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An improved algorithm for dispatching the minimum number of electric charging vehicles for wireless sensor networks

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Abstract

The very limited sensor battery energy greatly hinders the large-scale, long-term deployments of wireless sensor networks. This paper studies the problem of scheduling the minimum charging vehicles to charge lifetime-critical sensors in a wireless rechargeable sensor network, by utilizing the breakthrough wireless charging technology. Existing studies still employ a number of charging vehicles to charge sensors. The purchase cost of a charging vehicle however is not inexpensive. To further reduce the number of employed charging vehicles, we propose a novel approximation algorithm, by exploring the combinatorial properties of the problem. The techniques exploited in this paper are essentially different from that in existing studies. Not only do we show that the approximation ratio of the proposed algorithm is much better than that of the state-of-the-art, but also extensive experimental results demonstrate that the number of scheduled charging vehicles by the proposed algorithm is at least 10% less than that by the existing algorithms and the total travel energy consumption of the charging vehicles is also smaller than that by the existing algorithms.

Keywords Wireless sensor networks · Wireless energy transfer · Minimum number of dispatched charging vehicles · Approximation algorithm

1 Introduction

Wireless sensor networks (WSNs) are widely used in environmental monitoring, target tracking, medical and scientific exploration, etc [5, 26]. Since sensors usually are powered by batteries, their limited battery energy has become a severe restriction on the applications of large-scale sensor networks [1, 5, 17]. In order to reduce the number of energy-critical sensors and thus prolong the operation lifetime of WSNs, researchers proposed to enable sensors to harvest energy from their surrounding environments, such as solar power [21], wind power, etc [11, 19, 22]. However, renewable energy is highly affected by its surrounding environment and is usually temporally-varied and spatially-varied. For example, the energy generating rate in a sunny day can be up to three orders of magnitude higher than that in a cloudy day in a solar harvesting system [14] and the average energy harvesting rates of sensors vary significantly indoors and outdoors [6].

The recent breakthrough in the wireless energy transfer based on the magnetic resonance technology revolutionizes

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the way of replenishing sensor energy [12, 27]. By scheduling a charging vehicle to move in the vicinity of an energy-critical sensor, the sensor can be fast charged by the charging vehicle [20, 25, 29, 30]. Since there may be a large number of energy-critical sensors in a large-scale WSN and a charging vehicle is usually energy constrained, multiple charging vehicles are needed for replenishing the sensors, so as to support the sustainable operation of the network. However, the purchase cost of one charging vehicle is not cheap, which is from several hundred dollars to quite a few thousand dollars [3, 7, 13]. In order to reduce the total cost of the WSNs, especially the purchase cost and maintenance cost of charging vehicles, in this paper we study the problem of dispatching the minimum number of charging vehicles to replenish energy-critical sensors.

The charging vehicles minimization problem has attracted the attention of several researchers. For example, Dai et al. [5] proposed an approximation algorithm for the problem. However, the energy consumption of a charging vehicle in its charging tour may exceed the maximum energy capacity of the vehicle, then the vehicle is unable to return to the base station to replenish itself. In order to solve this problem, Liang et al. [14, 15] recently devised a novel approximation scheduling algorithm, while ensuring that the energy consumption of each charging vehicle in its tour is no more than the maximum battery capacity of the vehicle.

However, notice that the existing algorithms still schedule a lot of charging vehicles to charge sensors. Since the purchase cost of charging vehicles is not cheap, the scheduling of many charging vehicles will not only bring higher purchase cost but also incur higher vehicle maintenance cost. Thus, it is quite necessary to further reduce the number of charging vehicles.

1.1 Novelty of this work

The state-of-the-art [14, 15] delivered the minimum number of charging vehicles by the tree decomposition technique, which decomposes a large spanning tree into multiple smaller subtrees and one charging vehicle replenishes the sensors contained in one subtree. However, this technique only ensures that each vehicle consumes a fraction of its battery capacity in its charging tour, the vehicle may still have a significant amount of residual energy after it finishes its charging tour and returns to the base station. Then, the existing algorithms still schedule a number of charging vehicles to replenish sensors.

