Wireless Netw (2017) 23:2069–2081
DOI 10.1007/s11276-016-1271-6

Charging utility maximization in wireless rechargeable sensor networks

Xiaoguo Ye[1,2] · Weifa Liang[3]

Published online: 22 April 2016

Abstract Wireless energy transfer as a promising technology provides an alternative solution to prolong the lifetime of wireless rechargeable sensor networks (WRSNs). In this paper, we study replenishing energy on sensors in a WRSN to shorten energy expiration durations of sensors, by employing a mobile wireless charger to replenish sensors dynamically. We first formulate a novel sensor recharging problem with an objective of maximizing the charging utility of sensors, subject to the total traveling distance of the mobile charger per tour and the charging time window of each to-be-charged sensor. Due to the NP-hardness of the problem, we then propose an approximation algorithm with quasi-polynomial time complexity. In spite of the guaranteed performance ratio of the approximate solution, its time complexity is prohibitively high and may not be feasible in practice. Instead, we devise a fast yet scalable heuristic for the problem in response to dynamic energy consumption of sensors in the network. Furthermore, we also consider the online version of the problem where sensor replenishment is scheduled at every fixed time interval. We finally conduct extensive experiments by simulation to evaluate the performance of the proposed algorithms. Experimental results demonstrate that the proposed algorithms are very promising.

✉ Xiaoguo Ye
xgye@njupt.edu.cn

1 College of Computer, Nanjing University of Posts and Telecommunications, Nanjing 210003, Jiangsu, China

2 Jiangsu High Technology Research Key Laboratory for Wireless Sensor Networks, Nanjing 210003, Jiangsu, China

3 Research School of Computer Science, The Australian National University, Canberra, ACT 0200, Australia

Keywords Rechargeable sensor networks · Wireless energy transfer · Mobile charging vehicles · Sensor charging scheduling · Approximation algorithms · Charging utility

1 Introduction

The operational time of conventional wireless sensor networks (WSNs) usually is limited due to that sensors in such networks are mainly powered by energy-limited batteries. To prolong the network lifetime, extensive efforts have been taken in the past decade, including batch deployments of sensors, harvesting energy for sensors from their surrounding environments, etc [1–3]. Despite that these mentioned methods can improve the network lifetime in some degree, the network lifetime remains the main performance bottleneck in large scale deployment of WSNs. For example, the method of replacing batteries of sensors with the new ones can prolong the lifetime of sensor networks, however it is time-consuming, laborious for large-scale WSNs [4–6]. Especially, for WSNs deployed for dangerous surveillance and monitoring or inaccessible regions, it is almost impossible to replace sensor batteries. Alternatively, replacing expired sensors by a new batch of sensors is not environmentally friendly either, as most batteries are made by poisonous chemical materials that will pollute the soils and the environments [7]. Contrary to these mentioned works, a promising solution against the limited energy supplies has been explored in recent years, that is the renewable energy technology, which enables sensors to harvest ambient energy from their surroundings including solar energy, wind energy, etc [3, 8–10]. However, the temporally–spatially varying nature of renewable energy resources makes the prediction of sensor energy harvesting rates become very difficult. For example, it is shown that the differences of energy generating rates in sunny, cloudy and shadowy days can be up to three orders of magnitude in a solar harvesting system [11]. Thus, to recharge the sensors with stable energy sources is very crucial in maintaining the perpetual operations of WSNs. The recent breakthrough in wireless power transfer technology based on strongly coupled magnetic resonances makes this become possible, which has aroused widespread interest. Kurs et al. [12, 13] demonstrated that the wireless energy transfer technique is a promising technique to enable wirelessly transfer power with steady and high recharging rates. This technology provides an alternative solution to power sensors, and is promising to fundamentally solve the problem of limited lifetimes of WSNs via a stable, economic yet environmentally friendly solution.

In this paper, we employ a mobile wireless charger to replenish energy to sensors via wireless power transfer such that as many sensors as possible will not run out of their energy, while the total traveling distance of the charger per tour is bounded, due to its energy capacity. Obviously, a naive solution is that the mobile charger tends to preferentially charge its nearby sensors so as to charge more sensors. However, by doing so will result in that sensors with very low residual energy may not be charged on time if they are far away from the current location of the charger. To avoid this happening, we will devise a novel algorithm to schedule the mobile charger to charge sensors efficiently and effectively. We will introduce a new metric, *the charging utility*, to measure the charging quality of the charger that takes into account both the fairness of sensor charging and the number of sensors charged. We assume that each sensor has a charging time window, consisting of the release time and the charging deadline of the charging request from the sensor. We further assume that the mobile charger starts from the base station, travels along a close tour to charge sensors, and returns to the base station. The mobile charger can only travel a limited length per tour, due to the limited capacity of fuel loaded or electricity charged. Thus, finding an optimal close tour for the mobile charger to charge as many sensors as possible before their energy expirations poses a great challenge. In this paper we will tackle this challenge, by formulating this problem as a novel optimization problem with an objective of maximizing the charging utility, subject to both the traveling distance of the mobile charger and time windows of to-be-charged sensors.

Our main contributions in this paper can be summarized as follows. We first formulate a novel optimization problem of scheduling a mobile charger to charge energy-critical sensors, with an objective of maximizing the charging utility, subject to the total traveling distance of the mobile charger per tour and the time window of each to-be-charged sensor prior to its energy expiration. Due to the NP-hardness of the problem, we then propose an approximation algorithm with a guaranteed approximation ratio for the problem that takes quasi-polynomial time complexity. We also devise a fast yet scalable heuristic in response to dynamic energy consumptions of sensors. We thirdly devise an efficient algorithm for the online version of the problem where the sensor recharging requests dynamically arrive, and the system responses to these requests must be performed at every fixed time slot. We finally conduct experiments by simulations to evaluate the performance of the proposed algorithms. Experimental results demonstrate that the proposed algorithms are promising in terms of algorithm performance.

The rest of the paper is organized as follows. Section 2 reviews the related work. Section 3 introduces the network model and problem definition. Section 4 proposes an approximation algorithm. Section 5 proposes a fast, scalable heuristic. Section 6 develops an efficient algorithm for online version of the problem to deal with dynamic sensor recharging requests at each fixed time slot. Section 7 evaluates the performance of the proposed algorithms through experimental simulations, and Sect. 8 concludes the paper.

2 Related work

Wireless power transfer technology has an immense impact on wireless sensor networks, charging sensors without the constraints of wires and plugs. It provides a promising solution to prolong the lifetime of WSNs. Although a few studies have been conducted to explore mobile chargers to replenish energy to sensors, the deployment of this technology for sensor networks is still in its early infancy. Most existing studies considered sensor energy recharging and data collection routing jointly. For example, Shi et al. [14] considered replenishing sensor energy in a WSN, by employing a wireless charging vehicle to periodically charge each sensor. They took energy charging and data flow routing jointly, and formulated an optimization problem of maximizing the ratio of the vacation time of the wireless charging vehicle to the renewable energy cycle time. They assumed that the data rate of each sensor is unchanged, the shortest traveling path of the mobile charger is known or found in advance. They later extended their work to a general case where a mobile charger can charge multiple sensors simultaneously [15], for which they employed the mobile vehicle to charge sensors and collect sensing data simultaneously along its tours [16, 17]. Guo et al. [18] developed a framework of joint wireless energy replenishment and anchor-point based mobile data gathering, and considered various sources of energy consumptions and time-varying energy replenishments. They formulated the energy charging problem as a utility maximization problem under the constraints of flow conservation, energy balance and link capacity. Zhao et al. [19] considered a joint optimization of mobile data collection and energy charging to achieve a desirable balance between the energy replenishing range and data gathering latency by exploiting mobility. They formulated the charging and data collecting problem as an optimization problem to adjust data rates, link scheduling and flow routing to achieve maximum network utility. The disadvantage of these schemes of jointing data collection and wireless charging of mobile charger mentioned above lies in that mobile sink should move to the area where there is a heavy load of data collecting, while the mobile charger has to charge preferentially the sensors which are lacking of energy. It is very likely that the sensors with the least residual energy are located in the light load area.

