Maximizing Sensor Lifetime with the Minimal Service Cost of a Mobile Charger in Wireless Sensor Networks

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Abstract—Wireless energy transfer technology based on magnetic resonant coupling has emerged as a promising technology for wireless sensor networks, by providing controllable yet continual energy to sensors. In this paper, we study the use of a mobile charger to wirelessly charge sensors in a rechargeable sensor network so that the sum of sensor lifetimes is maximized while the travel distance of the mobile charger is minimized. Unlike existing studies that assumed a mobile charger must charge a sensor to its full energy capacity before moving to charge the next sensor, we here assume that each sensor can be partially charged so that more sensors can be charged before their energy depletions. Under this new energy charging model, we first formulate two novel optimization problems of scheduling a mobile charger to charge a set of sensors, with the objectives to maximize the sum of sensor lifetimes and to minimize the travel distance of the mobile charger while achieving the maximum sum of sensor lifetimes, respectively. We then propose efficient algorithms for the problems. We finally evaluate the performance of the proposed algorithms through experimental simulations. Simulation results demonstrate that the proposed algorithms are very promising. Especially, the average energy expiration duration per sensor by the proposed algorithm for maximizing the sum of sensor lifetimes is only 9 percent of that by the state-of-the-art algorithm while the travel distance of the mobile charger by the second proposed algorithm is only about from 1 to 15 percent longer than that by the state-of-the-art benchmark.

Index Terms—Rechargeable sensor networks, sensor charging scheduling, partial charging, sensor lifetime maximization, service cost minimization, mobile chargers, wireless energy transfer

1 Introduction

Wireless sensor networks (WSNs) play an important role in many monitoring and surveillance applications including environmental sensing, target tracking, structural health monitoring, etc [1], [13], [29]. As conventional sensors are powered by batteries, the limited battery capacity obstructs the large-scale deployment of WSNs. The wireless energy transfer based on magnetic resonant coupling revolutionizes energy supplies to wireless sensor networks [2], [8], [11], [12], [22], [26], [27]. Unlike sensor energy replenishments through energy harvesting that only provide temporally and spatially varying energy sources (e.g., solar energy and wind energy) [14], [16], [17], [19], the deployment of mobile chargers (mobile charging vehicles) to charge sensors wirelessly has been a new promising technology that ensures sensors can be charged with high yet stable charging rates, thereby they can operate continually [10], [11], [18], [23], [24], [25], [26], [28], [31].

It is however very challenging to design efficient charging scheduling algorithms for mobile chargers, due to following three inherent constraints on WSNs. The first constraint is that the energy consumption rates of different sensors are significantly different. Sensors near to the base station have to relay data for the other remote sensors, and thus consume much more energy than others [25]. In addition, the energy consumption rate of each sensor may change over time as its sensing data rate usually depends on the specific application of the WSN [20], [21]. The second one is that the battery technology has not been much improved in the past decades. It still takes a long time (e.g., 30-80 minutes) to fully charge a commercial off-the-shelf sensor battery [20]. The final constraint is that a mobile charger consumes its energy not only on sensor charging but also on its mechanical movement, thereby incurring high charging costs [21], [26].

Several recent studies have been conducted to address the mentioned challenges [15], [18], [21], [24]. For example, Xu et al. [24] studied the problem of scheduling k mobile chargers to charge a set of sensors wirelessly so that all the sensors in the set can be fully charged as quickly as possible, while Ren et al. [15] investigated the problem of dispatching a mobile charger to charge as many sensors as possible within a given time period. Shi et al. [18] employed a mobile

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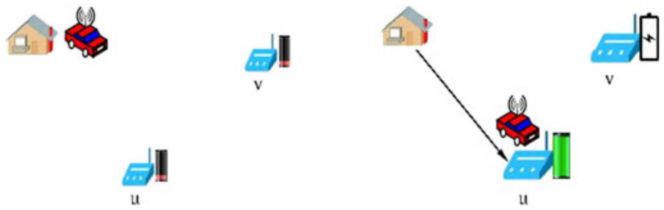
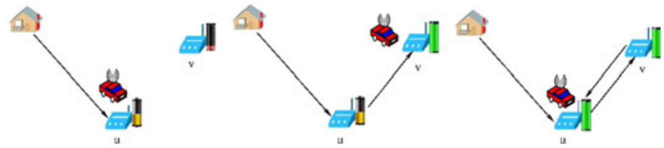


(a) two lifetime-critical sensors u and v and their residual lifetimes are 10 minutes

(b) sensor v has run out of its energy for 60-10=50 minutes when the mobile charger fully charges sensor u

Fig. 1. An illustration of the full-charging model.



(a) the charger first charges sensor u for 10 minutes

(b) the charger then fully charges sensor v

(c) the charger finally recharges sensor u to its full energy capacity

Fig. 2. An illustration of the partial-charging model.

(a) the travel distance of the charger in the full-charging model

(b) the travel distance of the charger in the partial-charging model

Fig. 3. The comparison of the travel distances of the mobile charger in the full-charging and partial-charging models, respectively.

charger to charge all sensors periodically such that the network can operate continually. Given a set of to-be-charged sensors with different residual lifetimes, Wang et al. [21] devised an adaptive algorithm to schedule a mobile charger to charge a proportion of sensors with an objective to maximize the amount of energy charged to sensors minus the amount of energy consumed on the mobile charger's traveling, while ensuring that each chosen sensor will be charged prior to its energy expiration.

Although the mentioned studies strive for the finest tradeoff between charging as many sensors as possible before their energy depletions and minimizing the travel cost of the mobile charger, there is still one major limit in these studies. That is, they all assumed that a mobile charger must charge a sensor to its full energy capacity. Since it takes a while (e.g., 30-80 minutes) to fully charge a commercial off-the-shelf sensor battery (e.g., Lithium battery) [20], this full-charging model will prevent the mobile charger from charging more sensors before these sensors expire their energy completely, especially when there are many lifetime-critical sensors to be charged at some moment. We here use an example to illustrate such a scenario. Assume that a WSN consists of two sensors u and v only, the residual lifetime of each of them is 10 minutes, and it takes an hour to fully charge either of them, as illustrated in Fig. 1a. If one mobile charger is deployed to charge the sensors by adopting the full-charging model, then one of them will be charged before its energy depletion, while the other must be dead for a period of $60-10=50$ minutes before it can be recharged, assuming that the travel time of the mobile charger between the two sensors is ignored, see Fig. 1b. It can be seen that in the full-charging model, some sensors can continue their operations without energy depletions, while the others may have been dead for a long time before they can be recharged again. However, the energy expirations of sensors for a long period may lead to severe consequences to the WSN. For example, in a WSN for early forest fire detections [7], the energy depletions of some sensors for several hours may delay the detection of a forest fire. Such a detection delay may result in the fire becoming uncontrollable, eventually incurring significant damages and casualties, since the forest fire can quickly spread by strong wind in a very short time [7].

In contrast, if a partial-charging model is adopted, the mobile charger can first charge sensor u for 10 minutes (the amount of energy charged to sensor u can support its operations for a while, e.g., 5 hours, see Fig. 2a), then charge sensor v to its full energy capacity (see Fig. 2b), and finally charge sensor u to its full energy capacity (see Fig. 2c). It can be seen that both of the sensors can be charged prior to their energy expirations under the partial-charging model. Note that although adopting the partial-charging model may increase the travel distance of the mobile charger (see Fig. 3), such an increase on the travel distance is worthy since the continuing operation of sensors is a fundamental requirement for most WSN applications. Otherwise, no sensing data will be generated by the dead sensors or "fresh" sensing data generated by other live sensors cannot be forwarded to the base station due to the energy expirations of relay sensors.

Unlike existing studies that adopt the full-charging model, in this paper we adopt a novel partial-charging model so that more sensors can be charged before their energy depletions or their energy expiration durations can be significantly shortened. Under this new partial-charging model, we investigate the problem of finding a charging tour for a mobile charger to charge a set of lifetime-critical sensors so that the sum of sensor lifetimes is maximized. On the other hand, we note that the mechanical movement of the mobile charger during its charging tour will consume energy too [21], [25]. We thus study the problem of finding a shortest charging tour for the mobile charger, while ensuring that the sum of sensor lifetimes is maximized, since there may be multiple charging tours with the maximum sum of sensor lifetimes. For example, in addition to the charging tour shown in Fig. 3b, another charging tour is to charge sensors u and v for six rounds, and each of the two sensors is charged for only ten minutes within each charging round. We can see that both of the sensors will not run out of their energy in this latter charging tour, but the charger travels much longer than that shown in Fig. 3b.

The challenges of the problems considered in this paper are as follows. (i) What is the amount of energy to be charged to each sensor each time? (ii) How to schedule the mobile charger to maximize the sum of sensor lifetimes? and (iii) How to find a charging tour for the mobile charger so that its travel distance is minimized? We note that these challenges have not been addressed by existing studies, as most existing work assumed that each sensor can be charged only once per charging tour, while we here allow each sensor to be charged multiple times and the amount of energy charged at each charging can be different. Also, existing work only focused on charging as many sensors as possible in time while we aim to maximize the sum of sensor lifetimes. In this paper we tackle the challenges by formulating two novel optimization problems and devising efficient algorithms for the problems.

The main contributions of this paper can be summarized as follows. We first propose a partial-charging model to increase sensor survival opportunities. We then formulate two novel optimization problems of scheduling a mobile charger to charge a set of sensors wirelessly with the aims to maximize the sum of sensor lifetimes and to minimize the travel distance of the charger while achieving the maximum sum of sensor lifetimes. We also propose efficient scheduling algorithms for the problems. We finally evaluate the performance of the proposed algorithms through experimental simulations. The simulation results demonstrate that the proposed algorithms are very promising. Especially, the average energy expiration duration per sensor by the proposed algorithm for maximizing the sum of sensor lifetimes is only 9 percent of that by the state-of-the-art algorithm while the travel distance of the mobile charger by the second proposed algorithm is only about from 1 to 15 percent longer than that by the state-of-the-art benchmark.

The remainder of the paper is organized as follows. Section 2 introduces the system model, notations, notions, and problem definitions. Section 3 calculates the maximum sum of sensor lifetimes, and Section 4 proposes an efficient charging scheduling algorithm so that the travel distance of the mobile charger minimized while keeping the sum of sensor lifetimes is maximized. Section 5 evaluates the performance of the proposed algorithm. Section 6 reviews related studies, and Section 7 concludes the paper.

2 Preliminaries

In this section, we first present the network model and charging model, then introduce notations and notions, and finally define the problems.

2.1 Network Model

We consider a rechargeable wireless sensor network $G_s = (V_s, E_s)$ deployed for environmental monitoring or event detections, where V_s is a set of sensors and a base station. There is an edge in E_s between any two sensors or a sensor and the base station if they are within the communication range of each other. Each sensor $v_i \in V_s$ is powered by a rechargeable battery with energy capacity B_i. Let $b_i(t)$ be the sensing data rate of sensor v_i at time t, which may vary over time. We assume that there is a routing protocol in G_s for sensing data collection that relays sensing data from individual sensors to the base station through multihop relays. For example, each sensor can upload its sensing data to the base station via a routing path with the minimum energy consumption.

