

Improving charging capacity for wireless sensor networks by deploying one mobile vehicle with multiple removable chargers[☆]



Tao Zou^a, Wenzheng Xu^{a,*}, Weifa Liang^b, Jian Peng^a, Yiqiao Cai^c, Tian Wang^c

^a College of Computer Science, Sichuan University, Chengdu, 610065, PR China

^b Research School of Computer Science, The Australian National University, ACT 2601, Australia

^c Department of Computer Science and Technology, Huaqiao University, Xiamen, 361021, PR China

ARTICLE INFO

Article history:

Received 26 December 2016

Revised 25 May 2017

Accepted 29 May 2017

Available online 7 June 2017

Keywords:

Rechargeable sensor networks
One charging vehicle with multiple removable chargers
Charging vehicle scheduling
Approximation algorithms
Combinatorial optimization problems

ABSTRACT

Wireless energy transfer is a promising technology to prolong the lifetime of wireless sensor networks (WSNs), by employing charging vehicles to replenish energy to lifetime-critical sensors. Existing studies on sensor charging assumed that one or multiple charging vehicles being deployed. Such an assumption may have its limitation for a real sensor network. On one hand, it usually is insufficient to employ just one vehicle to charge many sensors in a large-scale sensor network due to the limited charging capacity of the vehicle or energy expirations of some sensors prior to the arrival of the charging vehicle. On the other hand, although the employment of multiple vehicles can significantly improve the charging capability, it is too costly in terms of the initial investment and maintenance costs on these vehicles. In this paper, we propose a novel charging model that a charging vehicle can carry multiple low-cost removable chargers and each charger is powered by a portable high-volume battery. When there are energy-critical sensors to be charged, the vehicle can carry the chargers to charge multiple sensors simultaneously, by placing one portable charger in the vicinity of one sensor. Under this novel charging model, we study the scheduling problem of the charging vehicle so that both the dead duration of sensors and the total travel distance of the mobile vehicle per tour are minimized. Since this problem is NP-hard, we instead propose a $(3 + \epsilon)$ -approximation algorithm if the residual lifetime of each sensor can be ignored; otherwise, we devise a novel heuristic algorithm, where ϵ is a given constant with $0 < \epsilon \leq 1$. Finally, we evaluate the performance of the proposed algorithms through experimental simulations. Experimental results show that the performance of the proposed algorithms are very promising.

© 2017 The Authors. Published by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license.

(<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

1. Introduction

Wireless sensor networks (WSNs) are widely used in many applications, including ecological monitoring, structural health monitoring, traffic control, etc [9,17,19,29,35]. As sensors in traditional WSNs are mainly powered by energy-limited batteries, the lifetime of sensor networks is very limited. Sensors will not be functioning when their battery energy is run out. To prolong the lifetime of WSNs, extensive studies have been conducted in past years, and most of them focused on a fundamental problem—energy re-

plenishments of sensors. In general, there are two different sensor charging categories. One is to enable sensors to harvest energy from their surrounding environments including vibration energy, solar energy and wind energy [7,21,23]. The main drawback of this method is that the energy harvesting rate is extremely unstable due to the time-varying environment. For example, the amount of energy harvested from a solar panel is very low in a cloudy or rainy day. The instability poses great challenges in the efficient usage of harvested energy. Another is to employ mobile charging vehicles to travel to the vicinity of sensors and charge them, using wireless energy transfer [8,10,28]. Thus, sensors can be charged via the wireless energy transfer with highly stable charging rates.

Existing studies of sensor energy replenishment via wireless charging vehicles assumed that either just one charging vehicle is employed [15,20,22,24,31,34,37] or multiple vehicles are deployed [5,6,13,16,18,25,26,33,36]. However, such an assumption may have its limitation for a real sensor network. On one hand,

[☆] This document is a collaborative effort.

* Corresponding author.

E-mail addresses: scuzoutao@qq.com (T. Zou), wenzheng.xu3@gmail.com, wenzheng.xu@scu.edu.cn (W. Xu), wliang@cs.anu.edu.au (W. Liang), jianpeng@scu.edu.cn (J. Peng), caiyq@hqu.edu.cn (Y. Cai), cs_tianwang@163.com (T. Wang).

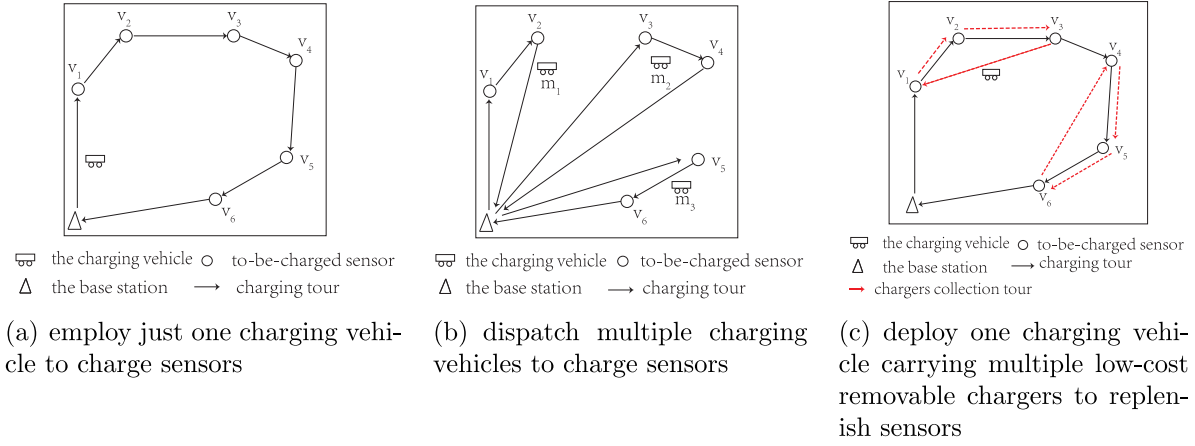


Fig. 1. An illustration of the charging model, which deploys one charging vehicle with multiple low-cost removable chargers.

when there is just one charging vehicle for charging sensors, some sensors may have already depleted their energy before the vehicle approaches them, because the charging capacity of the vehicle is very limited and it takes some time (e.g., 30–80 minutes) to fully charge a commercial sensor battery [26]. For example, assume that there are six energy-critical sensors v_1, v_2, \dots, v_6 in the network, which is illustrated in Fig. 1(a). Before charging sensor v_2 , the charging vehicle has to stay in the vicinity of sensor v_1 and fully charge v_1 . Similarly, before charging sensor v_6 , the vehicle has to fully charge the first five sensors v_1, v_2, \dots, v_5 . It can be seen that it is very likely that sensor v_6 has run out of its energy for a long time before the vehicle can visit it.

On the other hand, the employment of multiple charging vehicles can significantly reduce the dead durations of sensors. As shown in Fig. 1(b), the six sensors v_1, v_2, \dots, v_6 will be charged by three charging vehicles m_1, m_2 , and m_3 , assuming that sensors v_1 and v_2 will be charged by vehicle m_1 , sensors v_3 and v_4 will be replenished by m_2 , and the residual two sensors v_5 and v_6 will be recharged by m_3 . Each charging vehicle starts from the base station to charge sensors and returns to the base station after completing its charging task. It can be easily seen that the waiting time of each sensor before its charging in this multiple charging vehicles model is much shorter than that in the single charging vehicle model. However, it is usually too costly to invest and maintain many charging vehicles for sensor charging, since the investment cost of each charging vehicle is not cheap at all, its cost is usually from several hundred dollars to quite a few thousand dollars [2,3,11].

We can see that the existing studies either use just one charging vehicle but some sensors may deplete their energy for quite a while, or deploy multiple expensive charging vehicles to shorten sensor dead durations. A fundamental problem then is that, is it possible to improve the charging capacity with a low-cost of purchasing charging devices? We note that the existing works assumed that each charging vehicle can carry only one charger. In this paper, we propose a novel charging model. That is, we assume that one charging vehicle can carry multiple low-cost removable chargers with each charger being equipped with a wireless charging device and a portable high-volume battery. When there are energy-critical sensors to be charged, the charging vehicle can carry the multiple chargers and place one charger in the vicinity of one sensor to charge the sensor. Thus, multiple sensors, instead of a single one, can be charged simultaneously.

We here use an example to illustrate this novel charging model as follows, see Fig. 1(c). There are six to-be-charged sensors v_1, v_2, \dots, v_6 in the network. A charging vehicle can carry three

removable chargers mc_1, mc_2 , and mc_3 for sensor charging. The charging vehicle first places the three chargers in the vicinities of sensors v_1, v_2, v_3 , one charger for one sensor. That is, the vehicle visits sensor v_1 and places charger mc_1 in the vicinity of v_1 to charge v_1 , then leaves and visits sensor v_2 , and drops charger mc_2 at v_2 , finally places charger mc_3 in the vicinity of sensor v_3 . After the three chargers fully charge the three sensors, the charging vehicle revisits the three sensors for collecting the chargers. Then, the charging vehicle carries the three chargers for replenishing energy to the rest of the three sensors v_4, v_5 , and v_6 in a similar way. It can be seen that under the simultaneous charging model via one charging vehicle carrying multiple removable chargers, the charging capacity is much larger than that with only one charging vehicle. Furthermore, the cost of buying one portable charger usually is much cheaper than that of one charging vehicle, e.g., tens of dollars [30] vs. hundreds of dollars [2,3,11].

In this paper, we propose the novel simultaneous charging model, in which one charging vehicle can carry multiple low-cost, removable chargers to provide energy supply to sensors in a large-scale sensor network. Under this novel charging model, we study the charging scheduling of the charging vehicle so as to minimize not only the dead duration of sensors but also the travel distance of the charging vehicle. There are however two essential differences between the vehicle scheduling under this new charging model and that under the traditional model, in which one vehicle carries only one charger. One is that multiple sensors, instead of only one, will be replenished by the chargers simultaneously. The other difference is that the travel trajectory of the vehicle under the new charging model is more complicated, because the vehicle needs both placing chargers at sensors and revisiting sensors for collecting chargers. It is thus very challenging to devise efficient algorithms to schedule the charging vehicle under the new charging model. Therefore, existing scheduling algorithms are not applicable to this new sensor charging problem, and new algorithms are desperately needed. Specifically, in this paper we consider two vehicle scheduling problems under this novel charging model. We first investigate the problem of finding a shortest charging trajectory for the charging vehicle to charge a set of lifetime-critical sensors, assuming that residual lifetimes of sensors are not considered. We then study the problem of finding a charging trajectory for the vehicle so that both the longest dead duration of sensors and the total travel distance of the vehicle are minimized if the residual lifetime of each sensor must be taken into account.

The main contributions of this paper are highlighted as follows.