Unlike the existing studies, we exploit the combinatorial structure of the charging vehicles minimization deployment problem, and propose two new techniques: graph transformation technique (see Sect. 3.1) and circle decomposition technique (see Sect. 3.3). Based on the two novel techniques, we devise an improved approximation algorithm for the problem. Specifically, the first technique transforms a both node-weighted and edge-weighted graph G into another only edge-weighted graph G', such that the optimal values for the problem in G and G' are equal. Then, it is easier to solve the problem in the auxiliary graph G' as it is only edge-weighted. On the other hand, the second technique allows one charging vehicle to replenish as many sensors as possible in its charging tour, without having a large amount of residual energy after finishing the charging tour. Therefore, the proposed algorithm in this paper dispatches less number of vehicles to charge sensors than that by the state-of-the-art.

We also show that the approximation ratio of the proposed algorithm is at least 1.5 smaller than the ratio of the state-of-the-art [15] (see Theorem 1 in Sect. 4.2), which are $\frac{1.5}{1-\frac{A}{IE}}+1$ and $\frac{4}{1-\frac{A}{IE}}$, respectively, where IE is the energy capacity of a charging vehicle and A is the maximum amount of consumed energy for charging a sensor by the vehicle.

1.2 Contributions

The main contributions of this paper are highlighted as follows.

- In order to further minimize the purchase cost of charging vehicles, we propose a novel approximation algorithm to minimize the number of deployed charging vehicles, and the approximation ratio of the proposed algorithm is at least 1.5 smaller than the ratio of the state-of-the-art [15].
- Extensive experimental results demonstrate that the number of scheduled charging vehicles by the proposed approximation algorithm is at least 10% less than the state-of-the-art, which is closer to the optimal value. Also, the total travel energy consumption by the proposed algorithm is smaller than that by the existing algorithms.

The rest of this paper is organized as follows. Section 2 introduces the network model, charging model and defines the problem. Section 3 proposes a novel approximation algorithm for the charging vehicles minimization deployment problem. Section 4 analyzes the approximation ratio of the proposed algorithm. Section 5 evaluates the performance of the proposed algorithm by simulation experiments. Section 6 reviews the related work, and Sect. 7 concludes this paper.

2 Preliminaries

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

2.1 Network model

Consider a large-scale WSN for environmental monitoring or event monitoring, where n_s sensors and a base station r are randomly deployed in the network. The sensor network can be represented as an undirected graph $G_s = (V_s \cup \{r\}, E_s)$, where $V_s \cup \{r\}$ is the set of the n_s sensors and the base station r, and there is an edge (u, v) in E_s for any two nodes u and v in V_s. Denote by $d_{u,v}$ and $d_{u,r}$ the Euclidean distances between two sensors u and v, and a sensor u and the base station r, respectively.

Denote by B_v the battery capacity of each sensor v in G_s. Sensor v consumes its battery energy when it monitors and uploads data. Let the energy consumption rate of sensor v be ρ_v [15].

2.2 Charging model

Denote by $RE_v(t)$ the amount of residual battery of each sensor v at time t. Then, the residual lifetime $L_v(t)$ of sensor v at time t is $L_v(t) = \frac{RE_v(t)}{\rho_v}$. Every sensor v sends a charging request to the base station r when its residual lifetime $L_v(t)$ at some time t falls below a given time threshold L_c, e.g., 2 hours. Such a sensor v is referred to as a lifetime-critical sensor. Considering that there may be multiple sensors whose residual lifetimes are short, we define a lifetime-critical set V of sensors as $V = \{v \mid v \in V_s, L_v \leq \alpha L_c\}$, where α is a constant with $\alpha \geq 1$.

To prevent sensors from running out of their energy, we dispatch charging vehicles to replenish lifetime-critical sensors. Assume that one charging vehicle can replenish energy to a sensor at a rate of μ when it moves in the vicinity of the sensor. The vehicle travels at a speed of s and consumes η amount of its energy per unit length when it travels.