Notice that each sensor consumes its battery energy when performing sensing, data transmission, and reception [9]. We assume that each sensor $v_i \in V_s$ can monitor its residual energy $RE_i(t)$ and estimate its energy consumption rate $\hat{\rho}_i(t)$ in the near future, by adopting existing prediction techniques such as linear regressions. For example, $\hat{\rho}_i(t) = \omega\rho_i(t-1) + (1-\omega)\hat{\rho}_i(t-1)$, where $\hat{\rho}_i$ is the estimation and ρ_i is the actual value at that moment and ω is a given weight between 0 and 1. The base station keeps a copy of the energy depletion rate $\rho_i(t)$ and the residual energy $RE_i(t)$ of each sensor $v_i \in V_s$. Let $\theta\ (>0)$ be a given threshold, the updating of each sensor $v_i \in V_s$ on its energy consumption rate is performed as follows. If $|\hat{\rho}_i(t) - \hat{\rho}_i(t-1)| \le \theta$, no updating report is needed; otherwise, the updated energy consumption rate and the residual energy of v_i will be reported to the base station, and the base station performs necessary updating accordingly. The *residual lifetime* $l_i(t)$ of each sensor v_i at time t then is $l_i(t) = \frac{RE_i(t)}{\hat{\rho}_i(t)}$.

2.2 Charging Model

To maintain the long-term operation of a sensor network G_s, its sensors will be charged by a mobile charger at certain time points. For simplicity, in this paper we assume that there is only one mobile charger that is located at a depot r within the monitoring area of the WSN. The proposed algorithms can be easily extended to a network with multiple mobile chargers. The mobile charger starts from its depot to perform its charging tour and returns to the depot for recharging itself after the tour, and it can charge a nearby sensor with a fixed charging rate μ and move at a speed ν. Also, assume that the mobile charger consumes ξ units of energy on traveling per unit length.

Since the energy consumption rate of each sensor may experience significant changes for a long-term monitoring period, each sensor $v_i \in V_s$ sends a charging request $REQ_i = (t, v_i, RE_i, \rho_i, B_i - RE_i)$ to the base station when its residual lifetime l_i is below a given critical lifetime l_c (e.g., 2 hours) at time point t, where the charging request REQ_i contains the time point t issuing the request, the sensor ID v_i, its residual energy RE_i, its energy consumption rate ρ_i, and the maximum amount of energy $B_i - RE_i$ that can be charged. Once receiving the charging request from sensor v_i, the base station then dispatches the mobile charger to charge sensor v_i as well as some other lifetime-critical sensors in the network. Let V_1 be the set of sensors with residual lifetimes below the critical lifetime l_c, i.e., $V_1 = \{v_i \mid v_i \in V_s, l_i \le l_c\}$, and $V_2 = V_s \setminus V_1$. We assume that the duration spent on its traveling by the mobile charger per charging tour is much shorter than its time spent on charging sensors [25]. We further assume that the energy consumption rate of a sensor does not fluctuate too much within a charging tour, or such minor fluctuations can be neglected as the duration of a charging tour usually is short. But the energy consumption rate of each sensor is allowed to change at different charging tours.

To ensure that the base station will not receive any charging requests from other sensors before the mobile charger finishes its current charging tour, we find a set $V(\subseteq V_s)$ of to-be-charged sensors so that the total time for charging the sensors in V is less than the residual lifetime of each sensor in $V_s \setminus V$ minus the critical lifetime l_c, i.e., $\sum_{v_i \in V} \frac{B_i - RE_i}{\mu} < l_j - l_c$ for each sensor $v_j \in V_s \setminus V$, where μ is the charging rate of the mobile charger. Otherwise (the base station receives a new charging request from a sensor v when the charger is performing a charging tour), the mobile charger may be far from the location of sensor v, and the charger has to travel from its current location to the location of sensor v to charger v, as the residual lifetime of sensor v is very short. The travel distance of the charger thus is dramatically prolonged.

We find the set V of to-be-charged sensors as follows. Initially, let $V = V_1$ and $v_1, v_2, \ldots, v_{n_2}$ be the sensors in

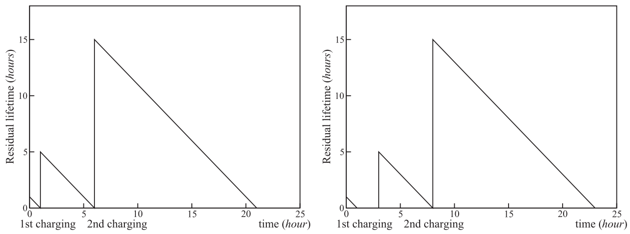
$V_2 = V_s \setminus V_1$ with $n_2 = |V_2|$. Without loss of generality, assume that $l_1 \leq l_2 \leq \cdots \leq l_{n_2}$, where l_j is the residual lifetime of sensor $v_j \in V_2$. If $\sum_{v_i \in V_1} \frac{B_i - RE_i}{\mu} < l_1 - l_c$, then $V = V_1$ is the current set of to-be-charged sensors. Otherwise, we move sensor v_1 from set V_2 to V. This procedure continues until we identify a sensor v_j with $\sum_{v_i \in V_1} \frac{B_i - RE_i}{\mu} + \sum_{j'=1}^{j-1} \frac{B_{j'} - RE_{j'}}{\mu} < l_j - l_c$, and the set of to-be-charged sensors then is $V = V_1 \cup \{v_1, v_2, \ldots, v_{j-1}\}$.

The *partial-charging* model is proposed as follows. Recall that RE_i is the amount of residual energy of sensor v_i at some time point t. The amount of energy that can be charged to sensor v_i at each time then ranges from 0 to $B_i - RE_i$, where B_i is the battery capacity of sensor v_i. Although we allow each sensor to be partially charged, it is not economical to charge only a small amount of energy to the sensor at each time, since the travel distance of the mobile charger can be significantly increased by scheduling the charger to visit the sensor many times in a single charging tour. We thus assume that at least a unit amount of energy Δ must be replenished at each charging. That is, the amount of energy charged to a sensor $v_i \in V_s$ at each time is a value in $\{\Delta, 2\Delta, \ldots, k_i\Delta, B_i - RE_i\}$, where $k_i = \lfloor \frac{B_i - RE_i}{\Delta} \rfloor$ is an integer. Assume that the value of Δ is large enough so that the value of $\max_{v_i \in V_S}\{\lfloor \frac{B_i}{\Delta} \rfloor\}$ is bounded by a constant k_{max}, e.g., $k_{max} = 5$.

Recall that each sensor v_i may be charged multiple times during each tour and the accumulated amount of energy received by sensor v_i is equal to $B_i - RE_i$. We assume that sensor v_i is charged by the mobile charger c_i times and an amount e_i^j of energy is charged at time t_i^j, where $1 \leq j \leq c_i$ and c_i is a positive constant with $c_i \leq \lceil \frac{B_i - RE_i}{\Delta} \rceil$ as Δ is the energy charging unit. Then, $\sum_{j=1}^{c_i} e_i^j = B_i - RE_i$. Denote by RE_i^j the residual energy of sensor v_i after the jth charging with $0 \leq j \leq c_i$. Note that RE_i^0 is the amount of residual energy of sensor v_i before any charging, i.e., $RE_i^0 = RE_i$. Then, sensor v_i will not deplete its energy before the $(j+1)$th charging if $t_i^{j+1} \leq t_i^j + \frac{RE_i^j}{\rho_i}$. Otherwise, it will run out of its energy from time $t_i^j + \frac{RE_i^j}{\rho_i}$ to time t_i^{j+1}

A *charging tour* C of the charger for sensors in V is defined as an order of pairs $(r, 0) \rightarrow (v'_1, e_1) \rightarrow (v'_2, e_2) \rightarrow \cdots \rightarrow (v'_{n'}, e_{n'}) \rightarrow (r, 0)$ with starting from and ending at depot r, where v'_j is a sensor in V, e_j is the amount of energy charged to sensor v'_j. A sensor can be charged multiple times in tour C, and $n' \geq n = |V|$. Denote by $w(C)$ the total length of tour C, i.e., $w(C) = \sum_{i=0}^{n'} d_{i,i+1}$, where $d_{i,i+1}$ is the Euclidean distance between nodes v'_i and v'_{i+1}, and $v'_0 = v'_{n'+1} = r$.

We assume that the total travel time of the mobile charger per charging tour is much shorter than its time spent on charging sensors, but not negligible. For example, it may take about one minute for the mobile charger traveling to the location of a sensor from its last charging sensor location, assuming the distance of the two sensors is 300 meters away and the travel speed of the charger is 5 m/s [10], i.e., $60\ s = \frac{300\ \text{m}}{5\ \text{m/s}}$. It then takes the charger 10 minutes to charge an amount Δ of energy to the sensor. We thus assume that the travel time of the charger from its current charging sensor location to its next to-be-charged sensor location can be approximated by a constant t_{travel}, e.g., $t_{travel} = 1$ minute. The value of t_{travel} can be predicted through historic chargings. Therefore, we divide time into equal time slots with each lasting τ units, i.e., $\tau = \frac{\Delta}{\mu} + t_{travel}$, where $\frac{\Delta}{\mu}$ is the time spent by the charger for charging an amount Δ of energy to a sensor and μ is the charging rate. We index the time slots by $1, 2, \ldots$.



(a) sensor v_i is charged in time

(b) sensor v_i has depleted its energy 2 hours already before the mobile charger charges it for the first time

Fig. 4. The mobile charger charges sensor v_i with $c_i = 2$ chargings and the residual lifetime l_i of sensor v_i initially is one hour.

2.3 Notions and Notations

Recall that each sensor v_i will be charged by the mobile charger c_i times in its current charging tour and an amount e_i^j of energy will be charged to v_i at time t_i^j, where $1 \leq j \leq c_i$ and $\sum_{j=1}^{c_i} e_i^j = B_i - RE_i$. We say that sensor v_i is charged *in time* by the mobile charger if and only if it can operate from time $(t + l_i)$ to $(t + l_i + \frac{B_i - RE_i}{\rho_i})$ $(= t + \frac{B_i}{\rho_i})$ without any energy depletions, where $l_i = \frac{RE_i}{\rho_i}$ is the residual lifetime of sensor v_i at time t. In other words, sensor v_i will not run out of energy before each of its c_i chargings, i.e., $t_i^j \leq t + l_i + \frac{\sum_{j'=1}^{j-1} e_i^{j'}}{\rho_i}$ for each j with $1 \leq j \leq c_i$, where t_i^j is the time at which the charger performs the jth charging to sensor v_i and $\sum_{j'=1}^{j-1} e_i^{j'}$ is the accumulated amount of energy charged to sensor v_i in the first $(j-1)$ chargings. Fig. 4a illustrates that sensor v_i is charged by the mobile charger in time, where $l_i = 1$ hour and $c_i = 2$.