- Unlike existing studies assumed that one charging vehicle can carry just one charger, we are the first to propose a novel si-

multaneous charging model, in which one vehicle can carry multiple low-cost, removable chargers. Under this novel charging model, not only are the dead durations of sensors significantly shortened, since the chargers can replenish multiple energy-critical sensors simultaneously, but also the cost of purchasing charging devices, including the vehicle and chargers, can be dramatically reduced, compared with the cost of buying many expensive charging vehicles.

- We then propose a $(3 + \epsilon)$ -approximation algorithm for minimizing the travel distance of the charging vehicle if the residual lifetimes of sensors can be ignored, where ϵ is a given constant with $0 < \epsilon \leq 1$. Otherwise, we devise a novel heuristic algorithm so as to minimize not only the longest dead duration of sensors but also the travel cost of the vehicle.
- We finally evaluate the performance of the proposed algorithms through extensive simulation experiments. Experimental results show that the proposed algorithms are very promising.

The rest of this paper is organized as follows. Section 2 introduces the system model and define the problems. Sections 3 and 4 propose the approximation and heuristic algorithms for the charging vehicle scheduling problems, respectively. Section 5 evaluates the performance of proposed algorithms by simulation experiments. Section 6 reviews the related work, and Section 7 concludes the paper.

2. Preliminaries

In this section, we first introduce the network model and propose a novel simultaneous charging model, we then define the problems.

2.1. Network model

We consider a large-scale wireless sensor network deployed in a two-dimensional area for environmental monitoring or target tracking. There are n_s sensors v_1, v_2, \dots, v_{n_s} in the network. Let V_s be the set of these sensors, i.e., $V_s = \{v_1, v_2, \dots, v_{n_s}\}$. A base station b_s is located at the center of the network for data gathering and network management. Each sensor $v_i \in V_s$ is powered by a rechargeable battery with energy capacity B and consumes its energy for data sensing and wireless data transmission. Assume that each sensor uploads its sensed data to the base station via a given routing path, e.g., the routing path with the minimum energy consumption.

Denote by RE_i^t the residual energy of each sensor $v_i \in V_s$ and $\rho_i(t)$ its energy consumption rate at time t . The residual lifetime of sensor v_i at time t thus is $l_i^t = \frac{RE_i^t}{\rho_i(t)}$. We say that sensor v_i is lifetime-critical if its residual lifetime l_i^t falls below a given threshold l_s , and it then sends a charging request to the base station b_s . After the base station b_s receives the charging request from sensor v_i , it will schedule a charging vehicle to charge a set V of lifetime-critical sensors with the residual lifetime of each sensor $v_j \in V$ being no greater than $\alpha \cdot l_s$, i.e., $V = \{v_j \mid v_j \in V_s, l_j^t \leq \alpha \cdot l_s\}$, where α is a given constant with $\alpha \geq 1$, e.g., $\alpha = 3$. For the sake of discussion, we use a weighted complete metric graph $G = (V \cup \{b_s\}, E; w : E \mapsto R^+)$, where there is an edge $(u, v) \in E$ for any two nodes u and v in set $V \cup \{b_s\}$, and $w(u, v)$ represents the Euclidean distance between nodes u and v .

2.2. A novel simultaneous charging model

To significantly shorten the dead durations of sensors, we propose a novel simultaneous charging model to improve the charging capacity. We assume that a mobile charging vehicle can carry K low-cost removable wireless chargers mc_1, mc_2, \dots, mc_K for

charging lifetime-critical sensors in the sensor network, and each charger is powered by a large-volume portable battery, where K is a given positive integer. The charging vehicle is located at the base station b_s initially. In each charging tour, the charging vehicle starts from the base station b_s , and will return to b_s for the energy replenishment of the vehicle itself and the K chargers after completing its charging tour. We assume the battery capacities of the charging vehicle and the K chargers are sufficient in a charging tour, i.e., the charging vehicle and chargers will not deplete their energy in a charging tour. For the convenience of discussion, we further assume that the number n of to-be-charged sensors in V is divisible by the number K of chargers, and let $n = q \cdot K$, where q is a positive integer. Notice that the proposed algorithms in this paper can be easily extended to the case that n is not divisible by K .

Assume that the vehicle moves at a constant speed of η and a charger replenishes a sensor at a charging rate μ . Also, assume that the charging times of different sensors are almost identical, i.e., $\Delta T \approx \frac{B}{\mu}$, since each to-be-charged sensor will run out of its energy very soon, where B is the sensor battery capacity.

Given a set V of to-be-charged sensors, assume that a *charging sequence* $C: v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_n$ of the sensors in V is delivered by a scheduling algorithm, where $n = |V|$. In the *simultaneous charging model*, the charging vehicle performs the charging task for sensors in V in the following order. The vehicle starts from the base station b_s and visits the first K sensors v_1, v_2, \dots, v_K one by one, by placing a charger in the vicinity of each of the K sensors. After the placement of a charger at v_K , the vehicle revisits the K sensors v_1, v_2, \dots, v_K for collecting the K chargers allocated to them after the K sensors are fully charged. Note that the K sensors are almost charged at the same time, as the travel time of the vehicle usually is much shorter than a sensor's charging time. The charging vehicle then performs charging to the next K sensors $v_{K+1}, v_{K+2}, \dots, v_{2K}$. This procedure continues until all sensors in the sequence C have been charged, and the vehicle finally returns to the base station b_s . We can see that the *travel trajectory* of the charging vehicle in the charging task is $C' : b_s \rightarrow (v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_K) \rightarrow (v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_K) \rightarrow (v_{K+1} \rightarrow v_{K+2} \rightarrow \dots \rightarrow v_{2K}) \rightarrow (v_{K+1} \rightarrow v_{K+2} \rightarrow \dots \rightarrow v_{2K}) \rightarrow \dots \rightarrow v_n \rightarrow b_s$. Denote by $w(C')$ the travel distance of the vehicle in trajectory C' .

It can be seen that a sensor $v_i \in V$ may or may not be charged in time in charging trajectory C' . Assume that sensor v_i is charged at time t_i . Recall that the residual lifetime of v_i at time t is l_i^t . We say that sensor v_i is charged *in time* if its charging time t_i is no later than $t + l_i^t$, i.e., $t_i \leq t + l_i^t$; otherwise, sensor v_i runs out of its energy from time $t + l_i^t$ to time t_i , and its dead duration is $t_i^d = \max\{t_i - t - l_i^t, 0\}$ for each sensor $v_i \in V$.

2.3. Problem definitions

In this paper, we consider the charging scheduling of the mobile charging vehicle and we distinguish our discussion into two cases.

Case one: we do not take the sensor energy expirations into consideration and study the problem of finding the shortest charging trajectory under the simultaneous charging model. Note that this case is applicable to a sensor network in which the network can tolerate the sensor data loss for some time. For example, in a sensor network for the structural health monitoring of a historic building, the building structure usually does not change too much in a period of several days.

Case two: we consider the sensor dead durations when the sensing data may change very quickly in a short time. We formally define the two vehicle scheduling problems for sensor charging as follows.

Given a set V of to-be-charged sensors at time t , a base station b_s , and a charging vehicle carrying K removable wireless chargers, the service cost minimization problem is to find a charging sequence $C: v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_n$ of the sensors in V so that the travel distance $w(C')$ of the vehicle in the corresponding travel trajectory C' under the simultaneous charging model is minimized, where $C': b_s \rightarrow (v_1 \rightarrow v_2 \dots \rightarrow v_K) \rightarrow (v_1 \rightarrow v_2 \dots \rightarrow v_K) \rightarrow (v_{K+1} \rightarrow v_{K+2} \dots \rightarrow v_{2K}) \rightarrow (v_{K+1} \rightarrow v_{K+2} \dots \rightarrow v_{2K}) \dots \rightarrow v_n \rightarrow b_s$.

It can be seen that the service cost minimization problem is NP-hard, since the well known NP-hard Travelling Salesman Problem (TSP) is one of its special cases when there is only one charger, i.e., $K = 1$.

Although some WSN applications are insensitive to sensor data loss for a while, other applications of sensor networks may pose stringent requirements on the continuous sensing data collections. For example, in a sensor network for forest fire monitoring, a forest fire may be quickly spread by strong wind in a very short time and the energy depletions of some sensors for several hours delay the detection of the forest fire. Therefore, it is desirable to shorten the dead durations of sensors as much as possible. This motivates us to consider another novel vehicle scheduling problem for sensor charging as follows.

Given a set V of to-be-charged sensors at time t with the residual lifetime l_i^t of sensor $v_i \in V$, a base station b_s , and a charging vehicle with K portable wireless chargers, the service cost minimization problem with the shortest sensor dead durations is to find a charging sequence $C: v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_n$ of the sensors in V so that travel distance $w(C')$ of the vehicle in the corresponding travel trajectory C' is minimized, while ensuring that the longest dead duration t_d^{\max} among sensors in V is minimized, where $t_d^{\max} = \max_{v_i \in V} \{t_i^d\}$, and t_i^d is the dead duration of sensor v_i in trajectory C' . That is, we first consider minimizing the longest dead durations of sensors. Since there may be multiple charging trajectories with the minimum longest dead duration, we aim to find the shortest one. Notice that the two objectives of minimizing the travel cost of the vehicle and minimizing the longest dead durations of sensors usually are contradictory and there may be no feasible solutions so that the optimal values of the two objectives are achieved at the same time.

3. Approximation algorithm for the service cost minimization problem

In this section, we propose a $(3 + \epsilon)$ -approximation algorithm for the service cost minimization problem, so that the travel distance of the vehicle for charging a set of sensors is minimized, where ϵ is a given constant with $0 < \epsilon \leq 1$. In the following, we first describe the approximation algorithm, and then analyze its performance.

3.1. Approximation algorithm

Given a graph $G = (V \cup \{b_s\}, E; w: E \mapsto R^+)$ and a constant ϵ with $0 < \epsilon \leq 1$, note that the weight $w(u, v)$ of each edge (u, v) in E represents the Euclidean distance of nodes u and v . The approximation algorithm first finds a $(1 + \xi)$ -approximate solution $C = b_s \rightarrow v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_n \rightarrow b_s$ for the TSP problem in G , by applying the Polynomial-Time Approximation Scheme (PTAS) in the two-dimensional Euclidean space of G with time complexity $O(n(\log n)^{O(\frac{1}{\xi})})$ [1], where $\xi = \frac{\epsilon}{3}$. Then, the algorithm schedules the charging vehicle to replenish sensors in V by the sequence C under the simultaneous charging model, and the travel trajectory of the vehicle is $C': b_s \rightarrow (v_1 \rightarrow v_2 \dots \rightarrow v_K) \rightarrow (v_1 \rightarrow v_2 \dots \rightarrow v_K) \rightarrow (v_{K+1} \rightarrow v_{K+2} \dots \rightarrow v_{2K}) \rightarrow (v_{K+1} \rightarrow v_{K+2} \dots \rightarrow v_{2K}) \dots \rightarrow v_n \rightarrow b_s$. The approximation algorithm is presented in Algorithm 1.