Liang et al. [7], on the other hand, advocated to decouple sensor energy charging from sensing data routing and they should be dealt separately, and formulated a novel optimization problem of minimizing the number of mobile charging vehicles needed, subject to the energy capacity constraint on each mobile vehicle. Xu et al. [20] considered a charging problem of scheduling multiple mobile vehicles to collaboratively charge sensors periodically for a given monitoring period. They formulated a novel service cost minimization problem of finding a series of charging scheduling for mobile chargers to maintain the operations of large scale WSNs during the period of a tour. Ren et al. [21] provided a novel charging paradigm and proposed efficient sensor charging algorithms, considering the requirements of dynamic sensing and transmission behaviors of sensors. They formulated a charging throughput maximization problem with an objective of maximizing the number of sensors charged (charging throughput) per charging tour.

In this paper we distinguish our work from these state-of-the-art works as follows. We study a novel mobile charging problem where the charging quality (utility) of sensors, not the charging quantity (the number of sensors charged) is considered. To measure the charging quality, we introduce the *charging fairness* concept among to-be-charged sensors, and a new metric for measuring the *charging utility* which is a sub-modular function. We adopt a realistic assumption, that is, each to-be-charged sensor has its charging time window, within which the sensor must be charged if keeping its functionalities such as sensing data and relaying for others. Otherwise, once a sensor is dead, it is no longer functioning during its expiration period, and some important sensing data from the sensor and other sensors will be lost. Thus, different sensors may have different charging time windows due to different energy consumption rates. We also take into account the maximum traveling distance of the mobile charger per tour in the problem formulation.

3 Modeling and problem formulation

3.1 Network model

We consider a sensor network consisting a set V of heterogeneous sensors and a stationary base station v_0 deployed over a rectangle region. The WSN can be represented by a weighted undirected graph $G = (V \cup \{v_0\}, E; \ell)$. E is the set of links between two sensors or a sensor and the base station within the transmission range of each other, and denote by $\ell(u, v)$ the Euclidean distance between node u and v if there is an edge between them. Each sensor $v_i \in V$ is equipped with a rechargeable battery with energy capacity $B_i, i = 0, 1, \ldots, |V|$. The sensor consumes energy on sensing, processing and data transmission. Each sensor v_i will send a recharging request $RR_i = (v_i, r_i, RE_i, p_i, B_i)$ to the base station once its residual energy RE_i falls below a predefined threshold θ, where v_i is its identity, r_i is its request release time, RE_i is its residual energy at that moment, p_i is its energy consumption rate, B_i is its battery energy capacity with $0 < \theta < 1$. We assume that each sensor will be fully-charged if the mobile charger visits it in a tour, and denote by t_i the arrival time when the mobile charger visits sensor v_i for the first time in a tour. Let c_i be the charging duration of sensor v_i. We further assume that the energy consumption of sensor v_i is negligible during its survival time interval $[r_i, r_i + RE_i/p_i]$. Thus, the charging duration c_i of sensor v_i is

$$c_i = (B_i - RE_i)/\mu. \tag{1}$$

where μ is the charging rate of the mobile charger. Theoretically, the residual energy RE_i can only support sensor v_i to operate up to RE_i/p_i time after sensor v_i issues its charging request. To avoid its energy expiration, sensor v_i should be charged before this deadline. Denote by d_i the charging deadline of sensor v_i, then

$$d_i = r_i + RE_i/p_i. \tag{2}$$

Therefore, sensor v_i should be charged within the time window $[r_i, d_i]$ prior to its energy expiration.

A mobile charger is a moving vehicle equipped with a powerful wireless charger that can keep information synchronized with the base station via a long range radio [22]. During each tour, it starts from the base station to charge sensors on its charging tour. Since the mechanical movement of the mobile charger is driven by petrol or electricity, so is its sensor charging, we thus assume that the total traveling distance of the mobile charger per tour is bounded by a given value L. The mobile charger travels in the network deployment region along a close tour and its charging rate μ for all sensors is identical. For each charging tour, the mobile charger starts from and ends at its depot where the vehicle will be recharged or refueled for its next tour. For simplicity, we assume that the depot of the mobile charger is co-located with the base station v_0 and has enough energy to charge all sensors in its per tour [14].

In our charging model, the charger can only charge one sensor each time. We assume that the mobile charger travels at a constant speed m_c. An example of this charging paradigm is illustrated in Fig. 1.

Assume that all charging requests of sensors are given to the base station in advance at the beginning of a new tour. The base station makes the mobile charger schedule that decides which sensors and in which order of the sensors to be charged. The charger then charges the sensors one by one, following the charging schedule. When the charger is traveling, the base station may still receive new charging requests from sensors. These new charging requests will be dealt with in the next tour. Let $V_c \subseteq V$ be the set of sensors to be charged. Obviously, sensors in V_c are merely potential sensors to be charged. In each tour of the mobile charger, it may not be able to charge all sensors in V_c due to its maximum traveling length. Let V^C be the set of sensors that are charged by the charger at its current charging tour C, clearly, $V^C \subseteq V_c \subseteq V$.

3.2 Charging utility

We adopt a utility metric to measure the quality of sensor charging, which is expressed by a sub-modular function. Let f be a sub-modular function. Then, $f: 2^V \mapsto \mathbb{R}^{\geq 0}$ satisfies the following three properties [23]:

(1) $f(\emptyset) = 0$;

(2) $f(V_1^C) \leq f(V_2^C)$, $\mathrm{where} V_1^C \subseteq V_2^C \subseteq V \mathrm{and} V \mathrm{is\ a}$ finiteset;

(3) $f(V_1^C \cup \{v_i\}) - f(V_1^C) \geq f(V_2^C \cup \{v_i\}) - f(V_2^C)$, $\mathrm{where} V_1^C \subseteq V_2^C \subseteq V \mathrm{and} \exists v_i \in V \setminus (V_1^C \cup V_2^C)$.

Obviously, the sub-modular function f is a monotonic increasing function, whose marginal utility gain decreases

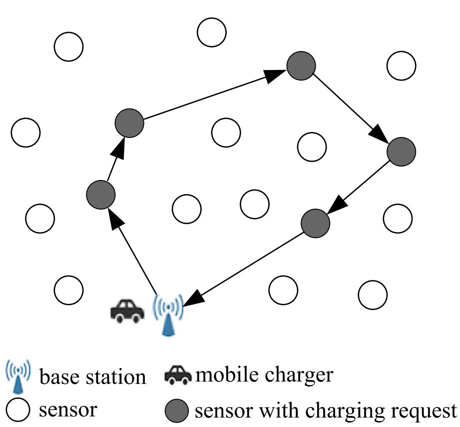

Fig. 1 An example of a mobile charger

with the increase of the number of elements. Recall that $V^C \subseteq V$ is a set of sensors charged for a charging tour C. Then, the *charging utility* of tour C is

$$U(C) = f(V^C) = \sum_{v_i \in V^C} u(v_i) \tag{3}$$

where $u(v_i)$ is the utility gain of charging sensor $v_i \in V^C$ with $i = 1, \ldots, |V^C|$, and is inversely proportional to its residual energy. This means a less residual energy sensor will have a higher utility gain. Function $u(v_i)$ thus is defined as

$$u(v_i) \propto \begin{cases} \frac{1}{RE_i}, & RE_i > \theta, \\ \frac{1}{\theta}, & RE_i \leq \theta. \end{cases} \tag{4}$$

where $\theta > 0$ is a given energy threshold of a battery and RE_i is the residual energy of sensor v_i for all i with $1 \leq i \leq |V_c|$ and $0 < RE_i \leq B_i$. When a sensor is nearly dead (the residual energy is θ), charging it will lead to the maximum gain in terms of the utilization function.