We note that the mobile charger may not be able to charge every sensor v_i in time and the sensor may deplete its energy several times before its last (i.e., the c_ith) charging in the current charging tour, especially when there are a large number of lifetime-critical sensors to be charged. Fig. 4b illustrates that sensor v_i has depleted its energy completely for 2 hours before the mobile charger performs the first charging to it. After the last charging, sensors v_i will not run out of energy until time $t_i^{c_i} + \frac{RE_i^{c_i}}{\rho_i}$, where $t_i^{c_i}$ is the time that the charger performs the last charging and $RE_i^{c_i}$ is the residual energy of sensor v_i after its last charging. Denote by l_{live}^i and l_{dead}^i the total live duration and dead duration of sensor v_i from time $t + l_i$ to time $t_i^{c_i} + \frac{RE_i^{c_i}}{\rho_i}$, where $t + l_i$ is the time point that sensor v_i will run out of energy if the mobile charger does not charge the sensor and $t_i^{c_i} + \frac{RE_i^{c_i}}{\rho_i}$ is the time point that the sensor will deplete its energy after the mobile charger has performed the last charging to the sensor. We thus define the *normalized lifetime* η_i of each sensor v_i in time interval $[t + l_i, t_i^{c_i} + \frac{RE_i^{c_i}}{\rho_i}]$ as the ratio of l_{live}^i to $l_{live}^i + l_{dead}^i$, i.e.,

$$\eta_i = \frac{l_{live}^i}{l_{live}^i + l_{dead}^i}, \tag{1}$$

where $l_{live}^i = \frac{B_i - RE_i}{\rho_i}$ as an amount $B_i - RE_i$ of energy will be charged to sensor v_i. For example, in Fig. 4b, $l_{live}^i = 5 + 15 = 20$ hours and $l_{dead}^i = 2$ hours. Then, $\eta_i = \frac{20}{20+2} = \frac{10}{11}$. Note that if sensor v_i does not deplete its energy before any of the c_i chargings, its normalized lifetime is $\eta_i = \frac{l^i_{live}}{l^i_{live}+l^i_{dead}} = \frac{l^i_{live}}{l^i_{live}+0} = 1$ since $l^i_{dead} = 0$ in this case, which is shown in Fig. 4a with $l^i_{live} = 20$ hours. The sum of normalized lifetimes η_{sum} of sensors in V then is

$$\eta_{sum} = \sum_{v_i \in V} \eta_i. \tag{2}$$

The meaning of the sum of sensor normalized lifetimes η_{sum} can be explained as follows. Recall that the normalized lifetime η_i of each sensor v_i implies the proportion of time that the sensor lives, which also can be interpreted as its live probability at any time point, by a charging tour if the charger replenishes sensor energy along the tour. The sum of normalized lifetimes η_{sum} thus represents the expected number of live sensors maintained in the network by the charging tour.

2.4 Problem Definitions

It is desirable that every sensor should be charged before its energy depletion, this goal however may not be met, since the energy consumption rates of sensors may vary over time and cannot be precisely predicted. Therefore, sometimes there may be a large number of to-be-charged sensors in the network and the mobile charger is not able to charge each of them before its energy expiration. As continuing operations of sensors is a fundamental requirement for most WSNs, the *sensor lifetime maximization problem* is defined as follows. Given a set V of to-be-charged sensors in network G_s at some time point t, for each sensor $v_i \in V$, denote by RE_i its residual energy, ρ_i its energy consumption rate, and $B_i - RE_i$ its energy charging demand. Recall that the mobile charger has a charging rate μ. The problem is to find a charging tour C for the mobile charger to charge the sensors in V so that the sum of the normalized lifetimes η_{sum} of sensors in V is maximized, subject to the constraint that the total amount of energy charged to each sensor $v_i \in V$ is equal to its energy demand $B_i - RE_i$. Denote by η^*_{sum} the maximum sum of normalized lifetimes of sensors in V.

Assume that the maximum sum of normalized lifetimes η^*_{sum} is given (the calculation of η^*_{sum} will be shown later), it is desirable to minimize the travel distance of the mobile charger due to its mechanical movement consuming lots of energy [25]. Given a set V of to-be-charged sensors, let $C = <(r,0) \rightarrow (v'_1, e_1) \rightarrow (v'_2, e_2) \rightarrow \cdots \rightarrow (v'_{n'}, e_{n'}) \rightarrow (r,0)>$ be a charging tour of the mobile charger with starting from and ending at depot r, where v'_j is a sensor in V, e_j is the amount of energy charged to sensor v'_j, and each sensor v_i in V may be charged multiple times in the tour. We then define *the service cost minimization problem with maximum sensor lifetime* as to find a charging tour C for the mobile charger so that its travel distance, $w(C)$, is minimized, subject to that the maximum sum of the normalized lifetimes η^*_{sum} of all sensor can be achieved, i.e.,

$$mininize \;\; w(C), \tag{3}$$

subject to

$$\sum_{v'_j \in C \& v'_j = v_i} e_j = B_i - RE_i, \;\; \forall v_i \in V \tag{4}$$

$$\eta_{sum} = \eta^*_{sum}, \tag{5}$$

where constraint (4) ensures that the total amount of energy in the multiple chargings to each sensor v_i in tour C is equal to its energy demand $B_i - RE_i$ and constraint (5) ensures that the sum of normalized lifetimes of all sensors is maximized. It can be seen that the service cost minimization problem is NP-hard, since the well-known NP-hard traveling salesman problem (TSP) is a special case of it.

3 Algorithm for the Sensor Lifetime Maximization Problem

In this section, we devise an efficient algorithm for the sensor lifetime maximization problem. The basic idea behind the algorithm is that the mobile charger can charge a sensor with only an amount Δ of energy at every time slot for a monitoring period. The problem is then reduced to a matching problem between sensors and time slots.

3.1 Algorithm

Given a set V of to-be-charged sensors, we create k_i virtual sensors $v_{i,1}, v_{i,2}, \ldots, v_{i,k_i}$ for each sensor $v_i \in V$, where $k_i = \lceil \frac{B_i - RE_i}{\Delta} \rceil$, B_i and RE_i are the energy capacity and residual energy of sensor v_i, respectively, and Δ is an energy charging unit. We can see that only one time slot is needed to charge every virtual sensor. Let $V' = \{v_{i,j} \mid v_i \in V, 1 \le j \le k_i\}$ be the set of virtual sensors and $k_{max} = \max_{v_i \in V}\{k_i\}$. Also, let $V'_j = \{v_{i,j} \mid v_{i,j} \in V', 1 \le i \le n\}$ be the set of the jth virtual sensors of all sensors in V' and $n'_j = |V'_j|$ with $1 \le j \le k_{max}$. We can see that sets $V'_1, V'_2, \ldots, V'_{k_{max}}$ form a partition of set V', i.e., $V'_j \cap V'_{j'} = \emptyset$ if $j \ne j'$ with $1 \le j$, $j' \le k_{max}$, and $V' = \cup_{j=1}^{k_{max}} V'_j$.

We iteratively find time slots at which the mobile charger charges virtual sensors in V'. That is, we find the time slots for charging virtual sensors in V'_j in the jth iteration with $1 \le j \le k_{max}$. Specifically, denote by $l_{i,j}$ and $l^{i,j}_{dead}$ the energy expiration time slot and dead duration of each sensor $v_i \in V$ before the jth charging (i.e., the jth iteration), respectively. Initially, $l_{i,1} = l_i$ and $l^{i,1}_{dead} = 0$, where $1 \le i \le n$. Let G'_0 be an empty graph, i.e., $G'_0 = \emptyset$, and $S' = \{s_1, s_2, \ldots, s_{n'}\}$ be a set of $n' (= |V'|)$ time slots.

In the jth iteration ($1 \le j \le k_{max}$), we first construct a bipartite graph $G'_j = (\cup_{j'=1}^{j} V'_{j'}, S', E'_j; w'_j)$ from graph $G'_{j-1} = (\cup_{j'=1}^{j-1} V'_{j'}, S', E'_{j-1}; w'_{j-1})$ and the virtual sensor set V'_j as follows. First, let $E'_j = E'_{j-1}$, the weight $w'_j(v_p, s_q)$ of each edge $(v_p, s_q) \in E'_{j-1}$ in graph G'_j is set to zero, rather than $w'_{j-1}(v_p, s_q)$ in graph G'_{j-1}. We then add an edge $(v_{i,j}, s_q)$ to E'_j for each virtual sensor $v_{i,j} \in V'_j$ and each time slot $s_q \in S'$. The weight $w'_j(v_{i,j}, s_q)$ of edge $(v_{i,j}, s_q)$ is equal to the normalized lifetime of sensor v_i if the charger performs the jth charging to it at time slot s_q, i.e., $w'_j(v_{i,j}, s_q) = \frac{l^i_{live}}{l^i_{live}+l^{i,j}_{dead}}$ if $q \le l_{i,j} + 1$ as the sensor will not run out of its energy until time slot $l_{i,j} + 1$; otherwise, $w'_j(v_{i,j}, s_q) = \frac{l^i_{live}}{l^i_{live}+l^{i,j}_{dead}+q-l_{i,j}-1}$, since the dead duration of sensor v_i will be prolonged from $l^{i,j}_{dead}$ to $l^{i,j}_{dead} + q - l_{i,j} - 1$ if the jth charging to the sensor is performed at the qth time slot. We then find a maximum weighted matching M_j in graph G'_j. Consider each virtual sensor $v_{i,j} \in V'_j$, assume that it is matched to time slot s_q in matching M_j. If $q \le l_{i,j}+1$, we remove the adjacent edges $(v_{i,j}, s_{q'})$ of $v_{i,j}$ from graph G'_j with $q' > l_{i,j}+1$, since sensor v_i is charged in time at the jth charging. Otherwise, we remove the adjacent edges $(v_{i,j}, s_{q'})$ of sensor $v_{i,j}$ with $q' \neq q$. Finally, we obtain the energy expiration time $l_{i,j+1}$ of sensor v_i before the $(j+1)$th charging (i.e., iteration) by charging sensor v_i at time slot s_q as virtual sensor $v_{i,j}$ is matched to time slot s_q in matching M_j, and the dead duration of sensor v_i before the $(j+1)$th charging is $l^{i,j+1}_{dead} = l^{i,j}_{dead} + \max\{q - l_{i,j} - 1,\ 0\}$. After the k_{max}th iteration, we obtain the time slot assigned to each virtual sensor in V' by matching $M_{k_{max}}$. In the end, we find a charging tour with the maximum sensor lifetime, by scheduling the mobile charger to charge the virtual sensor matched to node s_q at the qth time slot with an amount Δ of energy, where $1 \le q \le n'$.

The detailed algorithm is given in `Algorithm` 1.

Algorithm 1. `HeuristicMaxLifetime`

Input: A set V of to-be-charged sensors with the residual energy RE_i, energy consumption rate ρ_i, and energy demand $B_i - RE_i$ of each sensor v_i, and the energy charging unit Δ.

Output: a charging tour C of the mobile charger so that the sum of normalized sensor lifetimes is maximized

1: Create k_i virtual sensors $v_{i,1}, v_{i,2}, \ldots, v_{i,k_i}$ for each sensor v_i in V, where $k_i = \lceil \frac{B_i - RE_i}{\Delta} \rceil$. Let $V'_j = \{v_{1,j}, v_{2,j}, \ldots, v_{n,j}\}$, where $1 \le j \le k_{max}$;
2: Let $l_{i,1} = l_i = \lfloor \frac{RE_i}{\tau\rho_i} \rfloor$, $l^{i,1}_{dead} = 0$, graph $G'_0 = \emptyset$, and $S' = \{s_1, s_2, \ldots, s_{n'}\}$ with $n' = \sum_{i=1}^{n} k_i$;
3: **for** $j \leftarrow 1$ to k_{max} **do**
4 Construct bipartite graph $G'_j = (\cup_{j'=1}^{j} V'_{j'}, S', E'_j; w'_j)$ from $G'_{j-1} = (\cup_{j'=1}^{j-1} V'_{j'}, S', E'_{j-1}; w'_{j-1})$ and set V'_j;
5: Find a maximum weighted matching M_j in G'_j;
6: For each $v_{i,j} \in V'_j$, assume that it is matched to time slot s_q in M_j, remove its adjacent edges $(v_{i,j}, s_{q'})$ from graph G'_j with $q' > l_{i,j}+1$ if $q \le l_{i,j}+1$; otherwise, remove its adjacent edges $(v_{i,j}, s_{q'})$ with $q' \neq q$;
7: For each $v_{i,j} \in V'_j$, obtain the energy expiration time $l_{i,j+1}$ of sensor v_i before the $(j+1)$th charging by charging sensor v_i at time slot s_q. The dead duration of sensor v_i before the $(j+1)$th charging is $l^{i,j+1}_{dead} = l^{i,j}_{dead} + \max\{q - l_{i,j} - 1,\ 0\}$;
8: **end for**
9: Obtain the time slot assigned to each virtual sensor from matching $M_{k_{max}}$ and then find a charging tour C.

