Tour and Charging of Sensors

Require:
UAV charger UAV_c, base station v_{bs}, UAV total battery capacity E_{UAV}, UAV current energy $\triangle E_{\text{UAV}}$, distance the UAV can take $dist_{\text{GoBack}}$, destination distance $dist_d$, UAV velocity v, UAV Traveling Time t.

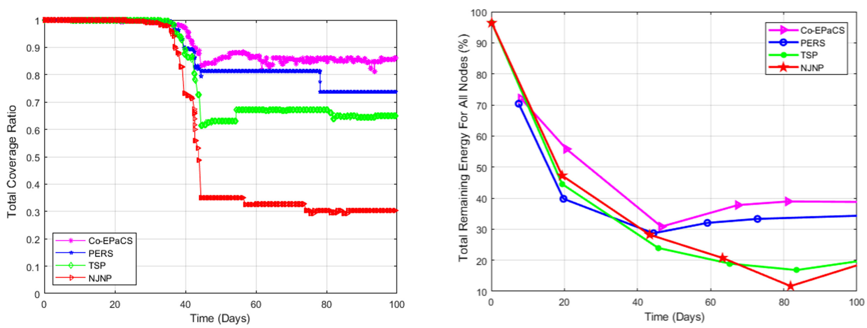
Ensure:
A charging tour $TOUR$ for the UAV_c so that in every charging tour an amount of energy e_j is charged to the sensors and the traveling length of the UAV_c is not greater than its total battery capacity E_{UAV}.

$V_c \leftarrow l_u$
for $i \leftarrow 1$ to length $|V_c|$ **do**
  $dist_{\text{GoBack}} \leftarrow \sqrt{(v_{\text{bs}}(Y) - UAV_c(Y))^2 + (v_{\text{bs}}(X) - UAV_c(X))^2}$
  $\triangle E_{\text{UAV}} \leftarrow E_{\text{UAV}} - (dist_{\text{GoBack}}/v \times e_f) + (t \times e_h) + (r \times e_t)$
  $dist_d \leftarrow \sqrt{(s_d(Y) - UAV_c(Y))^2 + (s_d(X) - UAV_c(X))^2}$
  if $\triangle E_{\text{UAV}} > \triangle E_{\text{UAV}\min}$ **then**
    if $dist_d < dist_{\text{UAV}}$ **then**
      choose s_d as destination
      $UAV_c(X) \leftarrow s_d(X),\ UAV_c(Y) \leftarrow s_d(Y)$
      $\triangle E_{\text{UAV}} \leftarrow \triangle E_{\text{UAV}} - dist_d/v \times e_f$
      UAV charges the sensor
    else
      if $\exists s_{d'} \in V_c,\ dist_{d'} < dist_{\text{UAV}}$ **then**
        choose $s_{d'}$ as destination
        $UAV_c(X) \leftarrow s_{d'}(X),\ UAV_c(Y) \leftarrow s_{d'}(Y)$
        $\triangle E_{\text{UAV}} \leftarrow \triangle E_{\text{UAV}} - dist_{d'}/v \times e_f$
        UAV charges the sensor
      else
        UAV flies back to the v_{bs}
      end if
    end if
  else
    UAV destination $\leftarrow v_{\text{bs}}$
  end if
  if $w_i \geq e_{\text{thresh}}$ **then**
    $l_u \leftarrow s_i + i^{\text{th}}$ node in l_w
    UAV charges all the sensor nodes in l_u, $e_j = \lfloor \frac{B_i - E_i}{2} \rfloor$
    if $l_u \leftarrow \emptyset$ **then**
      candidate nodes to be charged $\leftarrow l_w$
      UAV start to charge sensors in l_w
    else
      UAV flies back to v_{bs}
    end if
  end if
end for
return $TOUR$

To evaluate the performance of our proposed complete coverage energy knowledge partial charging scheme (Co-EPaCS), we compare Co-EPaCS with three existing algorithms, namely, TSP [5], NJNP [6] and PERS [22]. In algorithm Traveling Salesman Problem (TSP), an approximation of the shortest closed tour is calculated without considering the to-be-charged sensors energy expiration time. For Nearest Job Next with Preemption (NJNP), it acts greedily by prioritizing the requesting nodes located at the nearest position from the mobile charger. The mobile charger is forced to preempt its motion towards the next scheduled node if a new request from a closer node is received meanwhile. For Priority-based Energy Replenishment Scheme (PERS), sensors are sorted by the time they exhaust their energy in a round and the UAV charger will visit the sorted sensors one by one. Full charging model is adopted for all these three algorithms.