Denote by $G = (V \cup \{r\}, E, h : V \rightarrow R^+, w : E \rightarrow R^+)$ the network induced by set $V \cup \{r\}$, where V is the set of lifetime-critical sensors, E be the set of edges between any two nodes in $V \cup \{r\}$. For any two sensors u and v in V, $w(u, v)$ represents the travel energy consumption of one vehicle for traveling from sensor u to sensor v, that is, $w(u, v) = \eta \cdot d_{u,v}$, where $d_{u,v}$ is the Euclidean distance between sensors u and v and η is the traveling energy consumption of the vehicle per unit length. Similarly, $w(u, r)$ represents the travel energy consumption of one vehicle when it travels from sensor u to the base station r, i.e., $w(u, r) = \eta \cdot d_{u,r}$.

Notice that there may be a number of lifetime-critical sensors in the WSN. Since the battery capacity of every charging vehicle usually is limited, one charging vehicle may not have sufficient energy to charge all lifetime-critical sensors to their full energy capacities. Multiple charging vehicles thus may be needed to replenish them collaboratively.

Denote by IE the battery capacity of one charging vehicle. To ensure that one fully charged vehicle is able to replenish at least one sensor, assume that the battery capacity IE is not very small, that is,

$$IE \geq \max_{v \in V}\{2w(v, r) + h(v)\}, \tag{1}$$

where $2w(v, r)$ is the travel energy consumption of one vehicle when it moves from the base station r to the location of sensor v and returns from v to r, $h(v)(= B_v - RE_v)$ is the amount of energy for the vehicle charging sensor v.

Assume that P charging vehicles are needed to charge the n lifetime-critical sensors $v_1, v_2, \ldots v_n$ collaboratively, where P is to be determined by a charging scheduling algorithm with $P \geq 1$. Let the charging tours of these P charging vehicles be $C_1, C_2, \ldots C_P$, respectively, and the charging tour C_i of the ith charging vehicle is $C = r \rightarrow v_{i,1} \rightarrow v_{i,2} \rightarrow v_{i,3} \cdots \rightarrow v_{i,n_i} \rightarrow r$, where there are n_i sensors in tour C_i, $v_{i,j} \in V, 1 \leq i \leq P$, and $1 \leq j \leq n_i$.

Figure 1 illustrates that $P = 2$ charging vehicles are dispatched to replenish lifetime-critical sensors.

The total energy consumption $w(C_i)$ of one charging vehicle in tour C_i is

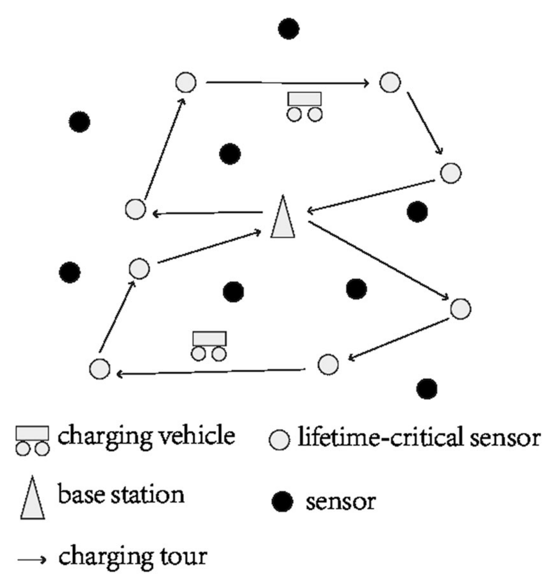

Fig. 1 An example of dispatching $P = 2$ vehicles to replenish lifetime-critical sensors

$$w(C_i) = \sum_{e \in E(C_i)} w(e) + \sum_{v \in V(C_i)} h(v), \tag{2}$$

where $\sum_{e \in E(C_i)} w(e)$ is the total travel energy consumption of the vehicle in tour C_i, and $\sum_{v \in V(C_i)} h(v)$ is the total charging energy consumption that the vehicle consumes for charging sensors in C_i.