Algorithm 1 Appo.

Input: A graph $G = (V \cup \{b_s\}, E; w: E \mapsto R^+)$ and a constant ϵ with $0 < \epsilon \leq 1$

Output: a charging trajectory C' of the vehicle with the shortest travel distance

- 1: Find a $(1 + \xi)$ -approximate solution $C = b_s \rightarrow v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_n \rightarrow b_s$ for the TSP problem in G , by applying the PTAS in [1], where $\xi = \frac{\epsilon}{3}$;
- 2: Obtain the travel trajectory C' from the charging sequence C , where $C' = b_s \rightarrow (v_1 \rightarrow v_2 \dots \rightarrow v_K) \rightarrow (v_1 \rightarrow v_2 \dots \rightarrow v_K) \rightarrow (v_{K+1} \rightarrow v_{K+2} \dots \rightarrow v_{2K}) \rightarrow (v_{K+1} \rightarrow v_{K+2} \dots \rightarrow v_{2K}) \dots \rightarrow v_n \rightarrow b_s$;
- 3: **return** trajectory C' .

3.2. Algorithm analysis

Although Algorithm 1 is elegant, its performance analysis is quite involved, which needs the deep exploration of the combinatorial properties of the problem. We analyze its approximation ratio and time complexity as follows.

Theorem 1. Given a graph $G = (V \cup \{b_s\}, E; w: E \mapsto R^+)$ with a charging vehicle carrying K removable chargers, and a constant ϵ with $0 < \epsilon \leq 1$, there is a $(3 + \epsilon)$ -approximation algorithm, i.e., Algorithm 1, for the service cost minimization problem under the simultaneous charging model, which takes time $O(n(\log n)^{O(\frac{1}{\xi})})$, where $n = |V|$ and $\xi = \frac{\epsilon}{3}$.

Proof. Let C_{TSP}^* be a shortest tour of the TSP problem in G , and C_{min}^* be a shortest travel trajectory of the service cost minimization problem in G . We show that Algorithm 1 delivers a $(3 + \epsilon)$ -approximation solution C' , by proving that (i) the length of tour C_{TSP}^* is no more than the length of trajectory C_{min}^* , i.e., $w(C_{TSP}^*) \leq w(C_{min}^*)$; (ii) the PTAS delivers a $(1 + \xi)$ -approximate solution C to the TSP problem, i.e., $w(C) \leq (1 + \xi) \cdot w(C_{TSP}^*)$; and (iii) the cost of trajectory C' is no more than three times the cost of tour C , i.e., $w(C') \leq 3 \cdot w(C)$. Then,

$$\begin{aligned} w(C') &\leq 3 \cdot w(C) \\ &\leq 3 \cdot (1 + \xi) \cdot w(C_{TSP}^*) \\ &= (3 + \epsilon) \cdot w(C_{TSP}^*) \\ &\leq (3 + \epsilon) \cdot w(C_{min}^*), \end{aligned} \quad (1)$$

i.e., trajectory C' is a $(3 + \epsilon)$ -approximate solution, where $\xi = \frac{\epsilon}{3}$.

We first show (i) that the length of the shortest tour C_{TSP}^* is not longer than the length of trajectory C_{min}^* , i.e., $w(C_{TSP}^*) \leq w(C_{min}^*)$. Notice that in trajectory C_{min}^* , the charging vehicle must visit each node in set $V \cup \{b_s\}$ at least once. We thus can construct a feasible solution C'_{min} to the TSP problem in G from trajectory C_{min}^* , by shortcutting repeated nodes in C_{min}^* . We can see that tour C'_{min} contains each node in $V \cup \{b_s\}$ once and only once, and the length of tour C'_{min} is no more than the length of trajectory C_{min}^* . Then, $w(C_{TSP}^*) \leq w(C'_{min}) \leq w(C_{min}^*)$, since tour C_{TSP}^* is a shortest tour for the TSP problem in G .

Claim (ii) $w(C) \leq (1 + \xi) \cdot w(C_{TSP}^*)$ holds, since the PTAS delivers a $(1 + \xi)$ -approximate solution C to the TSP problem in the two-dimensional Euclidean space of G [1].

We show claim (iii) that the cost of the travel trajectory C' is no more than three times the cost of tour C , i.e., $w(C') \leq 3 \cdot w(C)$. Denote by v_0 the base station b_s , i.e., $v_0 = b_s$. Recall that $C = v_0 \rightarrow v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_n \rightarrow v_0$, $C' = v_0 \rightarrow (v_1 \rightarrow v_2 \dots \rightarrow v_K) \rightarrow (v_1 \rightarrow v_2 \dots \rightarrow v_K) \rightarrow (v_{K+1} \rightarrow v_{K+2} \dots \rightarrow v_{2K}) \rightarrow (v_{K+1} \rightarrow v_{K+2} \dots \rightarrow v_{2K}) \dots \rightarrow v_n \rightarrow v_0$, and $n = q \cdot K$, where q is a positive integer. We first partition tour C into $(q + 1)$ segments $P_1, P_2, \dots, P_q, P_{q+1}$, where $P_j = v_{(j-1)K} \rightarrow$

$v_{(j-1)K+1} \rightarrow \dots \rightarrow v_{jK}$, $1 \leq j \leq q$, $P_{q+1} = v_{qK} \rightarrow v_0$, and $qK = n$. We also partition trajectory C' into $(q+1)$ sub-trajectories $P'_1, P'_2, \dots, P'_q, P'_{q+1}$, where $P'_j = v_{(j-1)K} \rightarrow (v_{(j-1)K+1} \rightarrow v_{(j-1)K+2} \dots \rightarrow v_{jK})$, $1 \leq j \leq q$, $P'_{q+1} = v_{qK} \rightarrow v_0$. Let $P'_{j,1} = v_{(j-1)K} \rightarrow v_{(j-1)K+1} \dots \rightarrow v_{jK}$, $P'_{j,2} = v_{jK} \rightarrow v_{(j-1)K+1}$, and $P'_{j,3} = v_{(j-1)K+1} \rightarrow v_{(j-1)K+2} \dots \rightarrow v_{jK}$. We can see that $w(P'_j) = w(P'_{j,1}) + w(P'_{j,2}) + w(P'_{j,3})$ and $w(P'_{j,2}) \leq w(P'_{j,3}) \leq w(P'_{j,1}) = w(P_j)$. Then, $w(P'_j) \leq 3 \cdot w(P_j)$. Therefore,

$$\begin{aligned} w(C') &= \sum_{j=1}^q w(P'_j) + w(P'_{q+1}) \\ &\leq \sum_{j=1}^q 3w(P_j) + w(P_{q+1}) \\ &\leq 3 \left(\sum_{j=1}^q w(P_j) + w(P_{q+1}) \right) \\ &= 3 \cdot w(C), \end{aligned} \quad (2)$$

where $w(P_{q+1}) = w(P'_{q+1})$. By combining the discussion, we know that Algorithm 1 delivers a $(3 + \epsilon)$ -approximate solution.

We finally analyze the time complexity of Algorithm 1. The algorithm first takes time $O(n(\log n)^{O(\frac{1}{\epsilon})})$ to find tour C by applying the PTAS in [1]. It then obtains travel trajectory C' from C in time $O(n)$. The time complexity of Algorithm 1 thus is $O(n(\log n)^{O(\frac{1}{\epsilon})})$. \square

4. Heuristic algorithm for the service cost minimization problem with the shortest sensor dead durations

In the previous section, we found a shortest charging trajectory of the vehicle to charge sensors if the residual lifetime of each sensor will not be taken into account. However, some sensor networks may have stringent requirements on continuous sensing and data collections of sensors for further processing, as the sensing data may change very quickly in a short time. In this section, we take the sensor residual lifetimes into consideration and investigate the service cost minimization problem with the shortest sensor dead durations. In the following, we first propose a novel procedure to find a charging trajectory so that the longest sensor dead duration is minimized, but the length of the trajectory may be long. We then devise an efficient heuristic algorithm to shorten the trajectory as much as possible while ensuring the minimum longest sensor dead duration.

4.1. Calculate the minimum longest sensor dead duration

Given a graph $G = (V \cup \{b_s\}, E; w: E \mapsto R^+)$, the residual lifetime l_i of each sensor $v_i \in V$, a mobile vehicle carrying K removable chargers, and the charging rate μ for charging a sensor, we note that the average vehicle travel time δ among K consecutive to-be-charged sensors usually is much shorter than the sensor charging time ΔT , e.g., several minutes vs. an hour, but is not neglected, where $\Delta T \approx \frac{B}{\mu}$, and B is the sensor battery capacity. Let $\tau = \Delta T + \delta$. We thus can divide time into equal time slots with each lasting τ units and index them by $1, 2, \dots$

The basic idea of the procedure for calculating the minimum longest sensor dead duration is to observe that K sensors are fully charged in every time slot by the K wireless chargers in the optimal solution, and $q (= \frac{n}{K})$ time slots are needed for charging the sensors in V , where $n = |V|$ and q is a positive integer. In other words, the optimal solution can be regarded as a K -to-one matching. The optimal solution can be found by obtaining a perfect

matching in an auxiliary graph, so that the maximum weight in the matching is minimized. In the following, we describe the procedure in detail.

Let S be the set of q time slot nodes, i.e., $S = \{s_1, s_2, \dots, s_q\}$, where node s_j represents the j th time slot. For each node s_j , we create K virtual nodes $s'_{(j-1)K+1}, s'_{(j-1)K+2}, \dots, s'_{jK}$, $1 \leq j \leq q$. Then, there are $qK = n$ virtual nodes. Let S' be the set of these $qK (= n)$ virtual nodes, i.e., $S' = \{s'_1, s'_2, \dots, s'_{K'}, s'_{K'+1}, s'_{K'+2}, \dots, s'_{2K'}, \dots, s'_{qK'}\}$.