4.2 Results and Discussions

Firstly, we compared the ratio of total coverage area and energy consumption of all nodes for the four algorithms against the simulation of time in days, as shown in Fig. 2. The results in Fig. 2(a) show that our proposed Co-EPaCS can still cover 87.24% of the target region after simulating 100 days, whereas PERS covers 73.71%, TSP covers 65.02% and NJNP only covers 30.37%.



(a) (b)

Fig. 2. (a) Total coverage ratio vs time. (b) Energy consumption of all nodes vs time.

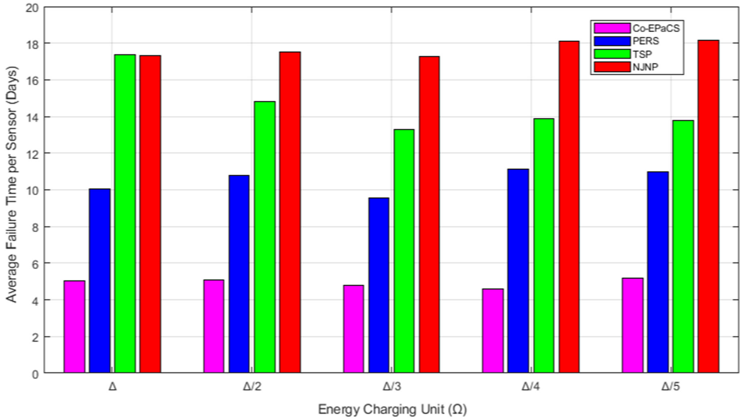
Figure 2(b) illustrates the total remaining energy percentage of all nodes after running a simulation of 100 days. The remaining percentage energy of all nodes for the Co-EPaCS algorithm is 38.72%, PERS is 34.36%, TSP is 20.02%, and NJNP is 18.17%. It can be seen that for NJNP and TSP algorithms their total initial energy of all nodes at the beginning of the simulation is about 96% then it significantly decreases at the end of the simulation. For Co-EPaCS and PERS, their total remaining energy at the beginning of the simulation is about 70% then it decreases at the end of the simulation, however, not significantly compared to TSP and NJNP algorithms. The rationale behind this, TSP and NJNP algorithms sends request message to the UAV when their energy level is low. The UAV receives the message it immediately flies out to the field to start the charging process. As a result, the UAV will consume more energy by moving inefficiently and redundantly. In contrast to TSP and NJNP, our proposed Co-EPaCS and PERS both use an energy threshold e_{thresh} to determine when the UAV should start the charging task, avoiding redundant movement of the UAV. Despite this, our Co-EPaCS algorithm still outperforms PERS because the UAV partially charges the sensors, whereas PERS, TSP and NJNP all adopts the full charging strategy.

Secondly, we investigate the performance of the four algorithms on the impact of energy charging strategy, by decreasing the energy charging unit Ω from $\triangle_i$ to $\frac{\triangle_i}{5}$. As shown in Fig. 3, full charging strategy is adopted when $\Omega = \triangle_i$, while partial charging strategy is adopted when Ω is $\frac{\triangle_i}{2}$, $\frac{\triangle_i}{3}$, $\frac{\triangle_i}{4}$ or $\frac{\triangle_i}{5}$. Figure 3(a) shows that our CO-EPaCS algorithm outperforms PERS, TSP and NJNP in terms of shortening the sensors energy expiration time in full charging strategy and partial charging strategy. The average failure time per sensor of Co-EPaCS is stable from 5.04 days to 5.20 days, PERS is from 10.06 days to 10.96 days, TSP is from 17.35 days to 13.80 days and NJNP is from 17.31 days to 18.17 days.

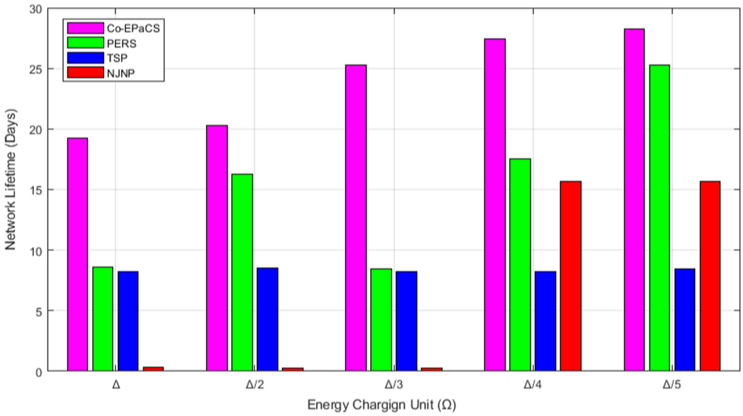
On the other hand, Fig. 3(b) implies the network lifetime, which is defined as the duration from the start of the simulation till the time the first coverage hole occurs. The network lifetime for Co-EPaCS keeps increasing from 19.2% to 28.25% when Ω decreases. The network lifetime for PERS increases when the value of Ω decreases from $\triangle_i$ to $\frac{\triangle_i}{2}$, then it drops down to 8.4% when $\Omega = \frac{\triangle_i}{3}$ and when Ω decreases from $\frac{\triangle_i}{3}$ to $\frac{\triangle_i}{5}$ it significantly increases to 25.25%. The Network lifetime for TSP is stable all throughout from 8.25 days to 8.4 days. The Network lifetime for NJNP is also stable from 0.33 days to 0.25 days, before it significantly increases to 15.66 days when the value of Ω is from $\frac{\triangle_i}{3}$ to $\frac{\triangle_i}{5}$. In summary, we can see from Fig. 3 the performances of our proposed Co-EPaCS algorithm achieves the finest trade-off between minimizing the failure time per sensor and prolonging the network lifetime. It can be noted that both Co-EPaCS and PERS provide greater results, since they both consider residual energy and coverage of sensors whereas TSP and NJNP only take into account the residual energy of the sensors.