Since the battery capacity IE of the vehicle is limited, the total amount of consumed energy of the vehicle for traveling and charging sensors should be no greater than the vehicle energy capacity IE, that is,

$$w(C_i) \le IE. \tag{3}$$

2.3 Problem definition

Given a set V of lifetime-critical sensors in a large-scale WSN at some time and the battery capacity IE of one charging vehicle, the *minimum vehicle deployment problem* is to find the minimum number P of charging tours for vehicles to fully charge sensors in V, subject to that the energy consumption of each vehicle in its charging tour is no greater than the battery capacity IE, that is,

$$\min(P), \tag{4}$$

subject to

$$w(C_i) \le IE, \quad 1 \le i \le P, \tag{5}$$

$$V \subseteq \cup_{i=1}^{P} V(C_i). \tag{6}$$

3 Approximation algorithm for minimizing the number of deployed charging vehicles

In this section, we present a novel approximation algorithm to minimize the number of deployed charging vehicles. Given a sensor network $G = (V \cup \{r\}, E, h : V \rightarrow R^+, w : E \rightarrow R^+)$, and the battery capacity IE of each charging vehicle, the basic idea of the proposed approximation algorithm is described as follows.

We first transform the original edge-weighted, node-weighted graph $G = (V \cup \{r\}, E, h : V \rightarrow R^+, w : E \rightarrow R^+)$ into another only edge-weighted auxiliary graph $G' = (V \cup \{r\}, E, w' : E \rightarrow R^+)$.

We then obtain an approximate shortest charging tour C visiting all nodes in graph G' by applying an existing TSP approximation algorithm, without considering the battery capacity IE of each vehicle.

We finally decompose the long charging tour C into several, say P, shorter charging tours $C_1, C_2, \ldots C_P$, such that the energy consumption in each tour C_i is no more than IE. Then, P charging vehicles are scheduled to replenish the lifetime-critical sensors in G along the P delivered charging tours.

We elaborate the approximation algorithm as follows.

3.1 Step 1: transform the original network *G*

Recall that in the original graph $G = (V \cup \{r\}, E, h : V \rightarrow R^+, w : E \rightarrow R^+)$, $h(v)$ is the amount of energy needed for one charging vehicle fully charging sensor v. Specially, $h(r) = 0$ for the base station r. $w(u, v)$ is the travel energy consumption of one vehicle for traveling from sensor u to sensor v.

We transform the edge-weighted and node-weighted graph G into another equivalent only edge-weighted auxiliary graph $G' = (V \cup \{r\}, E, w' : E \rightarrow R^+)$, where

$$w'(u, v) = w(u, v) + \frac{h(u) + h(v)}{2}, \tag{7}$$

for any two nodes u and v in $V \cup \{r\}$. Especially, the weight $w'(u, r)$ of each edge (u, r) between a sensor u in V to the base station r is

$$w'(u, r) = w(u, r) + \frac{h(u) + h(r)}{2} = w(u, r) + \frac{h(u)}{2}, \quad as\ h(r) = 0. \tag{8}$$

The rationale behind the graph transformation is that we will later show that an optimal solution to the minimum vehicle deployment problem in graph G' is also an optimal solution to the problem in the original graph G (see Lemma 1 in Sect. 4.1). It can be seen that it is easier to solve the problem in the auxiliary graph G', since the graph G is both edge-weighted and node-weighted, while graph G' is only edge-weighted.

3.2 Step 2: obtain an approximate shortest charging tour *C* in *G′*

It can be seen that the auxiliary graph $G' = (V \cup \{r\}, E, w' : E \rightarrow R^+)$ is a complete metric graph, where the edge weights in the graph satisfy the triangle inequality. We find an approximate shortest charging tour C for the TSP problem in graph G' by applying the Christofides approximation algorithm. Following [4], the length of tour C is at most 1.5 times the length of a shortest closed tour visiting nodes in G'.