We construct an auxiliary complete bipartite graph $G' = (V, S'; E'; w': E' \mapsto R^{\geq 0})$. There is an edge $(v_i, s'_j) \in E'$ between any sensor $v_i \in V$ and any virtual time slot $s'_j \in S'$, and the weight $w'(v_i, s'_j)$ of each edge (v_i, s'_j) is the dead duration of sensor v_i if it is charged by a wireless charger at the beginning of the k th time slot, i.e., $w'(v_i, s'_j) = \max\{0, (k-1)\tau - l_i\}$, where $k = \lceil \frac{j}{K} \rceil$, the virtual time slot s'_j corresponds to the k th real time slot $s_k \in S$, and l_i is the residual lifetime of sensor v_i . Note that $|V| = |S'| = n$ and G' is a complete bipartite graph, there must be a perfect matching in G' , e.g., a trivial perfect matching is to match sensor v_i to slot s'_i and $1 \leq i \leq n$. Also, it can be seen that the problem of calculating the minimum longest sensor dead duration is equivalent to the problem of finding a perfect matching in G' so that the maximum weight in the matching is minimized.

Denote by M_{opt} a perfect matching in G' with the minimum maximum edge weight and w_{opt} the maximum edge weight in M_{opt} . To find matching M_{opt} , assume that there is a guess w_g of w_{opt} . We create a subgraph $G'' = (V, S', E'')$ of graph G' , where E'' is the set of edges in G' with their weights no greater than w_g , i.e., $E'' = \{e \mid e \in E', w'(e) \leq w_g\}$. Note that the edges in subgraph G'' are unweighted. We later show that there is a perfect matching M in subgraph G'' if $w_g \geq w_{opt}$; otherwise ($w_g < w_{opt}$), there is no such a matching. Assume that the edges e_1, e_2, \dots, e_m in G' are sorted by their weights in non-decreasing order, i.e., $w'(e_1) \leq w'(e_2) \leq \dots \leq w'(e_m)$, where $m = n^2$. Then, we can find the optimal value w_{opt} through a binary search on the m different edge weights in G' .

Procedure 1 details the algorithm for calculating the minimum longest dead duration. We here use an example to illustrate the execution process of Procedure 1. Assume that there are four to-be-charged sensors v_1, v_2, v_3 , and v_4 that have already depleted their energy, i.e., $l_1 = l_2 = l_3 = l_4 = 0$, and the charging vehicle can carry $K (= 2)$ wireless chargers to charge the sensors. Procedure 1 will construct a complete bipartite graph $G' = (V, S'; E'; w': E' \mapsto R^{\geq 0})$, where $V = \{v_1, v_2, v_3, v_4\}$, $S' = \{s'_1, s'_2, s'_3, s'_4\}$, $E' = \{(v_i, s'_j) \mid \forall v_i \in V, \forall s'_j \in S'\}$, $w'(v_i, s'_1) = w'(v_i, s'_2) = 0$, $w'(v_i, s'_3) = w'(v_i, s'_4) = 1$, and $1 \leq i \leq 4$, since the dead duration $w'(v_i, s'_j)$ of sensor v_i is zero if it is charged at the first time slot (corresponding virtual time slots s'_1 and s'_2), and its dead duration $w'(v_i, s'_j)$ is $1 \cdot \tau$ if it will be replenished at the second time slot (corresponding virtual time slots s'_3 and s'_4). It can be seen that a perfect matching with the minimum longest dead duration in G' is $M_{opt} = \{(v_1, s'_1), (v_2, s'_2), (v_3, s'_3), (v_4, s'_4)\}$ and the minimum longest dead duration in matching M_{opt} is τ .

Lemma 1. Procedure 1 finds the minimum longest sensor dead duration in time $O(n^{2.5} \log n)$.

Proof. Since the problem of calculating the minimum longest dead duration is equivalent to the problem of finding a perfect matching in G' with the minimum maximum edge weight in the matching, we show that, given a guess w_g of w_{opt} , (i) there is a perfect matching M in subgraph G'' if $w_g \geq w_{opt}$; and (ii) there is no such a matching if $w_g < w_{opt}$. Then, Procedure 1 finds the optimal value w_{opt} .

We first show (i) that there is a perfect matching M in subgraph G'' if $w_g \geq w_{opt}$. Recall that M_{opt} is a perfect matching in G' with

Procedure 1 Calculate the minimum longest dead duration.**Input:** a graph $G = (V, E; w)$, residual lifetime l_i of $v_i \in V$ **Output:** A charging sequence C of sensors in V with the minimum longest dead duration

- 1: Let $S' = \{s'_1, s'_2, \dots, s'_n\}$;
- 2: Create a bipartite graph $G' = (V, S', E'; w' : E' \mapsto \mathbb{R}^{+0})$, where there is an edge $(v_i, s'_j) \in E'$ for $v_i \in V$ and $s'_j \in S'$, $w'(v_i, s'_j) = \max\{0, (k-1)\tau - l_i\}$, and $k = \lceil \frac{j}{K} \rceil$;
- 3: Sort the edges e_1, e_2, \dots, e_m in G' in non-decreasing order by their weights, i.e., $w'(e_1) \leq w'(e_2) \leq \dots \leq w'(e_m)$;
- 4: Let $lb = 1$ and $ub = m$; /* the lower and upper bounds on the edge index */
- 5: **while** $lb < ub$ **do**
- 6: Let $mid = \lfloor \frac{lb+ub}{2} \rfloor$;
- 7: Let $w_g = w'(e_{mid})$; /* a guess of w_{opt} */
- 8: Create a subgraph $G'' = (V, S', E'')$ of graph G' , where $E'' = \{e | e \in E', w'(e) \leq w_g\}$;
- 9: **if** there are no perfect matchings in G'' **then**
- 10: /* the guess w_g of w_{opt} is too small, i.e., $w_g = w'(e_{mid}) < w_{opt}$ */
- 11: Let $lb = mid + 1$;
- 12: **else**
- 13: /* $w'(e_{mid}) \geq w_{opt}$ */
- 14: Let $ub = mid$;
- 15: **end if**
- 16: **end while**
- 17: Let $w_{opt} = w'_{lb} (= w'_{ub})$;
- 18: Create a subgraph $G'_{opt} = (V, S', E'_{opt})$ of graph G' , where $E'_{opt} = \{e | e \in E', w'(e) \leq w_{opt}\}$;
- 19: Find a perfect matching M_{opt} in G'_{opt} ;
- 20: The charging sequence is $C = v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_n$, where sensor v_i is matched to virtual time slot s'_i in M_{opt} .

the minimum maximum edge weight. Consider the subgraph $G'' = (V, S', E'')$ of G' , where $E'' = \{e | e \in E', w'(e) \leq w_g\}$. For each edge $e \in M_{opt}$, we know that $w'(e) \leq w_{opt} \leq w_g$. Then, M_{opt} is subset of edge set E'' , i.e., $M_{opt} \subseteq E''$. Since M_{opt} is a perfect matching, there must be a perfect matching M in G'' , e.g., $M = M_{opt}$.

We then show claim (ii) that there is not any perfect matching in G'' if $w_g < w_{opt}$. We show the claim by contradiction. Suppose that there is a perfect matching M in G'' . Then, the maximum edge weight in M is strictly less than w_{opt} , since the weight of each edge in G'' is no more than w_g and $w_g < w_{opt}$. Then, matching M is a better solution than matching M_{opt} , which contradicts the assumption that M_{opt} is an optimal solution.

We finally analyze the time complexity of Procedure 1. It takes $O(\log m) = O(\log n)$ binary searches to find the optimal value w_{opt} , where $m = n^2$. In each search, it tests whether there is a perfect matching in G'' by applying the algorithm in [4], which runs in time $O(n^{2.5})$. The time complexity of the procedure thus is $O(n^{2.5} \log n)$. \square

4.2. Heuristic algorithm for minimizing service cost with the minimum longest sensor dead duration

Although Procedure 1 can find a charging trajectory with the minimizing the longest sensor dead duration, the length of the trajectory may be long, as the procedure does not consider sensor locations. In the following we propose an efficient heuristic algorithm to minimize the length of the travel trajectory while ensuring the minimum longest sensor dead duration.

Recall that Procedure 1 found the charging sequence of sensors in V by the perfect matching M_{opt} in graph $G'_{opt} = (V, S', E'_{opt})$, and the i th to-be-charged sensor v_i is the sensor node matched

to virtual time slot s'_i in matching M_{opt} . We term that a sensor $v_i \in V$ is *unexpired* if it is matched to a virtual time slot s'_j prior to its residual lifetime in matching M_{opt} , i.e., $(k-1)\tau \leq l_i$, where $k = \lceil \frac{j}{K} \rceil$, τ is the duration of each time slot, and l_i is the residual lifetime of sensor v_i ; otherwise $((k-1)\tau > l_i)$, sensor v_i is *expired*. Let V_{dead} be the set of expired sensors in V , i.e., $V_{dead} = \{v_i | v_i \in V, (k-1)\tau > l_i\}$. Also, let $V_{live} = V \setminus V_{dead}$. Furthermore, let $n_d = |V_{dead}|$ and $n_l = |V_{live}|$. Then, $n = n_d + n_l$. For the base station b_s , we create two virtual nodes r_s and r_f and their locations are the same as that of base station b_s .

The heuristic algorithm finds a much shorter charging trajectory by considering matching M_{opt} and the sensor locations as follows. The algorithm first partitions the sensors in $V (= V_{dead} \cup V_{live})$ into q disjoint subsets V_1, V_2, \dots, V_q , since only $q (= \frac{n}{K})$ time slots are needed to fully charge sensors in V . An energy-expired sensor $v_i \in V_{dead}$ is contained in subset V_k if it is matched to virtual time slot s'_j in M_{opt} , where $k = \lceil \frac{j}{K} \rceil$. On the other hand, we sort unexpired sensors v_1, v_2, \dots, v_{n_l} in V_{live} in non-decreasing order by their residual lifetimes, i.e., $l_1 \leq l_2 \leq \dots \leq l_{n_l}$, where $n_l = |V_{live}|$. For each sensor $v_i \in V_{live}$, we can see that it is still unexpired if it is replenished by a charger at a time slot from the k th time slot to the k' th time slot, where v_i is matched to s'_j , $k = \lceil \frac{j}{K} \rceil$, and $k' = \min\{\lfloor \frac{l_i}{\tau} \rfloor + 1, q\}$. We partition the sensors v_1, v_2, \dots, v_{n_l} one by one. To minimize the travel cost of the charging vehicle, sensor v_i is contained in its closest subset $V_{p_{min}}$ among subsets $V_k, V_{k+1}, \dots, V_{k'}$, where $p_{min} = \arg \min_{k \leq p \leq k'} \{d(v_i, V_p)\}$, $d(v_i, V_p) = \min_{v_j \in V_p} \{d_{i,j}\}$, and $d_{i,j}$ is the Euclidean distance between nodes v_i and v_j . In case each of the subsets $V_k, V_{k+1}, \dots, V_{k'}$ does not contain any node, sensor v_i is contained in the last subset $V_{k'}$. Note that some of the q subsets may contain none of the sensors after the partitioning.