3.3 Problem definition

Given a sensor network $G = (V \cup \{v_0\}, E; \ell)$ and a maximum traveling distance L per tour by a mobile charger, and a set of sensors V_c ($V_c \subseteq V$) to be charged with their charging time windows, the *charging utility maximization problem* is to find a close tour C ($C \subseteq V_c$) in G for the mobile charger such that the charging utility $U(C)$ of the charging tour C is maximized, subject to the total traveling distance L of the mobile charger and the charging time windows of sensors in C. In other words, the problem is to charge as many energy critical sensors as possible per tour if the total traveling distance is upper bounded by L.

In the following we formulate the charging utility maximization problem as an integer linear programming.

$\mathrm{maximize} U(C)$

subject to

$$\ell(C) \leq L \tag{5}$$

$$r_i \leq t_i \leq d_i \quad (0 \leq i \leq |V^C|) \tag{6}$$

$$t_{i+1} \geq t_i + c_i + \tau(v_i, v_{i+1}) \quad (0 \leq i \leq |V^C|) \tag{7}$$

$$V^C \subseteq V_c \tag{8}$$

where $U(C) = \sum_{v_i \in V^C} u(v_i)$. Recall that we denote by $\ell(v_i, v_j)$ the traveling length of the mobile charger from sensor v_i to v_j. Let $\tau(v_i, v_j)$ be the traveling time from sensor v_i to v_j, which is

$$\tau(v_i, v_j) = \ell(v_i, v_j)/m_c. \quad (9)$$

We denote by $\ell(C)$ the total traveling distance of the close charging tour C, bounded by the maximum traveling distance L, which is

$$\ell(C) = \sum_{i=1}^{|V^C|} \ell(v_{i-1}, v_i) + \ell(v_{|V^C|}, v_0) \quad (10)$$

Recall that t_i is the arrival time point of the mobile charger at sensor v_i, and c_i is the charging duration at sensor v_i. Each sensor v_i should be charged within its time window $[r_i, d_i]$, otherwise, its residual energy will run out. In other words, it should be charged after its request releasing time and no later than its charging deadline. For convenience, we assume that node v_{q+1} is a dummy node located at v_0, the depot of the mobile charger, we thus have $\ell(v_q, v_{q+1}) = \ell(v_q, v_0)$. The schedule of the charging tour C consists of a sequence of triples, (v_0, t_0, c_0), (v_1, t_1, c_1), $\ldots$,(v_i, t_i, c_i), $\ldots$,(v_q, t_q, c_q), $(v_{q+1}, t_{q+1}, c_{q+1})$, where $q = |V^C|$, $t_0 = 0, c_0 = 0, r_0 = 0, d_0 = \infty, t_{q+1} = \infty, c_{q+1} = 0, r_{q+1} = t_{q+1} - 1, d_{q+1} = t_{q+1} + 1$.

Theorem 1 Given a wireless rechargeable sensor network $G = (V \cup \{v_0\}, E; \ell)$ and a mobile charger, the charging utility maximization problem in G is NP-hard.

Proof We construct an instance of the problem, where the utility gain of charging sensor v_i is $u(v_i) = 1$, the charging duration of each sensor v_i is a constant c, and the time window $[r_i, d_i] = [0, T_{\max}]$ for each sensor $v_i \in V_c$, where $T_{\max} = \max\{d_1, \ldots, d_{|V_c|}, \frac{L}{m_c} + \frac{\sum_{v_i \in V_c} B_i}{\mu}\}$ is a constant. Obviously, this is a special case of the charging utility maximization problem, which also is an orienteering problem. It is well known that the orienteering problem is NP-hard [24]. The charging utility maximization problem thus is NP-hard too. □

4 An approximation algorithm

Since the charging utility maximization problem is NP-hard, in this section, we first devise an approximation algorithm through reducing it to the orienteering problem with Time Windows (OP-TW) [24]. An approximate solution to the latter [24] in turn returns an approximate solution to the former.

The *orienteering problem* with time windows is defined as follows. Given a directed weighted graph $G' = (V', E', \ell')$, denote by $\ell'(u, v)$ the length of arc $(u, v) \in E'$ from node u to v and $[R(v), D(v)]$ the time window of node $v \in V'$ that can only be visited no earlier than $R(v)$ and no later than $D(v)$ with $R(v) \le D(v)$, two nodes $s, t \in V'$ and an integer budget $B > 0$, the problem is to find an $s \rightsquigarrow t$ traveling path of length at most B to maximize the utility of visited nodes in the traveling path, assuming that each node has a non-negative utility value.

In the following we reduce the charging utility maximization problem to the orienteering problem with time windows.

Given a set V_c of sensors to be charged, we construct a directed weighted graph $G_c = (V_c \cup \{v_0\}, E_c, \ell)$, where $V_c \subseteq V$ and $E_c \subseteq E$. Assume that the base station v_0 has a time window $[0, \infty]$, which means that the mobile charger can stay at the base station all the time if no requests are received, or the mobile charger can return back to the base station at any time, but its traveling length is bounded by an integer L. In case L is not an integer, it can be scaled and rounded by the standard scaling and rounding techniques into an integer. The base station v_0 is not only the starting point but also the destination of the mobile charger. For each node $v_i \in V_c$, node v_i's time window is $[r_i, d_i]$ with charging duration c_i.

The proposed approximation algorithm for the charging utility maximization problem is as follows. It first generates an auxiliary node v'_0 with the same location as v_0. An auxiliary graph $G'_c = (V'_c, E'_c, \ell)$ is thus derived by adding node v'_0 to set V_c and adding arcs from node v'_0 to each node in V_c. Thus, $V'_c = V_c \cup \{v_0, v'_0\}$. Recall that the problem is to find a close tour with maximum charging utility of the mobile charger from node v_0 to v_0, it can be transformed to finding a path from node v_0 to v'_0 in auxiliary graph G'_c, since node v'_0 has the same location as node v_0. Then, it calls a recursive procedure with `Appro_R`$(V_c, v_0, v'_0, t_0, L, k)$ to obtain a closed tour C. Here, the input arguments are set by $v_s = v_0, v_e = v'_0, t_s = t_0$. The recursive level limitation k is set by a given value, i.e., $\lceil 1 + \log_2 |V_c| \rceil$, which determines the time complexity and approximation ratio of the solution delivered by the algorithm. We will analyze its time complexity and approximation ratio by Theorem 2. The detailed main algorithm `Appro_CUM` is described in Algorithm 1. It works as the algorithm framework by calling a proposed recursive procedure `Appro_R`, which is described in Algorithm 2.

Algorithm 1: `Appro_CUM` (V_c, t_0, L)

Input: A directed weighted graph $G_c = (V_c \cup \{v_0\}, E_c; \ell)$, the starting time $t_0 = 0$ at the depot v_0 and a given traveling length constraint L;

Output: A close tour C from v_0 to v_0 to maximize charging utility of the mobile charger.