Assume that the approximate shortest tour C of visiting lifetime-critical sensors in set V obtained by the Christofides algorithm is $C = r \rightarrow v_1 \rightarrow v_2 \rightarrow v_3 \cdots \rightarrow v_n \rightarrow r$, where $v_i \in V$. Figure 2 shows an example of a charging tour C obtained by the Christofides approximation algorithm, where there are $n = 8$ lifetime-critical sensors.

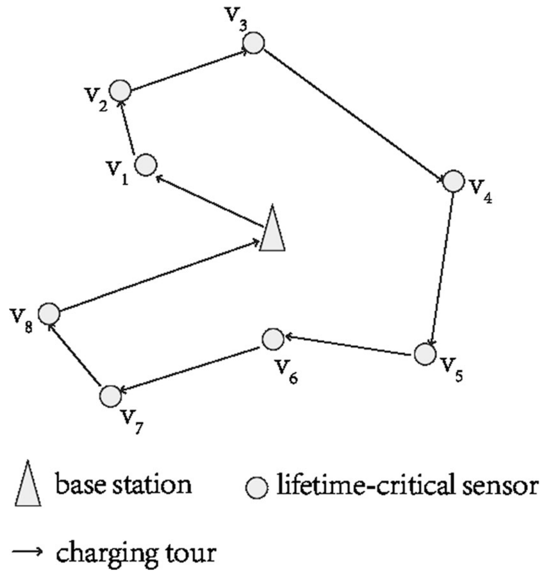

Fig. 2 An approximate shortest charging tour C of the TSP problem

3.3 Step 3: decompose tour *C* into shorter tours

Having the approximate shortest tour $C = r \rightarrow v_1 \rightarrow v_2 \rightarrow v_3 \cdots \rightarrow v_n \rightarrow r$, notice that the total amount of consumed energy $w(C)$ by one charging vehicle in tour C may exceed the battery capacity IE of the vehicle.

To ensure that the amount of consumed energy by one vehicle in its tour does not exceed IE, we decompose the long charging tour C into several, say P, shorter charging tours $C_1, C_2, \ldots, C_P$, with each tour C_i starting and ending at the base station r.

The charging tour C_1 of the first vehicle is

$$C_1 : r \rightarrow v_1 \rightarrow v_2 \cdots \rightarrow v_i \rightarrow r, \tag{9}$$

where the total energy consumption $w'(C_1)$ of one vehicle for replenishing the sensors $v_1, v_2, \ldots, v_i$ is no more than IE, that is

$$w'(C_1) \leq IE, \tag{10}$$

while the total energy consumption of the vehicle for replenishing sensors $v_1, v_2, \ldots, v_i, v_{i+1}$ is strictly larger than IE, i.e.,

$$w'(r \rightarrow v_1 \rightarrow v_2 \cdots \rightarrow v_i \rightarrow v_{i+1} \rightarrow r) > IE. \tag{11}$$

Generally, assume that we have found the charging tours $C_1, C_2, \ldots, C_k$ for the first k charging vehicles, and the first i sensors $v_1, v_2, \ldots, v_i$ have been assigned to be replenished by these k charging vehicles, then the charging tour C_{k+1} for the $(k+1)$th charging vehicle is

$$C_{k+1} : r \rightarrow v_{i+1} \rightarrow v_{i+2} \cdots \rightarrow v_j \rightarrow r, \tag{12}$$

where $w'(C_{k+1}) \leq IE, w'(C'_{k+1}) > IE$, and

$$C'_{k+1} : r \rightarrow v_{i+1} \rightarrow v_{i+2} \cdots \rightarrow v_j \rightarrow v_{j+1} \rightarrow r. \tag{13}$$

The tour decomposition procedure continues until all lifetime-critical sensors in V are assigned to charging vehicles. The detail algorithm for the minimum vehicle deployment problem is presented in Algorithm 1

Figure 3 shows that $P = 3$ charging tours are obtained by decomposing the tour C in Fig. 2.

4 Algorithm analysis

In this section, we will analyze the approximation ratio and the time complexity of the proposed approximation algorithm.