It must be emphasized that a sensor v_i contained in subset V_j after the sensor partitioning does not mean it must be charged at the j th time slot. It could be replenished at any of the first j time slots. One important property is that the number of sensors in the first j subsets V_1, V_2, \dots, V_j is no more than Kj after the sensor partitioning for each j with $1 \leq j \leq q$, and there is no need that every subset must contain K sensors.

Let $V_0 = \{r_s\}$ and $V_{q+1} = \{r_f\}$. Having the partitioned subsets V_1, V_2, \dots, V_q , the algorithm then finds a minimum cost tree T that spans all nodes in the $q+2$ subsets V_0, V_1, \dots, V_{q+1} as follows. For each subset V_j ($0 \leq j \leq q+1$), the algorithm finds a minimum spanning tree (MST) T_j of nodes in V_j if V_j is not empty. Then, the algorithm obtains tree T by connecting the $q+2$ trees T_0, T_1, \dots, T_{q+1} one by one. That is, trees T_j and T_{j+1} are connected by their closest edge (u_{min}, v_{min}) , i.e., $(u_{min}, v_{min}) = \arg \min_{u \in T_j, v \in T_{j+1}} \{d_{u,v}\}$, where $d_{u,v}$ is the Euclidean distance of nodes u and v , and $0 \leq j \leq q$.

The algorithm finally transforms tree T into a path C starting from node r_s and ending at node r_f . The path from r_s to r_f in tree T is first found. A graph H then is obtained from tree T by replicating the edges in T except the edges on the path. A Eulerian path from r_s to r_f thus can be found in graph H . The path C is obtained by shortcutting repeated nodes in the Eulerian path. Note that path C actually is a closed tour since its two ending nodes r_s and r_f are the virtual nodes of base station b_s . The heuristic is presented in Algorithm 2.

Theorem 2. Given a graph $G = (V \cup \{b_s\}, E; w : E \mapsto \mathbb{R}^+)$ with a charging vehicle carrying K removable chargers, and the residual lifetime l_i of sensor $v_i \in V$, there is a heuristic algorithm, i.e., Algorithm 2, for the service cost minimization problem with the shortest sensor dead duration, which takes time $O(n^{2.5} \log n)$, where $n = |V|$.

Algorithm 2 Heuristic.

Input: A graph $G = (V \cup \{b_s\}, E; w)$, residual lifetime l_i of sensor $v_i \in V$

Output: a shortest charging trajectory C' with the minimum longest dead duration

- 1: Invoke [Procedure 1](#) to calculate the minimum longest dead duration w_{opt} and the matching M_{opt} ;
- 2: Let $V_{dead} = \{v_i | v_i \in V, (k-1)\tau > l_i\}$, where $k = \lceil \frac{l_i}{\tau} \rceil$, v_i is matched to node s_j^i in matching M_{opt} , and let $V_{live} = V \setminus V_{dead}$;
- 3: Let $V_0 = \{r_s\}$ and $V_{q+1} = \{r_f\}$;
- 4: /* Partition nodes in $V = V_{live} \cup V_{dead}$ into q subsets */
- 5: Let $V_k = \emptyset$, $1 \leq k \leq q$;
- 6: For each sensor $v_i \in V_{dead}$, add v_i to subset V_k , where $k = \lceil \frac{l_i}{\tau} \rceil$;
- 7: Sort the sensors v_1, v_2, \dots, v_{n_l} in V_{live} in non-decreasing order by their residual lifetimes;
- 8: **for** each sensor $v_i \in V_{live}$ **do**
- 9: Let $k = \lceil \frac{l_i}{\tau} \rceil$ and $k' = \min\{\lfloor \frac{l_i}{\tau} \rfloor + 1, q\}$;
- 10: **if** none of subsets $V_k, V_{k+1}, \dots, V_{k'}$ contains any nodes **then**
- 11: Add sensor v_i to subset $V_{k'}$;
- 12: **else**
- 13: Add sensor v_i to its closest subset $V_{p_{min}}$;
- 14: **end if**
- 15: **end for**
- 16: Let tree $T = \{r_s\}$;
- 17: **for** each subset V_k ($1 \leq k \leq q+1$) **do**
- 18: **if** V_k contains some nodes **then**
- 19: Find an MST T_k of nodes in V_k ;
- 20: Assume that j is the maximum index so that V_j contains some nodes with $0 \leq j < k$;
- 21: Add T_k to tree T with the minimum weighted edge between nodes in V_j and nodes in V_k ;
- 22: **end if**
- 23: **end for**
- 24: Transform tree T into a path C from r_s to r_f ;
- 25: Obtain charging trajectory C' from C .

Proof. We analyze the time complexity of [Algorithm 2](#) as follows. It takes $O(n^{2.5} \log n)$ to invoke [Procedure 1](#) by [Lemma 1](#). Then, it takes time $O(n^2)$ to partition set V into q subsets. Let $n_j = |V_j|$, where $0 \leq j \leq q+1$. Then, $\sum_{j=0}^{q+1} n_j = n+2$. Also, finding the MST T_j in a graph induced by the nodes in subset V_j takes time $O(n_j^2)$ and merging tree T_j and tree T_{j+1} takes time $O(n_j \cdot n_{j+1})$. Thus, finding tree T takes time $O(\sum_{j=0}^{q+1} n_j^2 + \sum_{j=0}^q n_j n_{j+1}) = O((\sum_{j=0}^{q+1} n_j)^2) = O(n^2)$. Therefore, the time complexity of [Algorithm 2](#) is $O(n^{2.5} \log n) + O(n^2) = O(n^{2.5} \log n)$. \square

5. Performance evaluation

In this section, we evaluate the performance of the proposed algorithms through experimental simulation. We also study the impact of important parameters on the algorithm performance, including the network size, the sensor data rates, and the number of chargers employed.

5.1. Simulation environment

We consider a sensor network deployed in a $1000\text{ m} \times 1000\text{ m}$ square. A base station is located at the center of the area. The network consists of from 100 to 800 sensors, which are randomly deployed in the area. A charging vehicle is co-located with the base station and the vehicle moves at a speed of $s = 5\text{ m/s}$. The vehicle can carry K low-cost, removable chargers, where $K = 1, 2, \dots, 6$. Each charger can replenish energy to every sensor at a rate $\mu =$

5 W. The battery capacity of each sensor is $B = 10.8\text{ kJ}$ [24]. The data sensing rate b_i of each sensor v_i is randomly selected from an interval $[b_{\min}, b_{\max}]$, where $b_{\min} = 1\text{ kbps}$ and $b_{\max} = 10\text{ kbps}$ [24]. Each sensor uploads its sensing data to the base station via the path with the minimum energy consumption, where the real energy consumption model is adopted from [12]. The sensor sends a charging request to the base station when its residual lifetime is smaller than a given threshold $l_s = 2\text{ h}$. The monitoring period T in our simulation experiment is one year.

To evaluate the performance of the proposed algorithms [Appro](#) and [Heuristic](#), we also consider four existing benchmark algorithms [TSP](#), [EDF](#), [NETWRAP](#) [26] and [AA](#) [27]. Algorithm [TSP](#) does not consider the residual lifetimes of sensors and finds an approximate shortest charging tour for the vehicle. Algorithm [EDF](#) (Earliest Deadline First) schedules the charging vehicle to charge the sensors in increasing order of their residual lifetimes. Algorithm [NETWRAP](#) [26] selects the next to-be-charged sensor that has the smallest weighted sum of the residual lifetime of a sensor and the traveling time to the sensor. Finally, in the state-of-the-art algorithm [AA](#) [27], the vehicle chooses to charge a fraction of to-be-sensors, so that not only each chosen sensor is charged before its energy expiration but also the difference of the amount of energy charged to sensors and the energy consumption on vehicle traveling is maximized. Each experimental value is the average of the results by applying each mentioned algorithm to 20 different network topologies with the identical network size.

In the following we first study the performance of the proposed approximation algorithm [Appro](#) against algorithm [TSP](#) in [Section 5.2](#), if the residual lifetimes of sensors are not taken into consideration. Otherwise, in [Section 5.3](#) we compare the proposed heuristic algorithm with not only algorithm [TSP](#) but also other benchmarks [EDF](#), [NETWRAP](#), and [AA](#). Finally, In [Section 5.4](#), we investigate the impact of the number of chargers K on algorithmic performance.

5.2. Performance of the approximation algorithm

In this subsection, we evaluate the performance of the proposed algorithm [Appro](#) against algorithm [TSP](#). First, [Fig. 2\(a\)](#) shows that the longest sensor dead durations delivered by algorithms [Appro-2](#) and [Appro-3](#) (i.e., the number of chargers carried by the charging vehicle $K = 2, 3$) are much shorter than that by algorithm [TSP](#). For example, the longest sensor dead durations by algorithms [Appro-2](#) and [Appro-3](#) are about 38% ($\approx \frac{4188-2565}{4188}$) and 58% ($\approx \frac{4188-1731}{4188}$) shorter than that by algorithm [TSP](#) when the network size $n = 800$. Note that the performance of algorithm [Appro-1](#) (i.e., the vehicle carries only one charger ($K = 1$)) is identical to algorithm [TSP](#).

Then, [Fig. 2\(b\)](#) demonstrates that algorithms [Appro-2](#) and [Appro-3](#) can significantly shorten the average sensor dead duration. For instance, the average sensor dead durations per sensor during the monitoring period T delivered by algorithms [TSP](#), [Appro-2](#) and [Appro-3](#) are 6982 min, 2249 min, and 998 min, respectively, when there are 800 sensors in the network.