We here use an example to illustrate the execution of `Algorithm` 1. Assume that there are two to-be-charged sensors v_1 and v_2 in the network at some time point, and both of them have already run out of their energy, i.e., $l_1 = l_2 = 0$. Also, assume that the total live durations of the two sensors are $l^1_{live} = 100$ and $l^2_{live} = 200$ time slots, respectively. `Algorithm` 1 creates two virtual sensors $v_{i,1}$ and $v_{i,2}$ for each sensor v_i with $1 \le i \le 2$. Then, `Algorithm` 1 takes two iterations to find the charging sequence of the virtual sensors. In the first iteration, it first constructs a bipartite graph $G'_1 = (V'_1, S', E'_1, w'_1)$, where $V'_1 = \{v_{1,1}, v_{2,1}\}$, $S' = \{s_1, s_2, s_3, s_4\}$, $E'_1 = V'_1 \times S'$, $w'_1(v_{1,1}, s_1) = 1$, $w'_1(v_{1,1}, s_j) = \frac{l^1_{live}}{l^1_{live} + j - (l_{1,1}+1)} = \frac{100}{99+j}$ for $2 \le j \le 4$, $l_{1,1} = 0$; $w'_1(v_{2,1}, s_1) = 1$, $w'_1(v_{2,1}, s_j) = \frac{l^2_{live}}{l^2_{live} + j - (l_{2,1}+1)} = \frac{200}{199+j}$ for $2 \le j \le 4$, $l_{2,1} = 0$. It then finds a maximum weighted matching M_1 in G'_1, where $M_1 = \{(v_{1,1}, s_1), (v_{2,1}, s_2)\}$. That is, virtual sensor $v_{2,1}$ will deplete its energy for one time slot before its next charging. With the matching M_1, it calculates the energy expiration times of virtual sensors $v_{1,2}$ and $v_{2,2}$ as $l_{1,2} = l_{1,1} + \frac{l^1_{live}}{2} = 50$, $l_{2,2} = s_2 + \frac{l^2_{live}}{2} - 1 = 101$. Similarly, in the second iteration, `Algorithm` 1 finds a matching M_2 in G'_2, where $M_2 = \{(v_{1,1}, s_1), (v_{2,1}, s_2), (v_{1,2}, s_3), (v_{2,2}, s_4)\}$. In other words, the charging sequence of the virtual sensors is $v_{1,1} \to v_{2,1} \to v_{1,2} \to v_{2,2}$. Then, it can be seen that although both of the sensors v_1 and v_2 have run out their energy, sensor v_2 will deplete its energy for one time slot in the charging sequence, since its total live duration l^2_{live} is longer than that of sensor v_1 (i.e., $l^2_{live} = 200 > l^1_{live} = 100$).

3.2 The Optimal Energy Charging Unit

So far we assumed that the energy charging unit Δ is given in advance. However, the value of Δ may significantly impact the energy expiration durations of sensors. On one hand, a smaller energy charging unit Δ indicates that the mobile charger spends less time on charging every sensor each time. As a result, the waiting time of other to-be-charged sensors may be reduced. On the other hand, the smaller value Δ implies that mobile charger takes more time on its movements among to-be-charged sensors, since more times of chargings are needed to fully replenish the sensor with a smaller charging unit Δ. In the following, an optimal energy charging unit can be found so that the sum of normalized sensor lifetimes is maximized.

Let Δ_{max} be the maximum energy demand of the to-be-charged sensors, i.e., $\Delta_{max} = \max_{v_i \in V}\{B_i - RE_i\}$. Also, we assume that the energy charging unit Δ is a value in set $V_\Delta = \{\frac{\Delta_{max}}{p}, \frac{2\Delta_{max}}{p}, \ldots, \frac{(p-1)\Delta_{max}}{p}, \Delta_{max}\}$, where p is given positive integer, e.g., $p = 10$. For each value $\Delta = \frac{i}{p}\Delta_{max}$ ($1 \le i \le p$), we calculate the maximum sum η^Δ_{sum} of normalized sensor lifetimes under this specified value Δ, by invoking `Algorithm` 1. The optimal energy charging unit Δ_{OPT} thus is a value among all possible values in set V_Δ so that the maximum sum η^Δ_{sum} of normalized sensor lifetimes is maximized, i.e., $\Delta_{OPT} = \arg\max_{\Delta = \frac{i}{p}\Delta_{max}, 1 \le i \le p}\{\eta^\Delta_{sum}\}$.

3.3 Algorithm Analysis

The analysis of `Algorithm` 1 can be distinguished into two cases. Case 1: there are a limited number of sensors to be charged; and Case 2: there are a large number of sensors to be charged.

Case 1. we assume that the lifetime of any sensor for consuming an amount Δ of energy is no less than the total time of charging every sensor in V with an amount Δ of energy, i.e., $\frac{\Delta}{\rho_{max}} \ge n\tau$ (i.e., $n \le \frac{\Delta}{\tau\rho_{max}}$), where $\rho_{max} = \max_{v_i \in V}\{\rho_i\}$ is the maximum energy consumption rate of sensors in V, $\tau = \frac{\Delta}{\mu} + t_{travel}$ is the time for charging an amount Δ of energy to a sensor, μ is the charging rate of the mobile charger, t_{travel} is the travel time from a charging sensor to the next charging sensor, and t_{travel} is considered as a small constant. We will show that `Algorithm` 1 finds an optimal solution to the sensor lifetime maximization problem in this case.

Case 2 ($n > \frac{\Delta}{\tau\rho_{max}}$). `Algorithm` 1 may or may not find an optimal solution. Note that the number of to-be-charged sensors n at some time t usually is not very large since the energy consumption rates of different sensors significantly vary [25], and it is unlikely that a large proportion of sensors requires to be charged at the same time.

In the following we show that `Algorithm 1` finds an optimal solution for Case 1 by the following lemma.

Lemma 1. *Given a set V of to-be-charged sensors in G_s with the residual energy RE_i, energy consumption rate ρ_i, and energy demand $B_i - RE_i$ of each sensor $v_i \in V$, assume that $|V| = n \le \frac{\Delta}{\tau\rho_{max}}$. Then,* `Algorithm 1` *finds an optimal solution to the sensor lifetime maximization problem.*

Proof. Given an optimal charging tour C^* to the problem, assume that l^{*i}_{live} and l^{*i}_{dead} are the live and dead durations of sensor v_i in tour C^*, respectively, where $l^{*i}_{live} = \lfloor \frac{B_i - RE_i}{\rho_i \tau} \rfloor$. Then, the maximum sum of normalized sensor lifetimes is $\eta^*_{sum} = \sum_{i=1}^n \eta^*_i = \sum_{i=1}^n \frac{l^{*i}_{live}}{l^{*i}_{live} + l^{*i}_{dead}}$ by its definition. We now show that (i) the weight $w'_1(M_1)$ of matching M_1 in `Algorithm 1` is an upper bound on η^*_{sum}; and (ii) the sum of normalized sensor lifetimes of the charging tour C found by `Algorithm 1` is $w'_1(M_1)$. `Algorithm 1` then finds an optimal solution.

We first show that (i) the weight $w'_1(M_1)$ of matching M_1 is an upper bound on η^*_{sum}. We construct a matching M in graph G'_1 from tour C^*, by assigning virtual sensor $v_{i,1}$ to time slot node s^*_j if the mobile charger performs the first charging to sensor v_i at time slot s^*_j in tour C^* with $1 \le i \le n$. Denote by $l^{*i,1}_{dead}$ and $l^{*i,2}_{dead}$ the dead durations of sensor v_i before and after the first charging to the sensor in tour C^*, respectively. Then, $l^{*i}_{dead} = l^{*i,1}_{dead} + l^{*i,2}_{dead}$. Let $\eta'_i = \frac{l^{*i}_{live}}{l^{*i}_{live} + l^{*i,1}_{dead}}$. We can see that $\eta'_i \ge \eta_i$ since $\eta'_i = \frac{l^{*i}_{live}}{l^{*i}_{live} + l^{*i,1}_{dead}} \ge \frac{l^{*i}_{live}}{l^{*i}_{live} + l^{*i,1}_{dead} + l^{*i,2}_{dead}} = \frac{l^{*i}_{live}}{l^{*i}_{live} + l^{*i}_{dead}} = \eta^*_i$ and $l^{*i,2}_{dead} \ge 0$. As M_1 is a maximum weighted matching in G'_1, we have $w'_1(M_1) \ge w'_1(M) = \sum_{i=1}^n \eta'_i \ge \sum_{i=1}^n \eta^*_i = \eta^*_{sum}$.

We then prove that (ii) the sum of normalized sensor lifetimes of tour C is $w'_1(M_1)$. Assume that each virtual sensor $v_{i,j} \in V'$ is assigned to time slot t^j_i in charging tour C, where $1 \le i \le n$ and $1 \le j \le k_i$. For simplicity, we assume that $k_1 = k_2 = \cdots = k_n = k$. To this end, we show that the weight $w'_j(M_j)$ of matching M_j is equal to the weight $w'_1(M_1)$ of matching M_1 in `Algorithm 1` for $2 \le j \le k$, i.e., $w'_k(M_k) = \cdots = w'_2(M_2) = w'_1(M_1)$. Claim (ii) then holds, since the sum of normalized sensor lifetimes of tour C is $w'_k(M_k)$. In the following, we first construct k matchings $M'_1, M'_2, \ldots, M'_k$ from M_1. We then show (ii.a) $w'_k(M'_k) = \cdots = w'_2(M'_2) = w'_1(M'_1)$; (ii.b) $w'_1(M'_1) = M'_1(M_1)$; and (ii.c) $w'_j(M'_j) = M'_j(M_j)$, $2 \le j \le k$. We finally derive that $w'_k(M_k) = \cdots = w'_2(M_2) = w'_1(M_1)$.

We construct k matchings $M'_1, M'_2, \ldots, M'_k$ from M_1 in graph $G'_1, G'_2, \ldots, G'_k$, respectively. We sort the virtual sensors in V'_1 by their charging time slots t^1_i in M_1. Assume that $t^1_1 < t^1_2 < \cdots < t^1_n$. We can see that $t^1_i \ge i$ for each i with $1 \le i \le n$ since the charger can charge only one sensor at each time slot. We construct matching M'_j in graph G'_j from M_1, by assigning each virtual sensor $v_{i,j'} \in \cup_{j'=1}^{j} V'_{j'}$ to time slot node $i + (j'-1)n$ if $v_{i,1}$ is matched to time slot t^1_i in M_1, where $1 \le j' \le j$ and $1 \le j \le k$.

Having the constructions, we now prove claim (ii.a): $w'_k(M'_k) = \cdots = w'_2(M'_2) = w'_1(M'_1)$. Since we assume the lifetime of any sensor for consuming an amount Δ of energy is no less than the total time of charging every sensor with Δ energy, i.e., $\frac{\Delta}{\tau\rho_{max}} \ge n$, virtual sensor $v_{i,j}$ will not deplete its energy before its charging time slot $i + (j-1)n$ for each j with $2 \le j \le k$. Then, $w'_k(M'_k) = \cdots = w'_2(M'_2) = w'_1(M'_1)$.