Generate an auxiliary node v_0' with the same location as v_0;
{An auxiliary graph G_c' is derived by adding v_0' into $V_c \cup \{v_0\}$;}
$V_c' \leftarrow V_c \cup \{v_0, v_0'\}$
{k is the recursive depth}
$k \leftarrow \lceil 1 + \log_2 |V_c| \rceil$;
{Call **Algorithm** 2: `Appro_R` to obtain a close tour C from v_0 to v_0', since v_0 and v_0' have the same location coordinate}
$C \leftarrow$ `Appro_R`$(V_c, v_0, v_0', t_0, L, k)$;
return C.

Algorithm 2: `Appro_R` $(V_c, v_s, v_e, t_s, L, k)$

Input: A directed weighted graph $G_c' = (V_c \cup \{v_s, v_e\}, E_c; \ell)$, the starting time t_s at node v_s and a given traveling length constraint L;

Output: A path P from v_s to v_e to maximize charging utility of the mobile charger.

{Calculate the charging time c_s and the traveling time $\tau(v_s, v_e)$ of the mobile charger from v_s to v_e with the distance $\ell(v_s, v_e)$ and moving speed m_c};
$c_s \leftarrow (B_s - RE_s)/\mu$; $\quad \tau(v_s, v_e) \leftarrow \ell(v_s, v_e)/m_c$;
$t_e \leftarrow t_s + c_s + \tau(v_s, v_e)$;
{$[r_e, d_e]$ is the charging time window of sensor v_e}
if not $(\ell(v_s, v_e) \le L$ and $r_e \le t_e \le d_e)$ **then**
    {return empty path ' ' if not all constraints of sensor v_e is met.}
    $P \leftarrow$' ';
    return P;
end if
$P \leftarrow < v_s, v_e >$;
$max \leftarrow U(P)$; {$U(P)$ is charging utility of P}
if k == 0 **then**
    {recursive limit}
    return P;
end if
for each $v \in V_c$ **do**
    {Guessing the middle node visited}
    $v_m \leftarrow v$;
    for $1 \le L' \le L$ **do**
        {Guessing the length budget used}
        $L_m \leftarrow L'$; $\quad t_m \leftarrow t_s + c_s + L_m/m_c$;
        $P_{left} \leftarrow$ `Appro_R`$(V_c \setminus \{v_m\}, v_s, v_m, t_s, L_m, k-1)$;
        $P_{right} \leftarrow$ `Appro_R`$(V_c \setminus V(P_{left}), v_m, v_e, t_m, L - L_m, k-1)$;
        {$P_{left} \bullet P_{right}$ is the concatenation of P_{left} and P_{right}}
        if $U(P_{left} \bullet P_{right}) > max$ **then**
            $P \leftarrow P_{left} \bullet P_{right}$;
            $max \leftarrow U(P)$;
        end if
    end for
end for
return P.

Procedure `Appro_R` first guesses the middle node v_m in a tour of the mobile charger and the distance of the mobile charger L_m within the distance budget L traveled by the mobile charger from v_s to v_m, assuming that L is an integer. The guessing step is implemented by enumerating all candidate nodes as the middle node v_m as well as all possible values of L_m, $1 \le L_m \le L$. Noticing that we can use the standard scaling and rounding techniques to ensure that all values within the total distance budget L are integers and polynomially bounded. It then recursively finds a tour P_{left} from v_s to v_m with budget L_m, which means a tour P_{left} starts at v_s at time t_s and has to reach v_m with no longer than L_m. It also finds another tour P_{right} starting from v_m and ending at v_e with the budget $L - L_m$ to augment the nodes that are not covered by P_{left}, which means a tour P_{right} starts at v_m and has to reach v_e with no longer than $L - L_m$. It finally outputs the tour by concatenating P_{left} and P_{right}. We detail the approximation algorithm as follows.

Given the traveling distance constraint L and the time windows of each to-be-charged sensors, the algorithm will deliver a path from node v_s to v_e, and it will deliver a closed tour if setting $v_s = v_0$ and $v_e = v'_0$ with v'_0 located at node v_0. This closed charging tour can be the concatenations of several paths with head and tail docking.

In order to meet the traveling distance constraint of the mobile charger and time windows of sensors, procedure `Appro_R` $(V_c, v_s, v_e, t_s, L, k)$ calculates the charging time c_s of sensor v_s by $c_s = (B_s - RE_s)/\mu$ and the traveling time $\tau(v_s, v_e)$ from sensor v_s to v_e by $\tau(v_s, v_e) = \ell(v_s, v_e)/m_c$. Then the visiting time of node v_e is obtained by $t_e = t_s + c_s + \tau(v_s, v_e)$. It then verifies the distance constraint on the traveling path and time windows of sensor v_e. Let function $U(\cdot)$ represent the total charging utility of sensors covered in the traveling path of the mobile charger. A solution delivered by the algorithm is feasible only if all of the constraints are met. The detailed procedure `Appro_R` is described in Algorithm 2.

In the following we analyze the time complexity and approximation ratio of the proposed approximation algorithm.

Lemma 1 Let OPT be the optimal solution to the charging utility maximization problem and n_{OPT} the number of edges in OPT. Let P be the path returned by algorithm `Appro_CUM` $(v_i, t_i, v_j, t_j, V_c, L, k)$. Recall that $U(P)$ is the charging utility of path P. If $k \ge \lceil 1 + \log(n_{OPT}) \rceil$, then $U(P) \ge U(OPT)/\lceil 1 + \log(n_{OPT}) \rceil$.

Proof Following the analysis by Chekuri and Pál [24], the lemma follows. □

Theorem 2 Given a wireless sensor network $G = (V \cup \{v_0\}, E; \ell)$, there is an approximation algorithm `Appro_CUM` for the charging utility maximization problem with the approximation ratio of $O(\log \mathrm{OPT})$, which takes $O((2 \cdot |V_c| \cdot L)^{\log |V_c|}) = O((2 \cdot |V| \cdot L)^{\log |V|})$ time, where V_c ($\subseteq V$) is the set of sensors to be charged and OPT is the optimal solution of the problem.

Proof Denote by $T(k)$ the running time of `Appro_CUM` $(v_i, t_i, v_j, t_j, V_c, L, k)$. Obviously, $T(0) = 1$. Hence, $T(k) = |V_c| \cdot L \cdot (T(k-1) + T(k-1)) = 2 \cdot |V_c| \cdot L \cdot T(k-1) = (2 \cdot |V_c| \cdot L)^2 \cdot T(k-2) = \cdots = (2 \cdot |V_c| \cdot L)^k \cdot T(0) = (2 \cdot |V_c| \cdot L)^k$.

Following Lemma 1, denote by OPT the optimal solution to the problem and $n_{OPT} = |OPT|$ the number of edges in OPT. Let P be the path delivered by algorithm `Appro_CUM` $(v_i, t_i, v_j, t_j, V_c, L, k)$. If $k \ge \lceil 1 + \log(n_{OPT}) \rceil$, then $U(P) \ge U(OPT)/\lceil 1 + \log(n_{OPT}) \rceil \ge U(OPT)$. Hence, there is an approximation algorithm `Appro_CUM` for the charging utility maximization problem with an approximation ratio of $O(\log \mathrm{OPT})$, which takes $O((2 \cdot |V| \cdot L)^{\log |V|})$ time. □

5 A heuristic algorithm

Although the approximation algorithm delivers a solution with a guaranteed approximation ratio, its running time is not polynomial, and it suffers poor scalability in practice. In this section, we devise a fast yet scalable heuristic for the problem.