4.1 The equivalence of graphs *G* and *G'*

Lemma 1 *Given a graph* $G = (V \cup \{r\}, E, h : V \rightarrow R^+, w : E \rightarrow R^+)$ *and a battery capacity* IE *of each charging vehicle, transform the graph* G *into another graph* $G' = (V \cup \{r\}, E, w' : E \rightarrow R^+)$ *with* $w'(u,v) = w(u,v) + \frac{h(u)+h(v)}{2}$ *for any two nodes* u *and* v *in* $V \cup \{r\}$. *Then, the optimal number of the minimum vehicle deployment problem in graph* G' *is equal to the optimal one of the problem in the origin graph* G.

Proof Assume that the optimal solution to the minimum vehicle deployment problem in G consists of P_1 charging vehicles, and their charging tours are $C_1, C_2, \ldots, C_{P_1}$, respectively, where P_1 is a positive integer. Similarly, assume that the optimal solution to the problem in G'

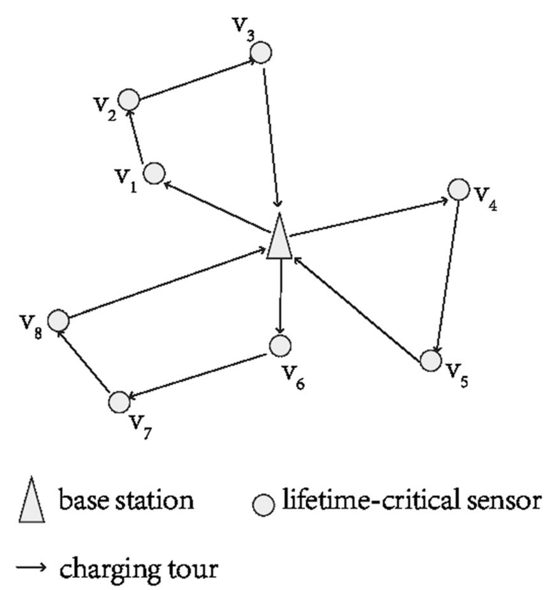

Fig. 3 $P = 3$ charging tours are obtained by decomposing the tour C in Fig. 2

consists of P_2 charging vehicles and their charging tours are $C'_1, C'_2, \ldots, C'_{P_2}$, respectively.

In order to show that the optimal values of the minimum vehicle deployment problem in G and G' are equal, in the following, we prove that $P_1 \geq P_2$ and $P_2 \geq P_1$.

We first prove $P_1 \geq P_2$. To this end, we only need to show that the P_1 charging tours in G form a feasible solution to the minimum vehicle deployment problem in G'. For each charging tour C_i of the P_1 charging tours, let $C_i = r \rightarrow v_{i,1} \rightarrow v_{i,2} \rightarrow v_{i,3} \cdots \rightarrow v_{i,n_i} \rightarrow r$, where $v_{i,j} \in V$, and $1 \leq i \leq P_1$. The total energy consumption $w(C_i)$ of C_i is

$$w(C_i) = \sum_{e \in E(C_i)} w(e) + \sum_{v \in V(C_i)} h(v). \tag{14}$$

Since the P_1 charging tours form a feasible solution to the problem in G, we have $w(C_i) \leq IE$. Consider the total energy consumption $w'(C_i)$ of tour C_i in graph G'

$$\begin{aligned} w'(C_i) &= w'(r, v_{i,1}) + \sum_{j=1}^{n_i-1} w'(v_{i,j}, v_{i,j+1}) + w'(v_{i,n_i}, r) \\ &= w(r, v_{i,1}) + \frac{h(v_{i,1})}{2} + \sum_{j=1}^{n_i-1} \Big(w(v_{i,j}, v_{i,j+1}) \\ &\quad + \frac{h(v_{i,j}) + h(v_{i,j+1})}{2} \Big) \\ &\quad + w(v_{i,n_i}, r) + \frac{h(v_{i,n_i})}{2} \\ &= \sum_{e \in E(C_i)} w(e) + \sum_{v_{i,j} \in V(C_i)} h(v_{i,j}), \\ &\quad \text{by Eq. (7) and Eq. (8)} \\ &= w(C_i) \ \leq \ IE. \end{aligned} \tag{15}$$