We then prove claim (ii.b): $w'_1(M'_1) = M'_1(M_1)$. On one hand, the weight $w'_1(M'_1)$ of matching M'_1 is no less than the weight $w'_1(M_1)$ of M_1, i.e., $w'_1(M'_1) \ge w'_1(M_1)$, since the dead duration of virtual sensor $v_{i,1}$ by charging it at time slot i is no more than that at time slot t^1_i and $i \le t^1_i$. On the other hand, the weight $w'_1(M'_1)$ of M'_1 is no more than weight $w'_1(M_1)$, i.e., $w'_1(M'_1) \le w'_1(M_1)$, as M_1 is a maximum matching in graph G'_1. Therefore, $w'_1(M'_1) = w'_1(M_1)$.

We finally show claim (ii.c): $w'_j(M'_j) = M'_j(M_j)$ for each j with $2 \le j \le k$. Following the construction of matchings $M_1, M_2, \ldots, M_k$ in `Algorithm 1`, we can see that $w'_1(M_1) \ge w'_2(M_2) \ge \cdots \ge w'_k(M_k)$. On one hand, the weight $w'_j(M'_j)$ of M'_j is no less than weight $w'_j(M_j)$, i.e., $w'_j(M'_j) \ge w'_j(M_j)$, since $w'_j(M'_j) = w'_1(M'_1) = w'_1(M_1) \ge w'_j(M_j)$. On the other hand, the weight $w'_j(M'_j)$ of M'_j is no more than $w'_j(M_j)$, i.e., $w'_j(M'_j) \le w'_j(M_j)$, as M_j is a maximum matching in graph G'_j. Therefore, $w'_j(M'_j) = w'_j(M_j)$.

In summary, `Algorithm 1` delivers an optimal solution to the problem for Case 1. □

We then have the following theorem.

Theorem 1. *Given a set V of to-be-charged sensors in a sensor network $G_s = (V_s, E_s)$ with the residual energy RE_i, energy consumption rate ρ_i, and energy demand $B_i - RE_i$ of each sensor $v_i \in V$, there is a heuristic algorithm,* `Algorithm 1`*, for the sensor lifetime maximization problem with time complexity $O(n^3)$, where $n = |V|$.*

Proof. We first show that `Algorithm 1` delivers a feasible solution to the problem, i.e., each virtual sensor in V' is matched to a time slot in S' in matching $M_{k_{max}}$ in graph $G'_{k_{max}}$. To this end, we show that each virtual sensor in $\cup_{j'=1}^{j} V'_j$ is matched to a time slot in S' in matching M_j in graph G'_j at Step 1 of `Algorithm 1` for each j with $0 \le j \le k_{max}$. We show this by induction on j. We can see that the claim holds for $j = 0$ as G'_0 is an empty graph. At iteration j with $1 \le j \le k_{max}$, the existence of such a matching is guaranteed by Hall's Theorem [4], which says that each virtual sensor in $\cup_{j'=1}^{j} V'_j$ is matched to a time slot in S' in matching M_j in graph G'_j if and only if for each subset V''_j of $\cup_{j'=1}^{j} V'_j$, the neighbor set $N(V''_j)$ of V''_j in graph G'_j satisfies $|N(V''_j)| \ge |V''_j|$. If $V''_j \cap V_j = \emptyset$, then $|N(V''_j)| \ge |V''_j|$ since graph G'_{j-1} is a subgraph of G'_j and each virtual sensor in V''_j is matched to a time slot in S' in matching M_{j-1}. Otherwise ($V''_j \cap V_j \ne \emptyset$), we know that $|N(V''_j)| \ge |V''_j|$ as there is an edge $(v_{i,j}, s_q)$ between a virtual sensor in $V''_j \cap V_j$ and every time slot $s_q \in S$, i.e., $|N(V''_j)| = |S'| = n' \ge |V'| \ge |V''_j|$. Furthermore, note that

Algorithm 1 does not remove any matched edges in M_j from graph G'_j at Step 1.

The time complexity analysis of Algorithm 1 is straightforward, omitted. □

4 Algorithm for the Service Cost Minimization Problem with Maximum Sensor Lifetime

In the previous section, we found a charging tour for the mobile charger so that the sum of the normalized sensor lifetimes of all sensors is maximized. However, the service cost of the mobile charger at its per charging tour may be expensive. In this section, we focus on minimizing the service cost of the mobile charger while ensuring that the maximum sum of normalized sensor lifetimes of sensors can be achieved, by proposing a novel heuristic for the problem. In the following, we first introduce the basic idea of the heuristic and then elaborate its implementation in details.

4.1 Algorithm Overview

Recall that we created k_i virtual sensors $v_{i,1}, v_{i,2}, \ldots, v_{i,k_i}$ for each sensor v_i in V, and $V' = \{v_{i,j} \mid v_i \in V, 1 \le j \le k_i\}$, where $k_i = \lceil \frac{B_i - RE_i}{\Delta} \rceil$. Each virtual sensor $v_{i,j} \in V'$ has its energy expiration time $l_{i,j}$ in Algorithm 1. Also, in matching $M_{k_{max}}$, virtual sensor node $v_{i,j}$ is matched to a time slot node s_q. We say that a virtual sensor $v_{i,j}$ is *unexpired* if it is charged in time by matching $M_{k_{max}}$, i.e., $q \le l_{i,j} + 1$. Otherwise ($q > l_{i,j} + 1$), it is *expired*. For the depot r of the mobile charger, we create two virtual nodes r_s and r_f and the location of each of the two nodes is the same as that of depot r.

The basic idea behind the heuristic is to find a r_f-rooted tree T spanning the nodes in $V' \cup \{r_s, r_f\}$ so that the weight of the tree is minimized, subject to two constraints: (1) the number of virtual sensors in the subtree rooted at each unexpired virtual sensor $v_{i,j}$ is no more than its energy deadline $l_{i,j} + 1$; and (2) the number of virtual sensors in the subtree rooted at each expired virtual sensor $v_{i,j}$ is equal to q, assuming that $v_{i,j}$ is matched to the qth time slot in matching $M_{k_{max}}$. Notice that constraints (1) and (2) ensure that the sum of normalized sensor lifetimes in the found charging tour will be maximized. Having the found tree T, a path P starting from r_s and ending at r_f can then be derived from T, and the length of P is not too much longer than the cost of the tree T. Finally, the mobile charger charges sensors in V along path P, where path P actually is a closed tour since its two end nodes r_s and r_f are the virtual nodes that are derived from the depot r.

4.2 Algorithm

We now construct tree T. Note that $n' = |V'|$ time slots are needed to charge all virtual sensors in V'.

We first partition the nodes in V' into n' disjoint sets $V'_1, V'_2, \ldots, V'_{n'}$, by their energy expiration times and matching $M_{k_{max}}$. An expired virtual sensor in V' is contained in set V'_q, assuming that the sensor is matched to time slot s_q in matching $M_{k_{max}}$, while an unexpired virtual sensor $v_{i,j} \in V'$ is contained in a set $V'_{j'}$ where j' is the maximum integer no greater than $\min\{l_{i,j} + 1, n'\}$ so that there are no expired virtual sensors in each set $V'_{j''}$ with $j' < j'' \le \min\{l_{i,j} + 1, n'\}$. In other words, j' is the latest time slot that virtual sensor $v_{i,j}$ will not deplete its energy if the mobile charger can charge it prior to that time slot. Note that some of the n' sets may contain none of the virtual sensors. We can see that the number of nodes in the first j sets is no more than j, i.e., $\sum_{j'=1}^{j} |V'_{j'}| \le j$, for each j with $1 \le j \le n'$, which will be shown later.

Having the n' partitioned sets, we group them into Y supersets $\mathcal{V}_1, \mathcal{V}_2, \ldots, \mathcal{V}_Y$, where Y is the number of integers satisfying that $\sum_{j'=1}^{j} |V'_{j'}| = j$ with $1 \le j \le n'$. That is, assuming that the first $y-1$ supersets $\mathcal{V}_1, \mathcal{V}_2, \ldots, \mathcal{V}_{y-1}$ contains the first j_{y-1} sets $V'_1, V'_2, \ldots, V'_{j_{y-1}}$, superset $\mathcal{V}_y$ then contains sets $V'_{j_{y-1}+1}, V'_{j_{y-1}+2}, \ldots, V'_{j_y}$, where $\sum_{j'=1}^{j_y} |V'_{j'}| = j_y$ and $1 \le y \le Y$. We can see that the mobile charger must charge virtual sensors in superset $\mathcal{V}_{y-1}$ before charging any virtual sensor in superset $\mathcal{V}_y$ for each y with $1 \le y \le Y$. Therefore, we can consider the charging sequence of the virtual sensors in $\mathcal{V}_1, \mathcal{V}_2, \ldots, \mathcal{V}_Y$ one by one. The detailed construction of tree T is given as follows.

Let $V'_0 = \{r_s\}$ and $V'_{n'+1} = \{r_f\}$. We add the nodes in sets $V'_0, V'_1, V'_2, \ldots, V'_{n'}$ to tree T one by one. Initially, T contains only node r_s. Assume that the nodes in sets $V'_0, V'_1, V'_2, \ldots, V'_j$ have been added to T and V'_j is not an empty set. Consider the next non-empty set V'_k with $k > j$. Assume that set V'_k is contained in superset $\mathcal{V}_y$. We find a subtree T_k that contains virtual sensors in V'_k and other $k - \sum_{j'=1}^{k} |V'_{j'}|$ unexpired residual virtual sensors in superset $\mathcal{V}_y$ so that the weighted sum of edges in T_k plus the minimum weight between T_k and the nodes in V'_j is minimized. To this end, for each unexpired residual virtual sensor v_i in superset $\mathcal{V}'_y$, we obtain a subtree T_k^i by expanding from a subtree containing only node v_i to a subtree contains virtual sensors in $V'_k \cup \{v_i\}$ and other $k - \sum_{j'=1}^{j} |V'_{j'}| - |V'_k \cup \{v_i\}|$ unexpired virtual sensors in a greedy way. Subtree T_k then is the tree with the minimum sum of tree weight plus the weight to nodes in V'_j, i.e., $T_k = \arg\min_{T_k^i} \{w(T_k^i) + w(e_{i,j})\}$, where $e_{i,j}$ is the minimum weighted edge between node v_i and the nodes in V'_j. Finally, we attach subtree T_k to the nearest node in V'_j in tree T and remove the nodes in T_k from $V'_{k+1}, V'_{k+2}, \ldots, V'_{n'}$. After we have added nodes in $V'_0 \cup V'_1 \cup V'_2 \cup \cdots \cup V'_{n'}$ to tree T, we connect node r_f to its nearest node in $V'_{n'}$.

The rest is to transform tree T to a path P from node r_s to node r_f while visiting nodes in V'. We first find the path from node r_s to node r_f in tree T. We then obtain a graph G'' by replicating the edges in tree T except the edges on the path and find a Eulerian path from node r_s to node r_f in graph G''. We finally find a path P by shortcutting repeated nodes in the Eulerian path. The detailed algorithm is given in Algorithm 2.