The basic idea of the proposed heuristic, `Heuristic_Offline`, is described as follows. We initially construct a close tour C consisting of all of the sensors in V_c, by applying the 1.5-approximation algorithm for the Traveling Salesman Problem (TSP) [25]. If the length $\ell(C)$ of tour C is not greater than the maximum traveling distance of the mobile charger L and each sensor in C can be charged within its charging time window, the solution is a feasible solution; otherwise, the tour C is infeasible, a feasible solution can be obtained through the modification on this infeasible solution, by removing the sensors from the infeasible solution one by one iteratively until the final solution is feasible.

Let C be the found tour containing all sensors in V_c which can be obtained by finding a minimum spanning tree (MST) and traversal on the MST. If the length of C and the charging time window of each node in C are met, the solution is the final solution. Otherwise, a node needs to be removed from the current tour C. We aim to choose such a sensor that has the minimum gain in terms of the objective function while a longer travel distance, i.e., a sensor with the minimum ratio of the utility gain to the length sum of its distances to the two neighboring nodes in the tour.

Specifically, let $\Delta U(C, v)$ be the amount of utility gain decrease due to the removal of sensor v from tour C. Obviously, we have

$$\Delta U(C, v) = U(C) - U(C \setminus \{v\}) = u(v) \quad (11)$$

which can be calculated by the residual energy of sensor v. We denote by

$$\Delta \ell(C, v) = \ell(C) - \ell(C \setminus \{v\}) \quad (12)$$

the length decrement of tour C due to the removal of sensor v from C. In order to obtain a tour with larger accumulative charging utility, we remove a sensor v with the smallest ratio of $\frac{\Delta U(C,v)}{\Delta \ell(C,v)}$ from C at each time until a feasible solution is obtained. The detailed algorithm `Heuristic_Offline` is described in Algorithm 3.

It takes $O(|V_c|^2)$ time to get an updated TSP tour via the construction of an MST from the metric graph induced by the nodes in the updated sensor set V_c. Within each iteration, it takes $O(|V_c|)$ time to find a node $v \in V_c$ with the minimum ratio $\frac{\Delta U(C,v)}{\Delta \ell(C,v)}$ from tour C, while the number of iterations of the algorithm is bounded by $|V_c|$. The algorithm thus takes $O(|V_c|^2) + O(|V_c|) \cdot |V_c| = O(|V|^2)$ time since $|V_c| \leq |V|$. □

6 Online algorithm

Although the running time of the heuristic in the previous section is polynomial, it is based on the assumption that all sensor charging requests are given (to the base station) in advance. However, in practice, sensor charging requests are dynamically sent to the mobile charger only when the sensors residual energy fall below a predefined threshold θ with $0 < \theta < 1$. In this section, we consider this online version of the problem, and devise an online heuristic for the problem of maximizing the charging utility for a given monitoring period T through charging scheduling at every fixed time slot of this monitoring period, with the assumption that sensor charging requests arrive at the base station dynamically. Assume that T is the maximum number of time slots per charging tour. Thus, the maximum period per tour is [0, T]. We denote by V_c^t the set of to-be-charged sensors at the time slot t, where sensor charging requests release times are issued no latter than time slot t, with $0 \leq t \leq T$. Recall that V_c is the set of to-be-charged sensors. Clearly, $V_c^t \subseteq V_c$, and $\bigcup_{t=0}^{T} V_c^t = V_c$.

Algorithm 3: `Heuristic_Offline` (V_c, t_0, L)

Input: $G_c = (V_c \cup \{v_0\}, E_c; \ell)$, the starting time $t_0 = 0$ at the depot v_0 and a given traveling length constraint L.

Output: A traveling tour C starts from base station v_0 and ends at v_0 to maximize charging utility.

Find an MST $\mathcal{T}$ in G_c; {set v_0 as a root}
Find an Euler tour C' by doubling the edges of $\mathcal{T}$, a closed tour C is then derived from C' by shortcutting repeated appearance of each node in C' by applying the 1.5-approximation algorithm for the TSP;
$finished \leftarrow$ false;
while not $finished$ **do**
  if $\ell(C) > L$ or (not all node deadlines are satisfied) **then**
    Find a node v with the minimum ratio $\frac{\Delta U(C,v)}{\Delta \ell(C,v)}$ in tour C, and remove it from C and G_c;
  else
    $finished \leftarrow$ true;
  end if
end while
Starting from v_0, traveling along C and ending at node v_0, a closed tour C is obtained;
return C.

Theorem 3 Given a wireless sensor network $G = (V \cup \{v_0\}, E; \ell)$, a set of to-be-charged sensor V_c and the distance constraint L of the traveling tour of the mobile charger, there is a fast, scalable heuristic algorithm `Heuristic_Offline` for the charging utility maximization problem, which takes $O(|V|^2)$ time, where $|V|$ is the number of sensors in the network.

Proof Algorithm `Heuristic_Offline` clearly yields a feasible solution to the charging utility maximization problem, because the solution delivered by algorithm `Heuristic_Offline` meets all of the constraints imposed on the problem. We now analyze the time complexity of algorithm `Heuristic_Offline` in the following.

The basic idea of the online algorithm is adopting a greedy strategy to dynamically decide which sensors to be charged. In order to maximize the charging utility, the mobile charger first charges the sensors with the maximum ratio of charging utility gain to traveling length increment. Meanwhile, it makes sure that both the time windows of to-be-charged sensors in tour C and the total traveling distance of the mobile charger must be met. When the mobile charger finishes charging a sensor, it sends an acknowledgment message to the base station and enquires about which sensor is to be the next one to be charged. The online algorithm will be executed in the base station to deliver a solution to the problem. After receiving the charging schedule from the base station, the mobile charger moves from its current location to the next to-be-charged sensor. When the mobile charger is traveling, the base station may continue receiving new charging requests from sensors as well. It is noteworthy that the base station decides which sensor is the next one based on requests received so far. In other words, the online algorithm delivers the solution by dynamically taking sensor charging requests and it is suitable for the more practical cases.

In the following, we identify which sensor should be added to the tour C dynamically. We aim to choose a sensor with the maximum utility gain while keeping a shorter travel distance to it. Specifically, let

$$\Delta U(C, v) = U(C \cup \{v\}) - U(C) \tag{13}$$

be the utility increment by inserting sensor v into tour C. Obviously, $\Delta U(C, v) = u(v)$, which can be calculated by residual energy of sensor v. Let

$$\Delta \ell(C, v) = \ell(C \cup \{v\}) - \ell(C) \tag{14}$$

be the length increment of tour C by inserting sensor v into it. For convenience, we denote by v_{cur} the sensor currently being charged. Hence,

$$\Delta \ell(C, v) = \ell(v_{cur}, v) + \ell(v, v_0) - \ell(v_{cur}, v_0). \tag{15}$$

Once sensor v is chosen to be appended to tour C, the length $\ell(C)$ is updated. Meanwhile, it should be guaranteed that the mobile charger can return to v_0 after charging a sensor $v \in V_c$ under the current traveling length margin of the mobile charger. Since the mobile charger charges the current sensor v_{cur} for charging duration c_{cur}, the current time slot t should be updated by $t + \tau(v_{pre}, v_{cur}) + c_{cur}$, where $\tau(v_{pre}, v_{cur})$ is the traveling time from the previous charged sensor v_{pre} to the current charged sensor v_{cur}. If none of the sensors in V_c^t can be found to be charged under the constraints, the mobile charger will wait for a time slot, updating t with $t = t + time\_slot$. Then, set V_c^t will be updated by inserting the sensors whose charging requests are received before time t. This procedure is iterated until no more sensors can be appended into the charging tour C. Finally, we get a close tour C as a solution to our problem. The detailed algorithm `Heuristic_Online` is described in Algorithm 4.