Thirdly, we investigate the impact of varying the UAV energy capacity by increasing $E_{UAV} = 10000\,\text{J}$ to $E_{UAV} = 350000\,\text{J}$. We compare the breach rate for the four algorithms against the UAV energy capacity, respectively.

In Fig. 4(a), it is not unexpected that the breach rate decreases as the E_{UAV} increases. Co-EPaCS outperforms PERS, TSP and NJNP by achieving the smallest and stable breach rate from 45% to 40%, PERS is from 47% to 42%, TSP is from 57% to 48% and NJNP is from 58% to 44%. We can see Co-EPaCS still outperforms other three algorithms. The reason for this is because PERS, TSP and NJNP all adopt the full charging model which increases the rate of coverage breach whereas our novel partial charging model can minimize the breach rate and provide a better result.



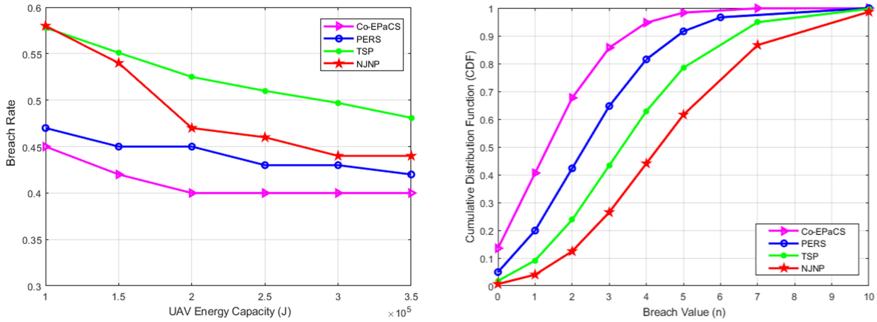
(a)



(b)

Fig. 3. (a) Average failure time per sensor vs time. (b) Network lifetime vs energy charging unit.

At last, we compared the changes of the four algorithms' cumulative distribution functions (CDFs) with the increase of burst value. A burst breach slot is defined as a coverage breach slot with two or more consecutive breach slots. The number of breach slots in each burst breach is defined here as burst value. As we can see in Fig. 4(b), the convergence speed for the proposed Co-EPaCS is faster than PERS, TSP and NJNP. Co-EPaCS outperforms the other three in terms of both the number of breach slot and burst breach. For example, when burst value is equal to 5, the cumulative probability for Co-EPaCS is 98.34%, for PERS is 91.60%, for TSP is 78.51% and for NJNP is 61.59%. This is because Co-EPaCS considers both the remaining energy and coverage degree of sensors.



(a) (b)

Fig. 4. (a) Breach rate vs energy capacity. (b) Cumulative distribution functions vs burst value.

Only the sensors who reaches e_{thresh} can be recharged in Co-EPaCS. In addition, the partial charging model can makes more sensors be recharged.

5 Conclusion

For past studies, the strategy widely used to recharge sensors is considering only the remaining energy of the sensors. However, in order to prevent the occurrence of coverage hole, it is insufficient taking into account only one factor. In this paper we consider both the remaining energy and coverage degree of sensors in terms of cover sets, propose Co-EPaCS, a complete coverage energy knowledge partial charging scheme that replenishes the energy of sensors in an efficient way to maintain the coverage of network and prolong the network lifetime. To validate the effectiveness of the proposed method, the total coverage ratio, energy consumption, network lifetime and Breach rate by Co-EPaCS are compared with PERS, TSP and NJNP in a wild scenario. Experimental results demonstrate that Co-EPaCS performs better than the compared approaches. In our future work, multiple UAV chargers will be considered. How to arrange multiple UAVs working together and recharging hundreds of sensor nodes effectively will be a challenge.

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