Finally, [Fig. 2\(c\)](#) plots the total travel distances of the charging vehicle during T by algorithms [TSP](#), [Appro-1](#), [Appro-2](#), and [Appro-3](#). We can see that the travel distance of the vehicle by algorithm [Appro-2](#) is about from 1.25 times to 2 times the distance by algorithm [TSP](#), which is smaller than the theoretic approximation ratio $(3 + \epsilon)$ of algorithm [Appro-2](#) by [Theorem 1](#). Also, the travel distance by algorithm [Appro-3](#) is only slightly longer than that by algorithm [Appro-2](#). Furthermore, [Fig. 2\(c\)](#) shows an interesting phenomenon. That is, the total travel distance of the vehicle during T by each of the mentioned four algorithms first increases in a larger sensor network, followed by decreasing with the increase of the network size when the network consists of more

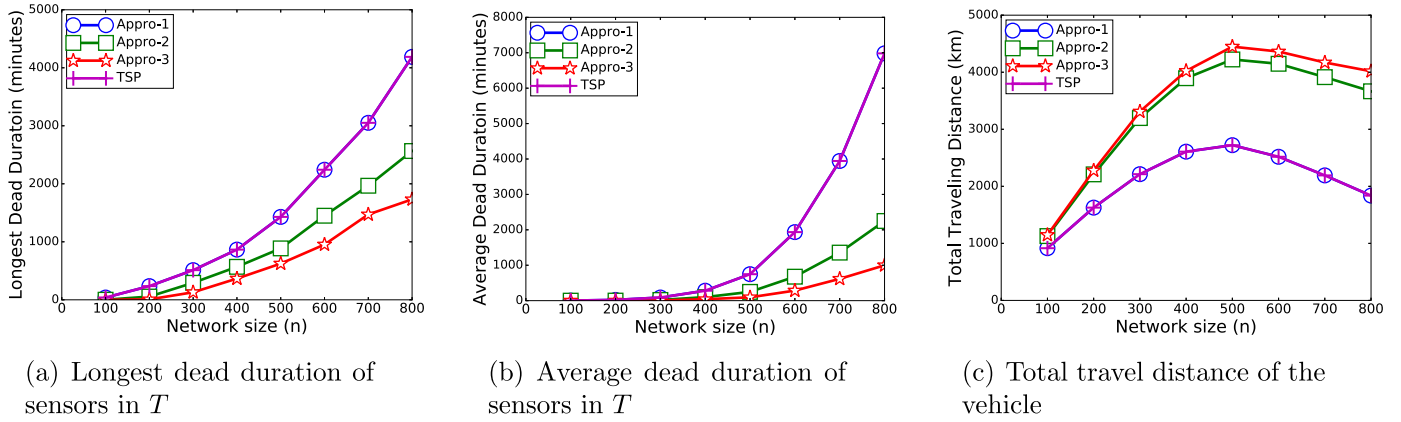


Fig. 2. Performance of algorithms Appro and TSP by increasing the network size n from 100 to 800 when the number of chargers $K = 1, 2, 3$.

than 500 sensors. The rationale behind the phenomenon is that although there are more to-be-charged sensors in each charging round when the network size increases, the number of charging rounds during T however significantly decreases. On the other side, the increase on the number of sensors in each charging round may only slightly increase the length of the vehicle travel trajectory, as the location of a newly added sensor usually is close to one of existing sensors.

In summary, the proposed algorithm Appro with a charging vehicle carrying multiple removable chargers can dramatically shorten sensor dead durations, while the travel distance of the charging vehicle is not too much longer than that by algorithm TSP.

5.3. Performance of the heuristic algorithm

In this subsection, we evaluate the proposed algorithm Heuristic by comparing it with algorithms Appro, TSP, EDF, NETWRAP, and AA, when the application of the sensor network is sensitive to energy expirations of sensors and thus the sensor dead durations must be shortened as much as possible.

Recall that in algorithm Heuristic we have made two assumptions. The first assumption is that the charging times ΔT of different sensors are almost identical, since each to-be-charged sensor will run out of its energy very soon. The second one is that the average vehicle travel time δ among K consecutive to-be-charged sensors usually is much shorter than the sensor charging time ΔT , but is not neglected.

We validate the practicality of the two assumptions through experiments. We first validate the first assumption that the charging times ΔT of different sensors are almost identical. Fig. 3(a) shows the coefficient of variation $CV_{\Delta T}$ of the sensor charging time ΔT by algorithm Heuristic when the number of chargers $K = 1, 2, 3$, where $CV_{\Delta T} = \frac{\sigma_{\Delta T}}{\mu_{\Delta T}}$, $\mu_{\Delta T}$ is the average charging time of different sensors and $\sigma_{\Delta T}$ is the standard deviation of ΔT . The coefficient of variation $CV_{\Delta T}$ can measure the extent of variability in relation to the average sensor charging time. From Fig. 3(a), it can be seen that the coefficient of variation $CV_{\Delta T}$ is no more than 0.07, which indicates that the variation of the sensor charging time ΔT is very small. We then verify the second assumption that the average vehicle travel time δ among K consecutive sensors is much shorter than the sensor charging time ΔT . Fig. 3(b) demonstrates that the average vehicle travel time δ is no more than 4 minutes whereas the sensor charging time ΔT is as long as 35 min. In addition, Fig. 3(c) plots that the analytical longest sensor dead duration by algorithm Heuristic matches its experimental longest dead duration very well, which means that the two assumptions given in

this paper only slightly influence experimental results, thus they are reasonable.

Fig. 4 illustrates the performance of different mentioned algorithms, by varying the network size from 100 to 800. Fig. 4(a) shows that the longest sensor dead duration by algorithm Heuristic-2 is much shorter than that by existing algorithms. For example, the longest dead durations by algorithms Heuristic-2, NETWRAP, Heuristic-1, EDF, Appro-2, Appro-1, TSP, and AA are about 260, 1300, 1350, 1350, 2500, 4200, 4200, 4700 min, respectively, when there are 800 sensors in the network. Also note that the performance of algorithm Heuristic-1 is identical to algorithm EDF (Earliest Deadline First) when the vehicle carries only a single charger (i.e., $K = 1$). Fig. 4(b) further presents that the average sensor dead duration by algorithm Heuristic-2 is much shorter than that by other algorithms. Finally, Fig. 4(c) shows that the total travel distance of the vehicle by algorithm Heuristic-2 is longer than existing algorithms. For example, the total travel distance by algorithm Heuristic-2 is about 2.2 times the distance by the state-of-the-art algorithm AA when the network size is 800. We however believe that the increase on the travel distance is worthwhile since the continuing operations of sensors are a fundamental requirement for the WSN, by noting that the longest sensor dead duration by algorithm Heuristic-2 is only about 5.5% ($\approx \frac{260 \text{ minutes}}{4,700 \text{ minutes}}$) of that by algorithm AA.

We then investigate the performance of the mentioned algorithms by increasing the maximum sensor data rate b_{\max} from 10 kbps to 20 kbps, when there are 500 sensors in the network. Fig. 5(a) and (b) demonstrate that the longest sensor dead duration and the average dead duration by each of the algorithms become longer with the increase of the maximum sensor data rate b_{\max} . The rationale behind is that sensors consume their energy faster with the increase of b_{\max} and they are more likely to run out of their energy before their energy charging. Fig. 5(a) and (b) also demonstrate that the longest and average dead durations by algorithm Heuristic-2 are much shorter than that by other algorithms. Fig. 5(c) illustrates that the total travel distance of the vehicle becomes longer with the increase of b_{\max} , since sensors must be charged more frequently when their energy consumption rates become faster.

5.4. The impact of the number of chargers

The rest is to study the impact of the number of chargers K on the performance of the proposed algorithms Heuristic and Appro, by varying K from 1 to 6, when the network size is 800. Fig. 6(a) and (b) show that the longest and average sensor dead durations by the two algorithms become much shorter when the

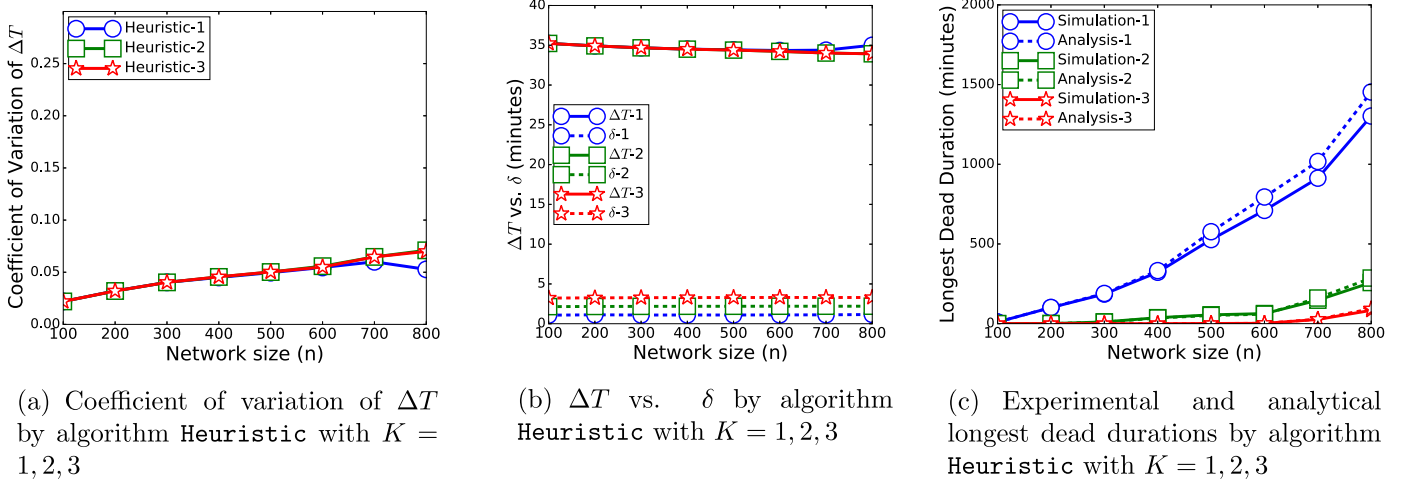


Fig. 3. The validation of the two assumptions (i) charging times ΔT of different sensors are almost identical and (ii) δ is significantly shorter than ΔT , in algorithm Heuristic when $K = 1, 2, 3$.

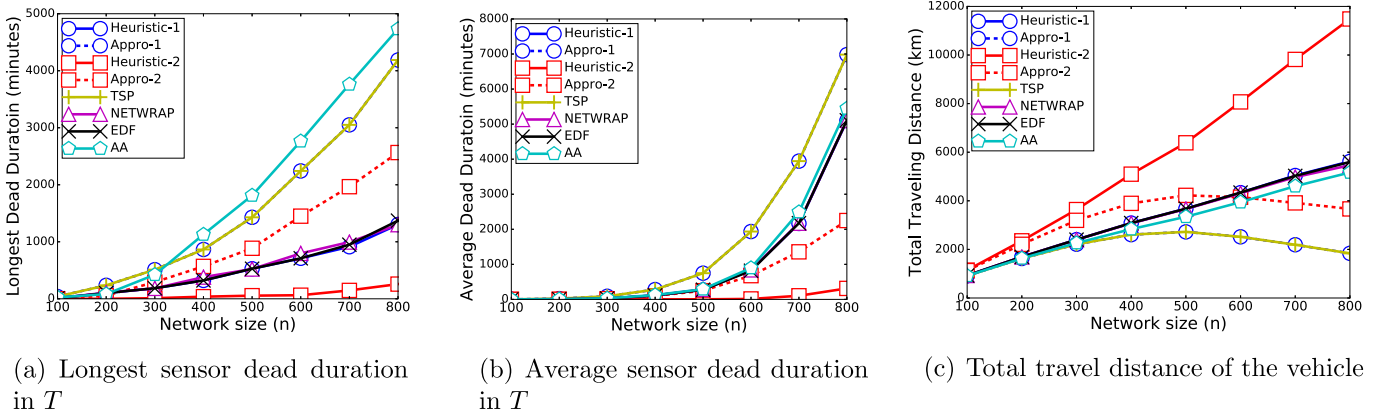


Fig. 4. Performance of algorithms Heuristic, Appro, TSP, EDF, NETWRAP, and AA by increasing the network size n from 100 to 800, when the number of chargers $K = 1, 2, 3$.