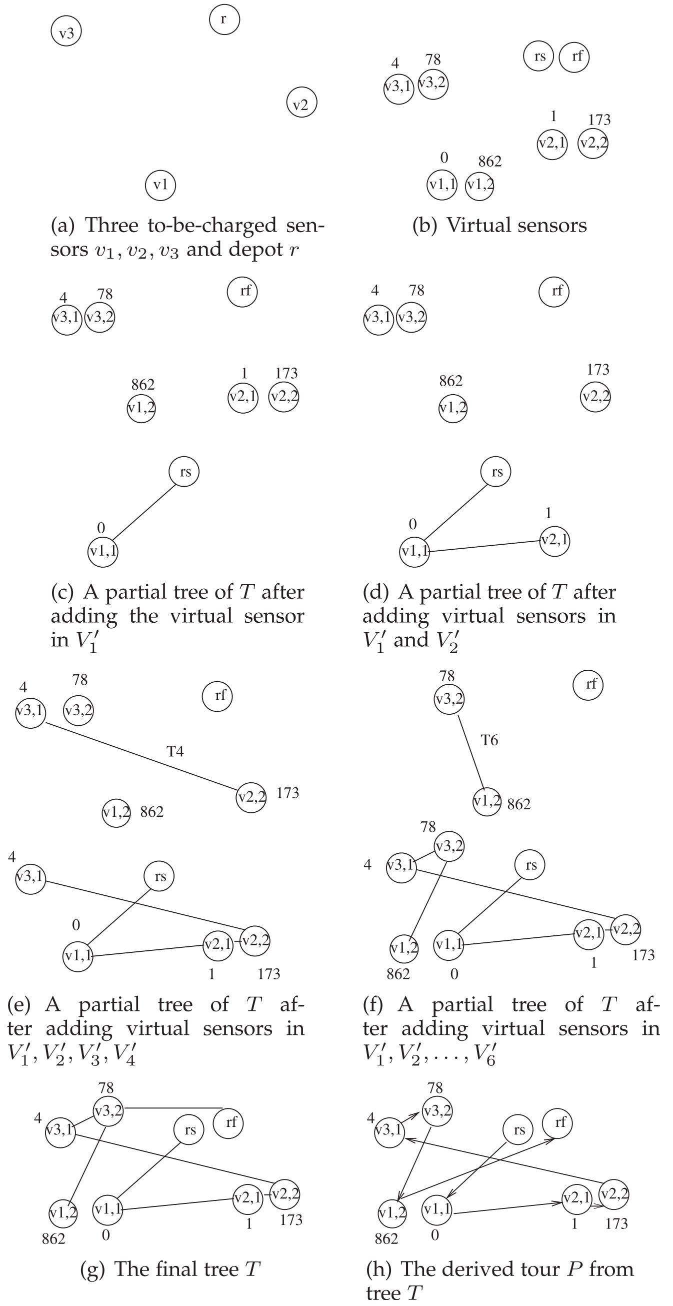
4.3 An Example of the Execution of Algorithm 2

We here use an example to illustrate the execution procedure and intermediate results of Algorithm 2. Assume that there are three to-be-charged sensors v_1, v_2, and v_3 in the network at some time point (see Fig. 5a), and their residual lifetimes are 0, 1, and 4 time slots, respectively. Two virtual sensors $v_{i,1}$ and $v_{i,2}$ are created for each sensor v_i with $1 \le i \le 3$ (see Fig. 5b). The energy expiration time and the matched time slot in matching $M_{k_{max}}$ found by Algorithm 1 are shown in Table 1. The partitioned six virtual sets by Algorithm 2 are $V'_1 = \{v_{1,1}\}$, $V'_2 = \{v_{2,1}\}$, $V'_3 = \{\}$, $V'_4 = \{v_{3,1}\}$, $V'_5 = \{\}$, $V'_6 = \{v_{1,2}, v_{2,2}, v_{3,2}\}$, respectively. The six virtual sets are then grouped into three supersets $\mathcal{V}_1 = \{V'_1\}$, $\mathcal{V}_2 = \{V'_2\}$, and $\mathcal{V}_3 = \{V'_3, V'_4, V'_5, V'_6\}$, respectively.

Algorithm 2. HeuristicMinCost

Input: Virtual sensor set V', their energy expiration times $l_{i,j}$s, matching $M_{k_{max}}$, and depot r.
Output: a charging tour P so that the length of the tour is minimized, while the sum of normalized sensor lifetimes is the same as that from matching $M_{k_{max}}$.

Partition virtual sensors in V' into n' sets $V'_1, V'_2, \ldots, V'_{n'}$ by their energy expiration times and matching $M_{k_{max}}$;
Group the n' sets into Y supersets $\mathcal{V}_1, \mathcal{V}_2, \ldots, \mathcal{V}_Y$;
Let set $V_0 = \{r_s\}$ and tree T contain only node r_s;
for $k \leftarrow 1$ to n' **do**
  if V'_k contains virtual sensors **then**
    Let $n_k = k - \sum_{j'=1}^{k-1} |V'_{j'}|$; // # of nodes in tree T_k;
    Assume that j is the maximum index so that V'_j contains virtual sensors with $0 \leq j < k$;
    if $|V'_k| = n_k$ **then**
      Tree T_k is an MST of a complete graph $G'_k = (V'_k, E'_k; w' : E'_k \mapsto \mathcal{R}^+)$, where $w'(u, v)$ is the Euclidean distance between any two virtual sensors u and v in V'_k;
    else
      Assume that set V'_k is contained in superset $\mathcal{V}_y$;
      for each unexpired node $v_i \in \cup_{V'_j \in \mathcal{V}_y} V'_j$ **do**
        Obtain a minimum weighted tree T^i_k covering nodes in set $V'_k \cup \{v_i\}$ and other $n_k - |V'_k \cup \{v_i\}|$ unexpired virtual sensors in $\cup_{V'_j \in \mathcal{V}_y} V'_j$ in a greedy way;
      end for
      Let $T_k = \arg\min_{T^i_k} \{w(T^i_k) + w(e_{i,j})\}$, where $e_{i,j}$ is the minimum weighted edge between node v_i and nodes in V'_j;
    end if
    Expand tree T by connecting subtree T_k to nodes V'_j using their minimum weighted edge;
    Let $V'_p \leftarrow V'_p \setminus V(T_k)$ for $k < p \leq n'$
  end if
end for
Add node r_f to tree T by connecting it to nodes in $V'_{n'}$ using their minimum weighted edge;
Obtain a graph G'' by replicating edges in tree T except the edges on the path from nodes r_s to r_f in tree T;
Find a Eulerian path from nodes r_s to r_f in G'';
Obtain a charging tour P by removing repeated nodes in the Eulerian path with shortcutting.



(a) Three to-be-charged sensors v_1, v_2, v_3 and depot r
(b) Virtual sensors
(c) A partial tree of T after adding the virtual sensor in V'_1
(d) A partial tree of T after adding virtual sensors in V'_1 and V'_2
(e) A partial tree of T after adding virtual sensors in V'_1, V'_2, V'_3, V'_4
(f) A partial tree of T after adding virtual sensors in $V'_1, V'_2, \ldots, V'_6$
(g) The final tree T
(h) The derived tour P from tree T

Fig. 5. An example of the execution of `Algorithm` 2.

Initially, tree T contains only node r_s. Virtual sensors in $V'_1, V'_2, \ldots, V'_6$ are added to T one by one, and a subtree T_j is found for each virtual set V'_j, $1 \leq j \leq 6$. Since virtual set V'_1 contains only one node $v_{1,1}$, a subtree T_1 containing only node $v_{1,1}$ is attached to tree T by connecting node $v_{1,1}$ to node r_s that is the nearest node in $V'_0 = \{r_s\}$ (see Fig. 5c). Similarly, a subtree T_2 containing only node $v_{2,1} \in V'_2$ is added to tree T by connecting $v_{2,1}$ to node $v_{1,1}$ that is the nearest node in $V'_1 = \{v_{1,1}\}$ (see Fig. 5d). For virtual set $V'_4 = \{v_{3,1}\}$ (set V'_4 is contained in superset $\mathcal{V}_3$), a subtree T_4 is found so that the subtree contains the node $v_{3,1}$ in V'_4 and other $4 - \sum_{j=1}^{4} |V'_j| = 4 - 3 = 1$ node in set $\cup_{V'_j \in \mathcal{V}_3} V'_j \setminus V'_4 = \{v_{3,1}, v_{1,2}, v_{2,2}, v_{3,2}\} \setminus \{v_{3,1}\} = \{v_{1,2}, v_{2,2}, v_{3,2}\}$, and the sum of the weight of tree T_4 plus the weight of the shortest edge between T_4 and the node in V'_2 is minimized, where tree T_4 contains virtual sensors $v_{3,1}$ and $v_{2,2}$ (see Fig. 5e). After subtree T_4 has been attached to tree T, there are only two virtual sensors $v_{1,2}, v_{3,2}$ left in V'_6. Subtree T_6 then contains only the two nodes and it is attached to tree T by connecting $v_{3,2}$ to $v_{3,1}$ (see Fig. 5f). Finally, node r_f is added to tree T by connecting it to node $v_{3,2}$ that is its nearest node in set V'_6 (see Fig. 5g).

A charging tour P is derived from tree T (see Fig. 5h), from which it can be seen that only sensor v_1 will be charged twice by the charger in the tour while both sensors v_2 and v_3 are charged only once, as two consecutive chargings for two virtual sensors derived from the same real sensor can be merged into one charging.

4.4 Incorporating the Charger Energy Capacity

In the charging model of Section 2.2, we assumed that the mobile charger has sufficient energy to charge to-be-charged sensors in each charging tour. However, this assumption

TABLE 1
The Energy Expiration Time and Matched Time Slot for Each Virtual Sensor

virtual sensor	$v_{1,1}$	$v_{1,2}$	$v_{2,1}$	$v_{2,2}$	$v_{3,1}$	$v_{3,2}$
expiration time	0	862	1	173	4	78
matched time slot	1	4	2	5	3	6

sometimes may not be practical, especially when there are a large number of to-be-charged sensors or the mobile charger itself is also energy-constrained [10], [11], [21]. Then, the charging tour delivered by `Algorithm 2` for the service cost minimization problem may be infeasible, since the total energy consumption by the mobile charger during the tour may exceed its energy capacity. In the following we show how to extend `Algorithm 2` to solve the problem under the energy capacity constraint on the mobile charger.

We assume that there is an energy capacity IE of the mobile charger and that the mobile charger can replace its battery or recharge itself at depot r when it depletes its energy. Given a set of to-be-charged sensors, denote by $C = <(r,0) \rightarrow (v'_1, e_1) \rightarrow (v'_2, e_2) \rightarrow \cdots \rightarrow (v'_{n'}, e_{n'}) \rightarrow (r,0)>$ the charging tour delivered by `Algorithm 2`. We split the charging tour C into several, say q, sub-tours $C_1, C_2, \ldots, C_q$, so that the total energy consumption of the charger in each sub-tour C_j is no more than its energy capacity IE, where $q > 1$ is to be determined. Assume that we have already found the first j sub-tours $C_1, C_2, \ldots, C_j$ and the first q_j sensors $v'_1, v'_2, \ldots, v'_{q_j}$ in tour C will be charged in the j sub-tours. Then, the $(j+1)$th sub-tour is $C_{j+1} = <(r,0) \rightarrow (v'_{q_j+1}, e_{q_j+1}) \rightarrow (v'_{q_j+2}, e_{q_j+2}) \rightarrow \cdots \rightarrow (v'_{q_{j+1}}, e_{q_{j+1}}) \rightarrow (r,0)>$, where the energy consumption of the mobile charger in sub-tour C_{j+1} is no more than its energy capacity IE but the it will consume more than IE energy for charging virtual sensors $v'_{q_j+1}, v'_{q_j+2}, \ldots, v'_{q_{j+1}}, v'_{q_{j+1}+1}$, or $v'_{q_{j+1}}$ is the last to-be-charged virtual sensor in tour C.