Algorithm 4: `Heuristic_Online` (V_c, t_0, L)

Input: $G_c^t = (V_c^t \cup \{v_0\}, E_c^t; \ell)$, $t_0 = 0$, and a traveling length constraint L. v_{cur} is the sensor which is just finished charging.

Output: A traveling tour C starts from base station v_0 and ends at v_0 to maximize charging utility.

1: $C = \{v_0\}$; $\ell(C) = 0$; $v_{cur} \leftarrow v_0$; $t \leftarrow t_0$;
2: Base station receives a message of acknowledgment from the mobile charger that means the charger has just finished charging the current sensor v_{cur}, and enquires about which sensor is the next one to be charged.
3: **while** $V_c^t \neq \emptyset$ and $\ell(C) < L$ **do**
4: Find a sensor $v \in V_c^t$ which has the maximum ratio $\frac{\Delta U(C,v)}{\Delta \ell(C,v)}$ and satisfies $\ell(C) + \Delta\ell(C, v) \leq L$ and the time window, where $\Delta\ell(C, v) = \ell(v_{cur}, v) + \ell(v, v_0) - \ell(v_{cur}, v_0)$.
5: **if** found **then**
6: Append node v to tour C, update the length of tour $\ell(C)$ by $\ell(C) \leftarrow \ell(C) + \Delta\ell(C, v)$, remove v from set V_c^t;
7: {Charging v, and update t}
8: $v_{pre} \leftarrow v_{cur}$; $v_{cur} \leftarrow v$; charge v_{cur} for time c_{cur}; $t \leftarrow t + \tau(v_{pre}, v_{cur}) + c_{cur}$;
9: **else**
10: {Wait for a time slot, update t and set V_c^t}
11: $t \leftarrow t + time\_slot$;
12: Update set V_c^t by appending sensors whose release times are not later than t;
13: **end if**
14: **end while**
15: The mobile charger returns to v_0;
16: **return** C.

Theorem 4 Given a wireless sensor network $G = (V \cup \{v_0\}, E; \ell)$ and the length constraint L of each traveling tour of the mobile charger, there is an online algorithm `Heuristic_Online` for the charging utility maximization problem, which takes $O(|V|^3)$ time, where $|V|$ is the number of sensors in G.

Proof Algorithm `Heuristic_Online` yields a feasible solution to the charging utility maximization problem, because the algorithm outputs a tour that meets all of the specified constraints of the problem. We now analyze the time complexity of algorithm `Heuristic_Online` in the following.

Within each iteration, it finds a sensor $v \in V_c$ with the maximum ratio $\frac{\Delta U(C,v)}{\Delta \ell(C,v)}$ of the charging utility to $\Delta \ell(C,v)$, satisfying $\ell(C) + \Delta \ell(C,v) \leq L$ and its time window of charging, and adds node v to C, this takes $O(|V_c|^2)$ time. Processing each sensor $v \in V_c$ takes $O(|V_c|)$ iterations. The algorithm thus takes $O(|V_c|^3) = O(|V|^3)$ time since $|V_c| \leq |V|$. □

7 Performance evaluation

In this section we first evaluate the performance of the proposed algorithms through experimental simulations. We then study the impact of the total traveling distance of the mobile charger L on algorithms performance.

7.1 Simulation environment setting

We consider WSNs with various sizes in our experiments as listed in Table 1, including small-size networks consisting of 5–25 sensors randomly deployed in a 50 m × 50 m square and large-scale networks consisting of 100–1000 sensors randomly deployed in a 500 m × 500 m square. The base station (the depot of the mobile charger) is located at one of the four corners of the monitoring area. Due to the dynamic nature of sensing activities, each sensor randomly sends its recharging requests within a given time period T. We here set $T = 5100$ s $L = 400$ m for small-size networks, and $T = 51{,}000$ s and $L = 8000$ and 16,000 m for large scale networks. We assume that the mobile charger travels at a constant speed 8 m/s and the wireless charging rate is 5 W [12], and the maximum energy capacity of sensor battery is 500 J. The charging duration depends on the residual energy of a battery and the charging rate of the mobile charger. Each value in figures is the mean of the results by applying each mentioned algorithm to 20 different network topologies of the same network size.

Table 1 Default parameters setting

Parameter	Value
Network size (small scale)	5–25
Sensing field (small scale)	50 m × 50 m
Given time period T (small scale)	5100 s
Traveling length limitation L	400 m
Network size (large scale)	100–500
Sensing field (large scale)	500 m × 500 m
Given time period T (large scale)	51,000 s
Traveling length limitation L	8000, 16,000 m
Battery capacity	500 J
Charging rating	5 W
Charger moving speed	8 m/s

Denote by `Optimum` the algorithm delivering an optimal solution to the problem and `EDF` the well-known earliest deadline first scheduling algorithm as the benchmarks for the performance evaluation of our proposed algorithms, the approximation algorithm `Appro_CUM`, the heuristic algorithm `Heuristic_Offline`, and the online algorithm `Heuristic_Online`, where algorithm `Optimum` performs exhaustive searches to obtain an optimal solution to the problem.

7.2 Performance evaluation of approximation and heuristic algorithms

We first evaluate the performance of the approximation algorithm `Appro_CUM`, the offline heuristic algorithm `Heuristic_Offline`, the online heuristic algorithm `Heuristic_Online` against algorithm `EDF` and `Optimum` in small-size networks by varying the network size from 5 to 25. Although algorithm `Optimum` can deliver an optimal solution, it is computationally expensive, which makes it impractical for large-scale networks. When the network size is 5 and 10, its running times are 6 and 415,985 ms respectively, on the PC with Intel i7 CPU 3.4 GHz, and 16 GB memory. When network size reaches 15 or above, algorithm `Optimum` fails to deliver any result due to its prohibitive running time. Furthermore, algorithm `EDF` is the worst among the mentioned algorithms.

When the network size is set to be 5 and 10 and the traveling distance of the mobile charger L is set at 400 m, the performance of algorithm `Appro_CUM` is about 91.9 and 90.6 % of the optimal one while their running times are 57, 15,049 ms, respectively, and the actual approximation ratios are 1.088 and 1.104, respectively, which is much better than its theoretical estimation. Figure 2 shows the performance of the proposed algorithms.

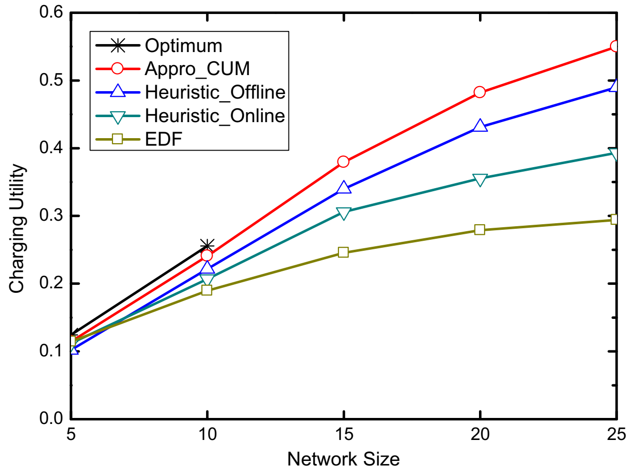

Fig. 2 The charging utility performance of both the approximation algorithm and the heuristic algorithms

The charging utility delivered by algorithm Heuristic_Offline is about 81.9 and 88.3 % of the optimal one when the network size is set to be 5 and 10. The charging utility delivered by algorithm Heuristic_Offline is 16.7, 38.5, 54.5 and 66.5 % higher than that delivered by algorithm EDF when the network size is 10, 15, 20 and 25, respectively. With the increase on network size, the performance gap between algorithm Heuristic_Offline and algorithm EDF becomes larger and larger. The charging utility delivered by algorithm Heuristic_Online is about 89.8 and 82.2 % of the optimal one by varying the network size from 5 and 10 and setting the dynamic scheduling time slot at 100 s. The performance of algorithm Heuristic_Online is 8.92, 24.6, 27.4 and 33.6 % higher than that of algorithm EDF when the network size is 10, 15, 20 and 25, respectively. Figure 2 also shows that the offline algorithm Heuristic_Offline outperforms the online algorithm Heuristic_Online significantly. The reason behind is that algorithm Heuristic_Offline is assumed to know all charging requests of a charging tour in advance. On the other hand, algorithm Heuristic_Online can schedule charging tasks dynamically.