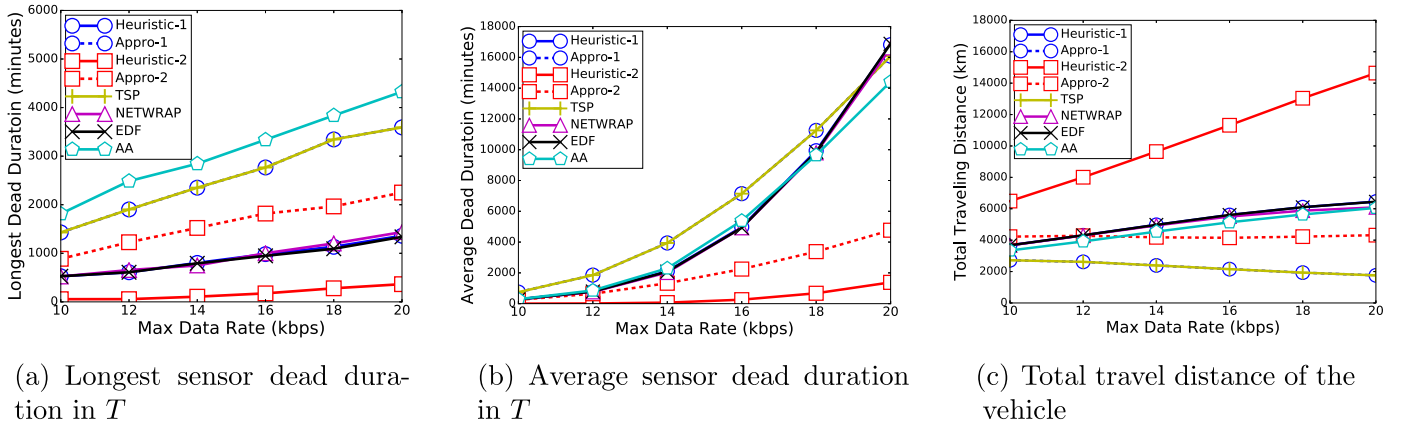


Fig. 5. Performance of algorithms Heuristic, Appro, TSP, EDF, NETWRAP, and AA by increasing the maximum sensor data rate b_{\max} from 10 kbps to 20 kbps, when network size is $n = 500$.

vehicle carries more removable chargers (i.e., a larger value of K). Also, the longest and average sensor dead durations by algorithm Heuristic are significantly shorter than those by algorithm Appro, since algorithm Heuristic takes the residual lifetimes of sensors into consideration while algorithm Appro considers only minimizing the travel distance of the vehicle. Fig. 6(c) demonstrates that the total travel distance by each of the two algorithms increases significantly when the number of chargers

K increases from 1 to 2, but only slightly increases with more chargers.

6. Related work

With the recent breakthrough in the efficient wireless energy transfer technology, the energy replenishment by mobile charging vehicles for WSNs has been studied in litera-

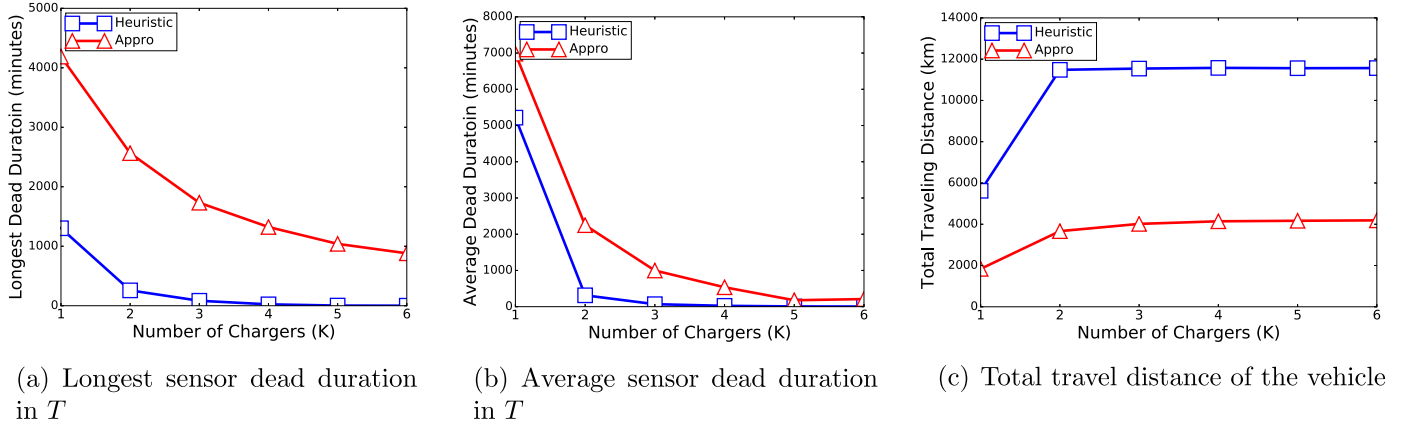


Fig. 6. Performance of algorithms Heuristic and Appro by varying the number of chargers K from 1 to 6 when network size is 800.

ture [5,13,20,22,24,25,26,32,36,37]. These studies can be classified into two categories, according to the number of deployed charging vehicles. In the first category, it is assumed that just one charging vehicle is employed [20,22,24,37], while in the second category, it is realized that the charging capacity of only one charging vehicle is limited and multiple charging vehicles thus are deployed to provide energy supply to sensors [5,13,25,26,32,36].

On one hand, researchers have studied the energy charging for sensors when only one charging vehicles is deployed [15,20,22,24,34,37]. For example, Peng et al. [20] designed a system for energy replenishment via wireless energy transfer in a sensor network, where a charging vehicle is dispatched to charge life-critical sensors. Furthermore, they built a proof-of-concept prototype and demonstrated that the performance of the proposed system is promising for a small-scale sensor network. Zhao et al. [37] proposed a joint design by employing a vehicle in a sensor network for both sensor charging and data gathering. Shi et al. [24] dispatched a mobile charging vehicle to provide energy to every sensor in a sensor network in a periodical way. They formulated the problem of finding a charging tour for the vehicle so that the ratio of its vacation time (i.e., the duration of the vehicle staying at the service station) to its charging cycle is maximized, and proposed a near-optimal solution. Ren et al. [22] considered the problem of charging the maximum number of sensors by a charging vehicle within a given time period, by taking into consideration the sensor charging time and vehicle travelling time. Xu et al. [34] investigated the problem of finding a charging tour such that the ratio of the amount of energy charged to sensors in the tour to the length of the tour is maximized. Lin et al. [15] extended the work of [34] by considering both sensor residual lifetimes and their spatial locations.

The charging capacity of one vehicle however is limited, because it still takes some time (e.g., 30–80 min to fully charge a commercial sensor battery [26]). Therefore, it is very likely that some sensors have run out of their energy for a long time before the charging vehicle visits them, especially when there are a large number of lifetime-critical sensors in a large-scale sensor network. To shorten the dead duration of sensors, extensive studies considered deploying multiple charging vehicles to charge lifetime-critical sensors [5,6,13,14,18,25,26,36]. For example, Wang et al. [25,26] considered the charging scheduling of multiple charging vehicles so as to minimize the weighted sum of the vehicle travelling time and the sensor residual lifetime. Zhang et al. [36] assumed that charging vehicles can charge not only sensors, but also transfer energy to each other. They discussed how to schedule multiple charging vehicles to replenish sensors so that the ratio of the payload energy to the overhead energy

is maximized. He et al. [13] proposed an on-demand charging paradigm, in which lifetime-critical sensors send charging requests and charging vehicles serve them in an on-demand way by the Nearest-Job-Next with Preemption discipline. Liang et al. [14] investigated the problem of scheduling the minimum number of vehicles to charge a set of lifetime-critical sensors and found approximate solutions. Jiang et al. [5] studied how to schedule multiple vehicles to charge sensors so as to maximize the coverage utility of the sensor network. Xu et al. [33] proposed an approximation algorithm for scheduling multiple charging vehicles to collaboratively charge sensors for an entire monitoring period so that the total movement cost of the vehicles is minimized, by considering that energy consumption rates of different sensors may vary significantly. When the depots of charging vehicles have not yet been deployed, Jiang et al. [6] jointly considered charging tour planning and depot positioning, and studied the problem of finding the minimum number of charging tours to visit sensors under the energy capacity constraint on each vehicle, and then placing the minimum number of depots for the found charging tours. In addition, Nikolettseas et al. [18] assumed that mobile nodes can transfer energy to each other in a wireless network, and studied how some nodes transfer energy to other nodes in a peer-to-peer manner, such that the energy in the network are balanced distributed in the nodes and the energy loss during the energy transfer among the nodes is minimized.

Unlike these existing studies assumed that one charging vehicle is equipped with just one wireless charger, in this paper we propose a novel simultaneous charging model, in which one vehicle can carry multiple low-cost, removable wireless chargers. By doing so, not only are the dead durations of sensors significantly shortened, since the chargers can charge multiple energy-critical sensors simultaneously, but also the cost of purchasing charging devices, including the vehicle and wireless chargers, is dramatically reduced, as the cost of a charger usually is much lower than that of a charging vehicle.

7. Conclusions

In this paper, we studied the sensor charging scheduling by deploying a mobile vehicle with multiple removable wireless chargers for a large-scale sensor network, under a novel charging model, in which the vehicle is equipped with multiple low-cost, removable chargers to charge multiple sensors at the same time. Based on this novel charging model, we proposed a $(3 + \epsilon)$ -approximation algorithm to find a shortest charging trajectory for the vehicle if the residual lifetimes of sensors are not considered. Otherwise, we devised a novel heuristic algorithm to obtain

a shortest charging trajectory while ensuring that the longest dead duration of sensors is minimized. We finally evaluated the performance of the proposed algorithms via simulation experiments and experimental results showed that the longest and average sensor dead durations by the proposed algorithms are much shorter than those by existing algorithms.

Acknowledgments

The work by Wenzheng Xu was supported by the National Natural Science Foundation of China (Grant No. 61602330) and the Fundamental Research Funds for the Central Universities (Grant No. 20822041A4031). Also, the work by Jian Peng was supported by National Natural Science Foundation of China (Grant No. U1333113 and 61303204).