4.5 Algorithm Analysis

Theorem 2. *Given a set V of to-be-charged sensors in a sensor network $G_s = (V_s, E_s)$ with each sensor $v_i \in V$ having its residual energy RE_i, energy consumption rate ρ_i, and energy demand $B_i - RE_i$, there is a heuristic algorithm, `Algorithm 2`, for the service cost minimization problem with the maximum sensor lifetime in time $O(n^4)$, where n is the number of to-be-charged sensors, i.e., $n = |V|$.*

Proof. We show that the solution delivered by `Algorithm 2` is feasible, by claiming that (i) the sum of nodes in the first j sets from sets $V'_1, V'_2, \ldots, V'_{n'}$ is no more than j, i.e., $\sum_{j'=1}^{j} |V'_{j'}| \leq j$, where $1 \leq j \leq n'$; and (ii) the sum of normalized sensor lifetimes derived from tour C is the same as that from matching $M_{k_{max}}$.

We first show that (i) $\sum_{j'=1}^{j} |V'_{j'}| \leq j$, $1 \leq j \leq n'$. Recall that we obtained sets $V'_1, V'_2, \ldots, V'_{n'}$ from set V' by their energy expiration times and matching $M_{k_{max}}$. The nodes in $\cup_{j'=1}^{j} V'_{j'}$ must be matched to a subset of time slot set $\{s_1, s_2, \ldots, s_j\}$ in matching $M_{k_{max}}$. Then, $\sum_{j'=1}^{j} |V'_{j'}| \leq j$.

We then show that (ii) the sum of normalized sensor lifetimes derived from tour C is the same as that from matching $M_{k_{max}}$. From the construction of tour C, we can see that an expired virtual sensor is charged at the same time slot as that in matching $M_{k_{max}}$, while an unexpired virtual sensor $v_{i,j}$ is charged at a time slot prior to its energy deadline $l_{i,j} + 1$. In other words, the live and dead durations of each sensor in V in tour C are the same as that in matching $M_{k_{max}}$, respectively. The time complexity analysis of `Algorithm 2` is straightforward, omitted. □

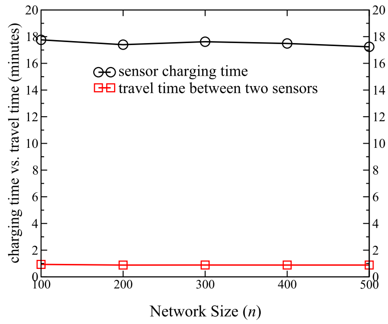
5 Performance Evaluation

In this section, we evaluate the performance of the proposed algorithms through experimental simulations. We also study the impact of important parameters on the algorithm performance including network size, data rates of sensors, the energy charging unit, and the energy capacity of the mobile charger.

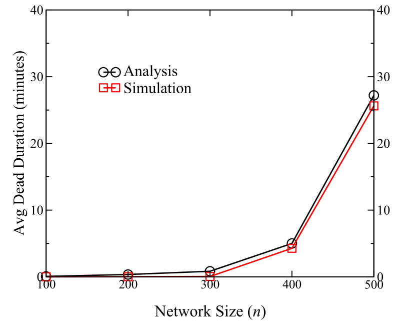
5.1 Simulation Environment

We consider a WSN consisting of from 100 to 500 sensors, which are uniformly deployed within a $1{,}000 \text{ m} \times 1{,}000 \text{ m}$ square area at random. Both the base station and the depot r are co-located at the center of the square. The battery capacity of each sensor $v_i \in V_s$ is $B_i = B = 10.8$ kJ [18]. The data sensing rate b_i of sensor v_i is randomly chosen from an interval $[b_{min}, b_{max}]$, where $b_{min} = 1$ kbps and $b_{max} = 10$ kbps [18]. We adopt the real sensor energy consumption model in [9]. The mobile charger travels at a constant speed of $\nu = 5$ m/s with an energy consumption rate of $\xi = 0.6$ kJ/m [11], [22] The charging rate of the mobile charger μ varies from a slow one $\mu_{min} = 1$ Watt to a fast one $\mu_{max} = 10$ Watts, and its default value is 5 Watts. Then, the time for fully charging a sensor battery varies from $\frac{B}{\mu_{max}} = \frac{10.8 \text{ kJ}}{10 \text{ Watts}} = 18$ minutes to $\frac{B}{\mu_{min}} = \frac{10.8 \text{ kJ}}{1 \text{ Watt}} = 3$ hours. Each to-be-charged sensor sends a charging request to the base station when its residual lifetime is below a critical lifetime $l_c = 2$ hours. The given monitoring period T_M is one year. Assume that each sensor v_i will run out of its energy $d_i \geq 0$ times during the period T_M, and it stops working during the time interval $[t^s_{i,j}, t^f_{i,j}]$ due to its jth energy depletion, where $1 \leq j \leq d_i$ The dead duration of sensor v_i in period T_M then is calculated as $\sum_{j=1}^{d_i} (t^f_{i,j} - t^s_{i,j})$.

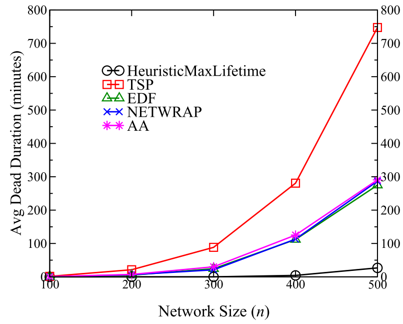
In addition to the proposed algorithms `HeuristicMaxLifetime` and `HeuristicMinCost`, we also implement algorithms `EDF`, `TSP`, `NETWRAP` in [20], and `AA` in [21] for benchmark purposes. In algorithm Earliest Deadline First (`EDF`), we sort to-be-charged sensors by their energy expiration deadlines and the mobile charger visits the sorted sensors one by one. In algorithm `TSP`, we calculate an approximately shortest closed tour visiting to-be-charged sensors without considering their energy expirations [4]. In algorithm `NETWRAP` [20], the mobile charger selects the next to-be-charged sensor that has the minimum weighted sum of the travel time of the charger to the sensor and the residual lifetime of the sensor. Finally, in the state-of-the-art algorithm `AA` [21], a mobile charger charges a proportion of to-be-charged sensors before their energy expirations, so as to maximize the total amount of energy charged to sensors minus the total traveling energy cost of the charger. Each value in figures is the average of the results by applying each mentioned algorithm to 100 different network topologies with the same network size.



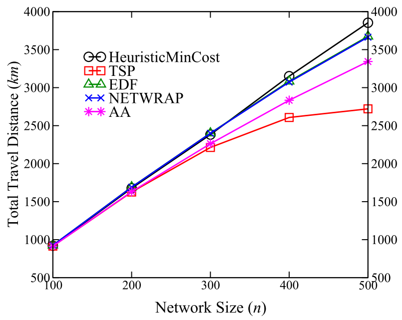
(a) sensor charging time vs. charger travel time by algorithm `HeuristicMaxLifetime`



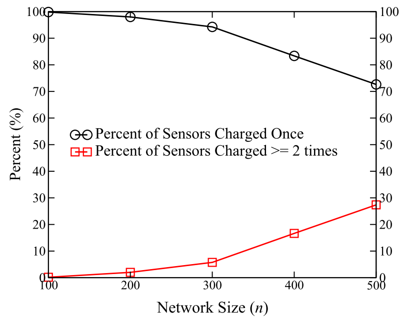
(b) Analytical and experimental average sensor dead durations by algorithm `HeuristicMaxLifetime`



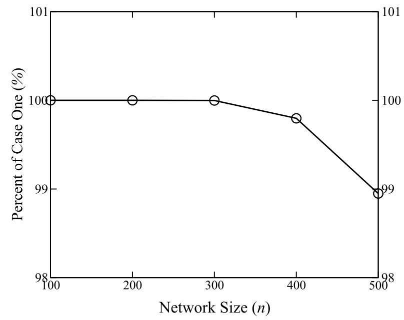
(c) Average dead duration per sensor during T_M



(d) Total travel distance of the mobile charger during T_M



(e) The percentages of sensors charged once and more than once, respectively



(f) Percent of Case 1

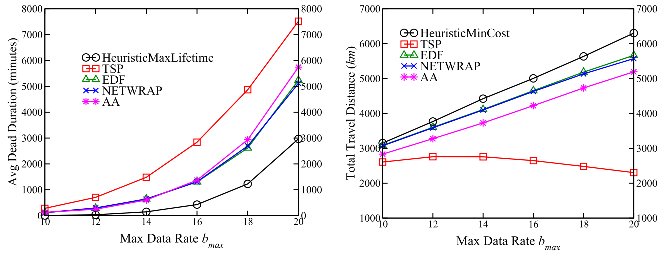
Fig. 6. Performance of algorithms `HeuristicMaxLifetime`, `HeuristicMinCost`, `TSP`, `EDF`, `NETWRAP`, and `AA` by varying the network size n from 100 to 500.

5.2 Algorithm Performance

Recall that in algorithm `HeuristicMaxLifetime`, we assumed that the average charger travel time between two consecutive to-be-charged sensors is much shorter than the sensor charging time for an amount of Δ energy, but is not neglected. We first validate the practicality of the assumption through experiments. Fig. 6a shows that the average charger travel time is no more than 1 minute while the sensor charging time is as long as 17 minutes. In addition, Fig. 6b demonstrates that the experimental average sensor dead duration by algorithm `HeuristicMaxLifetime` matches its analytical average dead duration very well, which means that the assumption only slightly affects experimental results, thus it is reasonable.

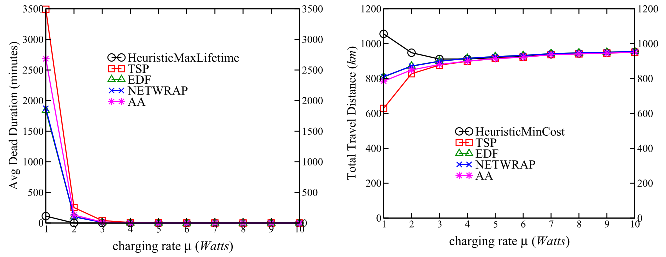
We then evaluate the performance of algorithms `HeuristicMaxLifetime` `HeuristicMinCost`, `TSP`, `EDF`, `NETWRAP`, and `AA`, by varying the network size n from 100 to 500. Fig. 6c shows the average energy dead duration per sensor delivered by these algorithms for a given monitoring period T_M, from which it can be seen that the average dead duration per sensor by the proposed algorithm `HeuristicMaxLifetime` is much shorter than that by algorithms `TSP`, `EDF`, `NETWRAP`, and `AA`. For example, the average dead duration by algorithm `HeuristicMaxLifetime` is only around 9 percent of that by algorithm `AA`, i.e., $9\% \approx \frac{26.8 \text{ minutes}}{290.7 \text{ minutes}}$. The rationale behind is that algorithm `HeuristicMaxLifetime` can find a charging tour so that the sum of normalized lifetimes of all sensors is maximized while the rest of the mentioned algorithms ignore minimizing the energy dead durations. Fig. 6c also demonstrates that the average dead duration delivered by algorithm `TSP` is the longest one among the mentioned algorithms, since algorithm `TSP` does not consider the energy expirations of to-be-charged sensors and schedules the mobile charger to charge the sensors along a shortest tour. Fig. 6d plots the total travel distance of the mobile charger delivered by the mentioned algorithms during the period of T_M. Algorithm `HeuristicMinCost` has the longest total travel distance, which is about from 1 to 15 percent longer than that by algorithm `AA`. Such a minor increase on the travel distance however is worthwhile as the average dead duration per sensor by the algorithm is only about 9 percent of that by algorithm `AA`, and the continuing operation of sensors usually is a fundamental requirement in many WSN applications. Notice that although each to-be-charged sensor is allowed to be charged multiple times, it is unnecessary that each sensor must be charged many times. Fig. 6e demonstrates the percentages of sensors charged once and more than once during a charging tour delivered by the proposed algorithm `HeuristicMinCost`, respectively, from which it can be seen that more than 70 percent of the sensors are charged only once. Finally, Fig. 6f shows that, in as high as 98 percent of the chargings during period T_M, the number of to-be-charged sensors falls into Case 1, for which algorithm `HeuristicMaxLifetime` delivers the maximum sum of the normalized lifetimes of sensors.