We now evaluate the performance of algorithms Heuristic_Offline, EDF and Heuristic_Online in large-scale networks by varying network size from 100 to 1000. The traveling distance L of the mobile charger is set at 8000 and 16,000 m respectively. Figure 3 illustrates the performance curves of the algorithms, from which it can be seen that the charging utility delivered by algorithm Heuristic_Offline always outperforms algorithm EDF. In Fig. 3(a), for example, when the network size is set at 200, 400, 600, 800, and 1000 respectively, while the traveling distance of the mobile charger L is set at 8000 m, the charging utility delivered by algorithm Heuristic_Offline is 395.9, 352.0, 299.6, 286.4, and 264.9 % higher than that of algorithm EDF. In contrast, the performance of algorithm Heuristic_Online is 176.0, 154.3, 141.0, 142.6, and 118.8 % higher than that of algorithm EDF when the dynamic scheduling time slot is set at 100 s. With the increase on network size, there are more opportunities for a sensor to be charged. Figure 3(b) indicates that the charging utility of algorithm Heuristic_Offline is around 262.1, 261.6, 219.6, 209.1, and 191.9 % higher than that of algorithm EDF by setting network size at 200, 400, 600, 800 and 1000, respectively, while the value of L is kept at 16,000 m. In contrast, the performance of algorithm Heuristic_Offline is 108.8, 92.3, 82.4, 79.1, and 65.5 % higher than that of algorithm Heuristic_Online. It is noteworthy that algorithm Heuristic_Online is

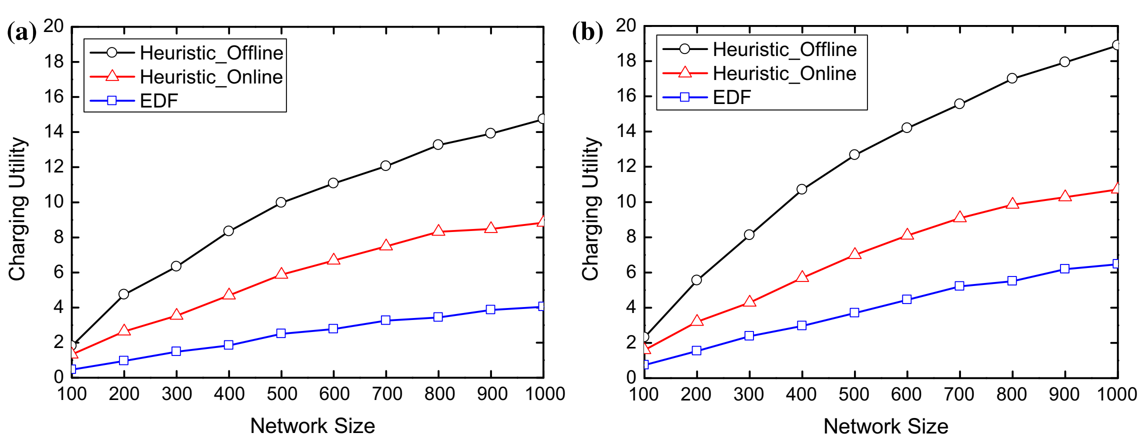

Fig. 3 The charging utility performance of algorithm Heuristic_Offline, EDF and Heuristic_Online by varying the network size and setting a given traveling length constraint. **a** $L = 8000$ m. **b** $L = 16{,}000$ m

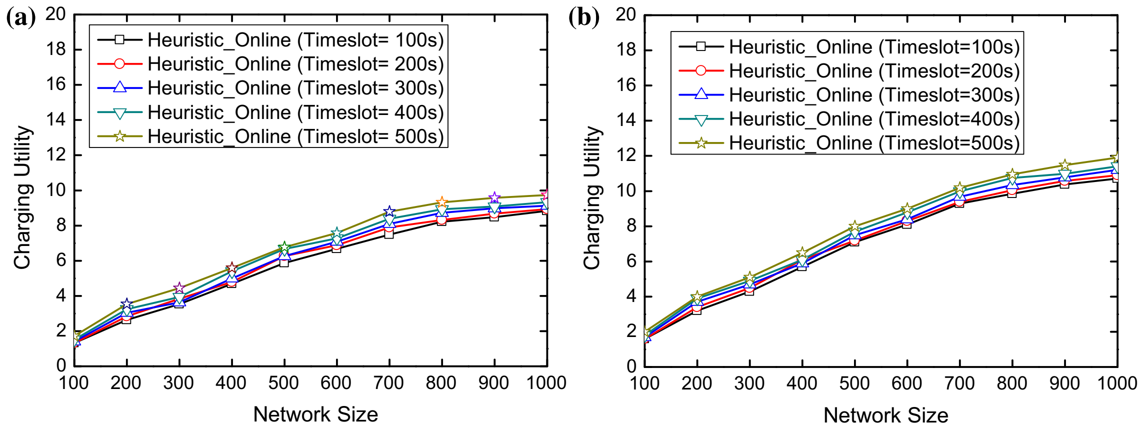

Fig. 4 The charging utility performance of algorithm `Heuristic_Online` by varying the dynamic scheduling time slot and setting a given traveling length constraint. **a** $L = 8000$ m. **b** $L = 16{,}000$ m

practical in reality to deal with charging requests dynamically.

Figure 3 also demonstrates that the charging utility of the algorithms grows with the increase of the traveling distance of the mobile charger L. For example, when $L = 16{,}000$ m and network size is set at 1000, the charging utility of algorithm `Heuristic_Offline` is 28.2 % higher than that when $L = 8000$ m. The performance of algorithm `Heuristic_Online` at $L = 16{,}000$ m is 21.2 % higher than that at $L = 8000$ m. It also shows that the charging utility performance of the proposed algorithms `Heuristic_Offline` and `Heuristic_Online` grows with the increase of network size. Moreover, the longer L is, the more charging utility algorithm `Heuristic_Offline` will achieve. The proposed algorithms are scalable and practical for large-scale networks.

We finally study the impact of the dynamic scheduling interval, time slot, of algorithm `Heuristic_Online` on its charging utility performance. Figure 4 demonstrates the charging utility performance of algorithm `Heuristic_Online`. When the traveling length of the mobile charger L is set at 8000 m, the charging utility delivered by algorithm `Heuristic_Online` keeps at the almost identical level when the time slot intervals are set at 100, 200, 300, 400 and 500 s and the network size varies from 100 to 1000. When L is set at 16,000 m and the time slot intervals varies from 100 to 500 s, the charging utility performance of algorithm `Heuristic_Online` also keeps at the almost identical level too.