References

- [1] S. Arora, Polynomial time approximation schemes for euclidean traveling salesman and other geometric problems, *J. ACM* 45 (5) (1998) 753–782.
- [2] S. Chen, Y. Shu, B. Yu, C. Liang, Z. Shi, J. Chen, Demo: mobile wireless charging and sensing by drones, in: *Proc. 14th Int. Conf. Mobile Syst. Applicat. Services (MobiSys) Companion*, 2016, p. 99.
- [3] L. Fu, P. Cheng, Y. Gu, J. Chen, T. He, Optimal charging in wireless rechargeable sensor networks, *IEEE Trans. Veh. Technol.* 65 (1) (2016) 2780–2791.
- [4] J. Hopcroft, R.M. Karp, An $n^{5/2}$ algorithm for maximum matchings in bipartite graphs, *SIAM J. Comput.* 2 (4) (1973) 225–231.
- [5] L. Jiang, H. Dai, X. Wu, G. Chen, On-demand mobile charger scheduling for effective coverage in wireless rechargeable sensor networks, in: *Proc. Int. Conf. Mobile Ubiquitous Syst. Comput. Netw. Services*, Springer, 2013, pp. 732–736.
- [6] G. Jiang, S.K. Lam, Y. Sun, L. Tu, J. Wu, Joint charging tour planning and depot positioning for wireless sensor networks using mobile chargers, *IEEE ACM Trans. Netw.* (2017). To appear.
- [7] A. Kansal, J. Hsu, M. Srivastava, V. Raghunathan, Harvesting aware power management for sensor networks, in: *Proc. 43rd ACM Annu. Design Automat. Conf.*, 2006, pp. 651–656.
- [8] A. Karalisa, J.D. Joannopoulos, M. Soljacic, Efficient wireless non-radiative mid-range energy transfer, *Ann. Phys.* 323 (1) (2008) 34–48.
- [9] S. Kim, S. Pakzad, D. Culler, J. Demmel, G. Fenves, S. Glaser, M. Turon, Health monitoring of civil infrastructures using wireless sensor networks, in: *Proc. Int. Conf. Inform. Process. Sensor Netw.*, 2007, pp. 254–263.
- [10] A. Kurs, A. Karalis, R. Moffatt, J.D. Joannopoulos, P. Fisher, M. Soljacic, Wireless power transfer via strongly coupled magnetic resonances, *Science* 317 (5834) (2007) 83–86.
- [11] Z. Li, Y. Peng, W. Zhang, D. Qiao, J-roc: a joint routing and charging scheme to prolong sensor network lifetime, in: *Proc. 19th IEEE Int. Conf. Netw. Protocols (ICNP)*, 2011, pp. 373–382.
- [12] J. Li, P. Mohapatra, Analytical modeling and mitigation techniques for the energy hole problem in sensor networks, *Pervas. Mob. Comput.* 3 (3) (2007) 233–254.
- [13] H. Liang, L. Kong, Y. Gu, J. Pan, T. Zhu, Evaluating the on-demand mobile charging in wireless sensor networks, *IEEE Trans. Mob. Comput.* 14 (9) (2015) 1861–1875.
- [14] W. Liang, etc., Maintaining large-scale rechargeable sensor networks perpetually via multiple mobile charging vehicles, *ACM Trans. Sensor Netw.* 12 (2) (2016). Article 14.
- [15] C. Lin, D. Han, J. Deng, G. Wu, P²s: a primary and passer-by scheduling algorithm for on-demand charging architecture in wireless rechargeable sensor networks, *IEEE Trans. Veh. Technol.* (2017). To appear.
- [16] T. Liu, B. Wu, H. Wu, J. Peng, Low-cost collaborative mobile charging for large-scale wireless sensor networks, *IEEE Trans. Mob. Comput.* (2016). To appear.
- [17] M. Ma, Y. Yang, Sencar: an energy-efficient data gathering mechanism for large-scale multihop sensor networks, *IEEE Trans. Parallel Distrib. Syst.* 18 (10) (2007) 1476–1488.
- [18] S. Nikolettseas, T.P. Raptis, C. Raptopoulos, Wireless charging for weighted energy balance in populations of mobile peers, *Ad Hoc Netw.* 60 (2017) 1–10.
- [19] J. Panchard, S. Rao, M.S. Sheshshayee, P. Papadimitratos, S. Kumar, J. Hubaux, Wireless sensor networking for rain-fed farming decision support, in: *Proc. 2nd ACM SIGCOMM Workshop Netw. Syst. Develop. Region*, 2008, pp. 31–36.
- [20] Y. Peng, Z. Li, W. Zhang, D. Qiao, Prolonging sensor network lifetime through wireless charging, in: *Proc. IEEE 31st Real-Time Syst. Symp. (RTSS)*, 2010, pp. 129–139.
- [21] M. Rahimi, H. Shah, G. Sukhatme, J. Heideman, D. Estrin, Studying the feasibility of energy harvesting in a mobile sensor network, in: *Proc. IEEE Int. Conf. Robotics Automat. (ICRA)*, volume 1, 2003, pp. 19–24.
- [22] X. Ren, etc., Maximizing charging throughput in rechargeable sensor networks, in: *Proc. 23rd IEEE Int. Conf. Comput. Commun. Netw. (ICCCN)*, 2014, pp. 1–8.
- [23] X. Ren, etc., Data collection maximization in renewable sensor networks via time-slot scheduling, *IEEE Trans. Comput.* 64 (7) (2015) 1870–1883.
- [24] Y. Shi, L. Xie, Y.T. Hou, H.D. Sherali, On renewable sensor networks with wireless energy transfer, in: *Proc. 30th IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2011, pp. 1350–1358.
- [25] C. Wang, J. Li, Y. Yang, Multi-vehicle coordination for wireless energy replenishment in sensor networks, in: *Proc. IEEE 27th Int. Parallel Distrib. Process. Symp. (IPDPS)*, 2013, pp. 1101–1111.
- [26] C. Wang, J. Li, F. Ye, Y. Yang, NETWRAP: an NDN based real-time wireless recharging framework for wireless sensor networks, *IEEE Trans. Mob. Comput.* 13 (6) (2014) 1283–1297.
- [27] C. Wang, J. Li, F. Ye, Y. Yang, Recharging schedules for wireless sensor networks with vehicle movement costs and capacity constraints, in: *Proc. 11th IEEE Int. Conf. Sensing Commun. Netw. (SECON)*, 2014, pp. 468–476.
- [28] C. Wang, J. Li, Y. Yang, F. Ye, Improve charging capability for wireless rechargeable sensor networks using resonant repeaters, in: *Proc. IEEE 35th Int. Conf. Distrib. Comput. Syst. (ICDCS)*, 2015, pp. 133–142.
- [29] T. Wang, etc., Cascading target tracking control in wireless camera sensor and actuator networks, *Asian J. Control* 19 (4) (2017) 1–15.
- [30] Wireless chargers on Amazon [Online]. Available: https://www.amazon.com/s/ref=nb_sb_noss_2?url=search-alias.
- [31] W. Xu, W. Liang, X. Jia, Z. Xu, Maximizing sensor lifetime in a rechargeable sensor network via partial energy charging on sensors, in: *Proc. 13th IEEE Int. Conf. Sensing Commun. Netw. (SECON)*, 2016, pp. 1–9.
- [32] W. Xu, W. Liang, X. Lin, Approximation algorithms for min-max cycle cover problems, *IEEE Trans. Comput.* 64 (3) (2015) 600–613.
- [33] W. Xu, W. Liang, X. Lin, G. Mao, Efficient scheduling of multiple mobile chargers for wireless sensor networks, *IEEE Trans. Veh. Technol.* 65 (9) (2016) 7670–7683.
- [34] W. Xu, W. Liang, X. Ren, X. Lin, On-demand energy replenishment for sensor networks via wireless energy transfer, in: *Proc. IEEE Int. Symp. Personal Indoor Mobile Radio Commun. (PIMRC)*, 2014, pp. 1269–1273.
- [35] L. Yu, N. Wang, X. Meng, Real-time forest fire detection with wireless sensor networks, in: *Proc. IEEE Int. Conf. Wireless Commun. Netw. Mobile Comput.*, volume 2, 2005, pp. 1214–1217.
- [36] S. Zhang, J. Wu, S. Lu, Collaborative mobile charging for sensor networks, in: *Proc. IEEE 9th Int. Conf. Mobile Ad-Hoc Sensor Syst. (MASS)*, 2013, pp. 84–92.
- [37] M. Zhao, J. Li, Y. Yang, Joint mobile energy replenishment and data gathering in wireless rechargeable sensor networks, in: *Proc. Int. Teletraffic Congr. (ITC)*, 2011.



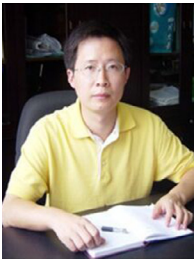
Tao Zou received the BSc degree in computer science from Sichuan University, P.R. China, in 2015. He is a second year master student in computer science at Sichuan University. His research interests include wireless sensor networks and mobile computing.



Wenzheng Xu received the BSc, ME, and Ph.D degrees in computer science from Sun Yat-Sen University, Guangzhou, China, in 2008, 2010, and 2015, respectively. He is currently a special associate professor at Sichuan University. He was a visitor at both the Australian National University from 2012 to 2014 and Chinese University of Hong Kong in 2016. His research interests include wireless ad hoc and sensor networks, approximation algorithms, combinatorial optimization, graph theory, online social networks, and mobile computing.



Weifa Liang received the PhD degree from the Australian National University in 1998, the ME degree from the University of Science and Technology of China in 1989, and the BSc degree from Wuhan University, China in 1984, all in computer science. He is currently a full 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.



Jian Peng is a professor at College of Computer Science, Sichuan University. He received his B.A. degree and PhD degree from the University of Electronic Science and Technology of China (UESTC) in 1992 and 2004, respectively. His recent research interests include wireless sensor networks, big data, and cloud computing.



Yiqiao Cai received the B.S. degree from Hunan University, Changsha, China, and the Ph.D. degree from Sun Yat-Sen University, Guangzhou, China, in 2007 and 2012, respectively. He is currently a Lecturer with the College of Computer Science and Technology, Huaqiao University, Xiamen, China. His current research interests include wireless sensor networks, differential evolution, multiobjective optimization, and other evolutionary computation techniques.



Tian Wang received his BSc and MSc degrees in Computer Science from the Central South University in 2004 and 2007, respectively. He received his PhD degree in City University of Hong Kong in 2011. Currently, he is an associate professor in the National Huaqiao University of China. His research interests include wireless sensor networks, social networks and mobile computing.