We study the performance of different algorithms, by varying the maximum data rate b_{max} from 10 to 20 kbps while setting $b_{min} = 1\ kbps$ and $n = 400$. Fig. 7a implies that the average dead duration per sensor by each of the algorithms increases with the growth of b_{max} from 10 to 20 kbps. As a result, there are more to-be-charged sensors in each charging tour, and each to-be-charged sensor thus is more likely to deplete its energy before it can be replenished. Fig. 7a also indicates that the average dead duration per sensor by algorithm `HeuristicMaxLifetime` is the shortest one while the one delivered by algorithm `TSP` is the longest one. On the



(a) Average dead duration per sensor during T_M (b) Total travel distance of the mobile charger during T_M

Fig. 7. Performance of algorithms `HeuristicMaxLifetime`, `HeuristicMinCost`, `TSP`, `EDF`, `NETWRAP`, and `AA` by varying the maximum data rate b_{max} from 10 to 20 kbps while $n = 400$.



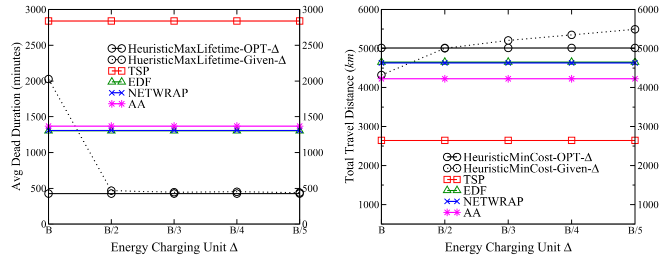
(a) Average dead duration per sensor during T_M (b) Total travel distance of the mobile charger during T_M

Fig. 8. Performance of algorithms `HeuristicMaxLifetime`, `HeuristicMinCost`, `TSP`, `EDF`, `NETWRAP`, and `AA` by varying the charging rate μ from 1 to 10 Watts while $n = 100$.

other hand, Fig. 7b exhibits an interesting phenomenon. That is, the total travel distance of the mobile charger delivered by any of algorithms `HeuristicMinCost`, `EDF`, `NETWRAP`, and `AA` becomes longer with the increase of b_{max}, while the one by algorithm `TSP` slightly decreases. The rationale is that there are more to-be-charged sensors in each charging tour when the maximum data rate b_{max} increases, the number of charging tours during period T however significantly decreases. Since the first four algorithms schedule the mobile charger by taking sensor energy expirations into consideration, the travel distances by them in each tour will become significantly longer with the increase of b_{max}. In contrast, in algorithm `TSP`, although the increase on the number of to-be-charged sensors in each charging tour will increase the travel distance of the mobile charger, such an increase is insignificant as algorithm `TSP` does not consider sensor energy expirations, and to-be-charged sensors usually are close to the base station.

We also examine the performance of the mentioned algorithms by increasing the charging rate μ from a slow charging rate 1 Watt to a fast charging rate 10 Watts. Fig. 8a shows that the average sensor dead duration by each of the mentioned algorithms dramatically decreases with a faster charging rate μ, as the charging time per sensor is significantly shortened if the mobile charger replenishes it quicker. Fig. 8a also demonstrates that the average sensor dead duration by algorithm `HeuristicMaxLifetime` is much shorter than those by the other algorithms. For example, the average sensor dead durations by algorithms `HeuristicMaxLifetime`, `TSP`, `EDF`, `NETWRAP`, and `AA` are about 112, 3,500, 1,840, 1,870, and 2,700 minutes respectively, when the charging rate μ is 1 Watt. On the other hand, Fig. 8b plots that the total travel distance by algorithm `HeuristicMinCost` is only about from 1 to 34 percent longer than that by the state-of-the-art algorithm `AA`.

We further investigate the impact of the energy charging unit Δ on algorithm performance, by decreasing Δ from B to $\frac{B}{5}$. It can be seen that, $\Delta = B$ indicates that the full-charging model is adopted while $\Delta = \frac{B}{2}, \frac{B}{3}, \frac{B}{4}$, or $\frac{B}{5}$ means that the partial-charging model is adopted. Fig. 9a implies that the average dead duration per sensor by algorithm `HeuristicMaxLifetime-Given-Δ` significantly decreases when the value of Δ decreases from B to $\frac{B}{2}$. This demonstrates that the proposed partial-charging model can shorten sensor energy expiration durations. Fig. 9a also indicates that the average dead duration by the algorithm slightly decreases with the decrease of Δ from $\frac{B}{2}$ to $\frac{B}{5}$. In contrast, Fig. 9a shows that the performance of algorithms `TSP`, `EDF`, `NETWRAP`, and `AA` do not change with the decrease of Δ as they adopt the full-charging model. Furthermore, Fig. 9a demonstrates



(a) Average dead duration per sensor during T_M (b) Total travel distance of the mobile charger during T_M

Fig. 9. Performance of algorithms `HeuristicMaxLifetime`, `HeuristicMinCost` `TSP`, `EDF`, `NETWRAP`, and `AA` by decreasing the energy charging unit Δ from B to $\frac{B}{5}$ while $b_{min} = 1$ kbps, $b_{max} = 16$ kbps, and $n = 400$.

that the average dead duration per sensor by algorithm `HeuristicMaxLifetime-OPT-Δ` is from 4 to 9 percent shorter than that by algorithm `HeuristicMaxLifetime-Given-Δ`, where the optimal energy charging unit Δ_{OPT} of the former algorithm is found by the proposed method in Section 3.2. On the other hand, Fig. 9b implies that the total travel distance by algorithm `HeuristicMinCost-Given-Δ` increases with the decrease of Δ.

We finally study the impact of the energy capacity of the mobile charger IE on the performance of the proposed algorithm `HeuristicMinCost`, by varying IE from 100 to 2,000 kJ. The mobile charger then can travel from only about 170 ($\approx \frac{100 \text{ kJ}}{0.6 \text{ kJ/m}}$) meters to no more than 3,400 ($\approx \frac{2{,}000 \text{ kJ}}{0.6 \text{ kJ/m}}$) meters per tour. Fig. 10 shows that the total travel distance of the mobile charger delivered by algorithm `HeuristicMinCost` dramatically decreases with the increase of the energy capacity IE, as the mobile charger can replenish more sensors per charging tour with a larger capacity IE. Also, the total travel distance by algorithm `HeuristicMinCost` is no more than 18 percent ($\approx \frac{1978 \text{ km} - 1676 \text{ km}}{1676 \text{ km}}$) longer than that by the algorithm without the energy capacity constraint, even when the mobile charger is very energy-constrained (i.e., $IE = 100$ kJ).

6 Related Work

Wireless energy replenishment as a promising mechanism for prolonging the lifetime of WSNs has been recently studied in literature [6], [15], [18], [20], [21], [24], [30]. Zhang et al. [30] considered the problem of scheduling multiple mobile chargers to optimize energy usage effectiveness to fully charge a set of sensors, where the sensor charging time is ignored, there is an energy capacity on each mobile charger, and mobile

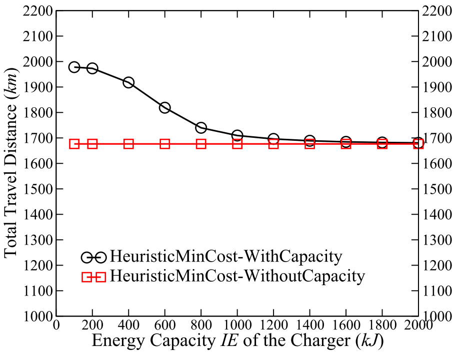


Fig. 10. Performance of algorithm HeuristicMinCost, by increasing the energy capacity IE of the mobile charger from 100 to $2{,}000$ kJ.

chargers are allowed to transfer energy among themselves. Xu et al. [24] studied the problem of scheduling k mobile chargers to charge a set of sensors so that the sensors can be fully charged as soon as possible, while Ren et al. [15] investigated the problem of scheduling a mobile charger to charge as many sensors as possible within a given time period, by taking both the sensor charging time and the travel time of the charger into consideration. Shi et al. [18] employed a wireless charger to periodically charge all sensors such that the network can perpetually operate. Wang et al. [20] proposed an algorithm in which a mobile charger replenishes the next sensor that has the minimum weighted sum of the travel time of the mobile charger to the sensor and the residual lifetime of the sensor. Given a set of to-be-charged sensors with different residual lifetimes, they also provided an adaptive algorithm to schedule a mobile charger to charge a proportion of the sensors before their energy expirations, with the objective to maximize the total amount of energy charged to sensors minus the total traveling energy cost of the charger [21]. He et al. [6] investigated a mobile charging problem using a Nearest-Job-Next with preemption, and provided analytical results on the number of charging requests served and the charging latency of each sensor, assuming that the arrival times of sensor charging requests follow Poisson's distribution.

Different from these mentioned studies that adopt a simple full-charging model, we are the first to adopt a novel partial-charging model so that more sensors can be charged before their energy depletions. Also, unlike the previous studies that ignore the energy expiration durations of sensors, we study the problem of scheduling a mobile charger to charge sensors so that the sum of normalized sensor lifetimes is maximized, while the travel distance of the charger is minimized.

There are some related studies in the Orienteering Problem with Time Windows (OP-TW) [3]. Given an edge-weighted graph $G = (V, E)$ and two nodes s and t, each node v in V is associated with a time window $[R(v), D(v)]$. The OP-TW problem is to find a $s - t$ walk in G so that the number of nodes visited within their time windows in the walk is maximized. Chekuri [3] devised a polynomial-time $O(\max\{\log OPT, \log \frac{L_{max}}{L_{min}}\})$-approximation algorithm for the problem, where L_{max} and L_{min} are the lengths of the longest and shortest time windows, respectively. We note that the OP-TW problem is essentially different from the problems in this paper, since the objective of the OP-TW problem is to find a $s - t$ walk so as to visit as many nodes as possible within their time windows, while in this paper every to-be-charged sensor must be charged and some sensors thus may be charged at time points after their deadlines. Therefore, the proposed algorithms in [3] cannot be applied to the problems in this paper.

7 Conclusions

In this paper we studied the use of a mobile charger to wirelessly charge sensors in a rechargeable sensor network so that the sum of sensor survival times can be maximized while keeping the travel distance of the mobile charger minimized. Unlike existing studies that assumed a mobile charger must charge a sensor to its full energy capacity before charging the next one, we are the first to propose a partial energy charging model for sensor charging to shorten sensor dead durations, under which we first formulate two novel optimization problems of dispatching a mobile charger to charge a set of sensors, which are to maximize the sum of the sensor lifetimes and to minimize the travel distance of the charger while ensuring that the maximum sum of sensor lifetimes is achieved. We then proposed an efficient algorithm for each of the two problems, and we finally evaluated the performance of the proposed algorithms through experimental simulation. The simulation results demonstrated that the proposed algorithms are very promising.

Acknowledgments

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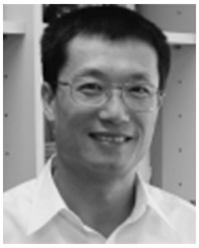

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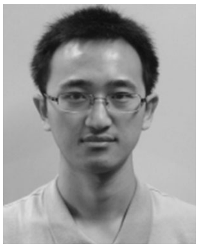

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