8 Conclusion

In this paper we studied the problem of finding a charging tour for a mobile charger in wireless rechargeable sensor networks with the objective to maximize the sensor charging utility, subject to the total traveling distance of the mobile charger and the charging time window of each sensor. Due to the NP-hardness of the problem, we then proposed an approximation algorithm with guaranteed approximation ratio if the problem size is small; otherwise, we devised a fast yet scalable heuristic. We also developed an online heuristic if energy charging requests from sensors need to be dynamically responded. Finally, we evaluated the performance of the proposed algorithms against the famous earliest deadline first scheduling (EDF) algorithm through experimental simulations. The simulation results demonstrate that the solution delivered by the approximation algorithm is comparable to the optimal one when the problem size is small. Otherwise, the proposed heuristic significantly outperforms the well-known EDF heuristic.

Acknowledgments It is acknowledged that Xiaoguo Ye's work was supported by both Chinese National Natural Science Foundation Grants (Nos. 61572260, 61373017, 61572261, and 71301081) and the Scientific and Technological Support Project of Jiangsu Province China, under Grant No. BE2015702.

References

1. Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., & Cayirci, E. (2002). Wireless sensor networks: A survey. *Computer Networks*, *38*(4), 393–422.
2. Yick, J., Mukherjee, B., & Ghosal, D. (2008). Wireless sensor network survey. *Computer Networks*, *52*(12), 2292–2330.
3. Liang, W., Ren, X., Jia, X., & Xu, X. (2013). Monitoring quality maximization through fair rate allocation in harvesting sensor networks. *IEEE Transactions on Parallel and Distributed Systems*, *24*(9), 1827–1840.
4. Tong, B., Wang, G., Zhang, W., & Wang, C. (2011). Node reclamation and replacement for long-lived sensor networks. *IEEE Transactions on Parallel and Distributed Systems*, *22*(9), 1550–1563.
5. Xu, X., & Liang, W. (2011). Placing optimal number of sinks in sensor networks for network lifetime maximization. In

Proceedings of IEEE international conference on communications (ICC), IEEE (pp. 1–6).
6. Yuan, Z., Tan, R., Xing, G., Lu, C., Chen, Y., & Wang, J. (2008). Fast sensor placement algorithms for fusion-based target detection. In *Proceedings of real-time systems symposium (RTSS)*, IEEE (pp. 103–112).
7. Liang, W., Xu, W., Ren, X., Jia, X., & Lin, X. (2014). Maintaining sensor networks perpetually via wireless recharging mobile vehicles. In *Proceedings of 39th conference on local computer networks (LCN)*, IEEE (pp. 270–278).
8. Jiang, X., Polastre, J., & Culler, D. (2005). Perpetual environmentally powered sensor networks. In *Proceedings of fourth international symposium on information processing in sensor networks (IPSN)*, ACM (pp. 463–468).
9. Kansal, A., Hsu, J., Zahedi, S., & Srivastava, M. B. (2007). Power management in energy harvesting sensor networks. *ACM Transactions on Embedded Computing Systems*, *6*(4), 32.
10. Ren, X., Liang, W., & Xu, W. (2013). Use of a mobile sink for maximizing data collection in energy harvesting sensor networks. In *Proceedings of 42nd international conference on parallel processing (ICPP)*, IEEE (pp. 439–448).
11. Rahimi, M., Shah, H., Sukhatme, G., Heideman, J., & Estrin, D. (2003). Studying the feasibility of energy harvesting in a mobile sensor network. In *Proceedings of international conference on robotics and automation (ICRA)*, IEEE (Vol. 1, pp. 19–24).
12. Kurs, A., Karalis, A., Moffatt, R., Joannopoulos, J. D., Fisher, P., & Soljačić, M. (2007). Wireless power transfer via strongly coupled magnetic resonances. *Science*, *317*(5834), 83–86.
13. Kurs, A., Moffatt, R., & Soljačić, M. (2010). Simultaneous mid-range power transfer to multiple devices. *Applied Physics Letters*, *96*(4), 044102.
14. Shi, Y., Xie, L., Hou, Y. T., & Sherali, H. D. (2011). On renewable sensor networks with wireless energy transfer. In *Proceedings of INFOCOM*, IEEE (pp. 1350–1358).
15. Xie, L., Shi, Y., Hou, Y. T., Lou, W., Sherali, H. D., & Midkiff, S. F. (2012). On renewable sensor networks with wireless energy transfer: The multi-node case. In *Proceedings of 9th annual IEEE communications society conference on sensor, mesh and ad hoc communications and networks (SECON)*, IEEE (pp. 10–18).
16. Xie, L., Shi, Y., Hou, Y. T., Lou, W., Sherali, H. D., & Midkiff, S. F. (2013). Bundling mobile base station and wireless energy transfer: Modeling and optimization. In *Proceedings of INFOCOM*, IEEE (pp. 1636–1644).
17. Xie, L., Shi, Y., Hou, Y. T., Lou, W., & Sherali, H. D. (2013). On traveling path and related problems for a mobile station in a rechargeable sensor network. In *Proceedings of fourteenth ACM international symposium on mobile ad hoc networking and computing*, ACM (pp. 109–118).
18. Guo, S., Wang, C., & Yang, Y. (2013). Mobile data gathering with wireless energy replenishment in rechargeable sensor networks. In *Proceedings of INFOCOM*, IEEE (pp. 1932–1940).
19. Zhao, M., Li, J., & Yang, Y. (2011). Joint mobile energy replenishment and data gathering in wireless rechargeable sensor networks. In *Proceedings of 23rd international teletraffic congress (ITC)*, IEEE (pp. 238–245).
20. Xu, W., Liang, W., Lin, X., Mao, G., & Ren, X. (2014). Towards perpetual sensor networks via deploying multiple mobile wireless chargers. In *Proceedings of 43rd international conference on parallel processing (ICPP)*, IEEE (pp. 80–89).
21. Ren, X., Liang, W., & Xu, W. (2014). Maximizing charging throughput in rechargeable sensor networks. In *Proceedings of 23rd international conference on computer communication and networks (ICCCN)*, IEEE (pp. 1–8).
22. Li, Z., Peng, Y., Zhang, W., & Qiao, D. (2011). J-RoC: A joint routing and charging scheme to prolong sensor network lifetime. In *Proceedings of 19th international conference on network protocols (ICNP)*, IEEE (pp. 373–382).
23. Ren, X., Liang, W., & Xu, W. (2015). Quality-aware target coverage in energy harvesting sensor networks. *IEEE Transactions on Emerging Topics in Computing*, *3*(1), 8–21.
24. Chekuri, C., & Pál, M. (2005). A recursive greedy algorithm for walks in directed graphs. In *Proceedings of 46th annual symposium on foundations of computer science (FOCS)*, IEEE (pp. 245–253).
25. Christofides, N. (1976). Worst-case analysis of a new heuristic for the traveling salesman problem. Technical Reports 388, Management Sciences Research Group, Carnegie-Mellon University, Pittsburgh PA.

Xiaoguo Ye received the Ph.D. degree from Southeast University, China in 2005, the M.E. degree from Nanjing University of Posts and Telecommunications, China in 2000, all in computer science. He is currently an Associate Professor in the College of Computer at Nanjing University of Posts and Telecommunications. His research interests include routing algorithms and protocols design for wireless ad hoc and sensor networks, combinatorial optimization, and graph theory.

Weifa Liang (M'99–SM'01) received the Ph.D. degree from the Australian National University in 1998, the M.E. degree from the University of Science and Technology of China in 1989, and the B.Sc. degree from Wuhan University, China in 1984, all in computer science. He is currently a Professor in the Research School of Computer Science at the Australian National University. His research interests include design and analysis of energy-efficient routing protocols for wireless ad hoc and sensor networks, cloud computing, graph databases, design and analysis of parallel and distributed algorithms, approximation algorithms, combinatorial optimization, and graph theory. He is a senior member of the IEEE.