Therefore, an optimal solution with P_1 charging tours $C_1, C_2, \ldots, C_{P_1}$ for the minimum vehicle deployment

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Algorithm 1 `Appro`

Require: Graph $G = (V \cup \{r\}, E, h : V \rightarrow R^{+}, w : E \rightarrow^{+})$, the battery capacity IE of each charging vehicle
Ensure: The minimum number of charging vehicles P, and their charging tours $C_1, C_2, \ldots, C_P$

Transform graph G into another edge-weighted auxiliary graph $G' = (V \cup \{r\}, E, w' : E \rightarrow R^{+})$, where $w'(u,v) = w(u,v) + \frac{h(u)+h(v)}{2}$ for any two nodes u and v in $V \cup \{r\}$;
Find an approximate shortest charging tour $C : r \rightarrow v_1 \rightarrow v_2 \cdots \rightarrow v_n \rightarrow r$ in graph G' by applying the Christofides algorithm for the TSP problem;
$P \leftarrow 0, i \leftarrow 1, j \leftarrow 1$, where i and j are indexes of the first and last lifetime-critical sensors in the next tour, respectively;
while $j \leq n$ **do**
    $C_P : r \rightarrow v_i \rightarrow v_{i+1} \cdots \rightarrow v_j \rightarrow r$;
    if $w'(C_P) \leq IE$ **then**
        if $j == n$ **then**
            /* the last charging tour */
            $C_P : r \rightarrow v_i \rightarrow v_{i+1} \cdots \rightarrow v_n \rightarrow r$;
        else
            /* Contain one more sensor */
            $j \leftarrow j + 1$;
        end if
    else
        $j \leftarrow j - 1$;
        $C_P : r \rightarrow v_i \rightarrow v_{i+1} \cdots \rightarrow v_j \rightarrow r$;
        $P \leftarrow P + 1$;
        /* Initialize the next charging tour */
        $C_P \leftarrow r$;
        $j \leftarrow j + 1$;
        $i \leftarrow j$;
    end if
end while
return P, charging tours $C_1, C_2, \ldots, C_P$;

problem in graph G is a feasible solution to the problem in auxiliary graph G'. Then $P_1 \geq P_2$.

The proof of $P_2 \geq P_1$ can be shown similarly, omitted. Therefore, $P_1 = P_2$, that is, the optimal value of the minimum vehicle deployment problem in graph G' is equal to the optimal value of the problem in the origin G. □

4.2 The analysis of the approximation ratio of algorithm Appro

Theorem 1 *Given a graph* $G = (V \cup \{r\}, E, h : V \to R^+, w : E \to R^+)$ *and a battery capacity* IE *of each charging vehicle, assume* $A = \max_{v \in V}\{2w(v, r) + h(v)\}$ *with* $A \leq IE$. *Then, the approximation ratio* $\frac{P}{P_*}$ *of algorithm* Appro, *i.e., the number* P *of deployed vehicles by algorithm* Appro *to that of the optimal value* P_*, *is*

$$\frac{P}{P_*} \leq \frac{1.5}{1 - \frac{A}{IE}} + 1, \tag{16}$$

which is at least 1.5 smaller than that by the state-of-the-art [15], *where the approximation ratio in* [15] *is* $\frac{4}{1-\frac{A}{IE}}$. *Also, the time complexity of algorithm* Appro *is* $O(n^3)$, *where* $n = |V|$.

Proof Assume that an optimal solution to the minimum vehicle deployment problem consists of P_* charging tours $C_1^*, C_2^*, \ldots, C_{P_*}^*$. Let C^* be an shortest charging tour of the TSP problem for the lifetime-critical sensor set V.

We first obtain a lower bound on P_*. It can be seen that a closed tour C visiting nodes in $V \cup \{r\}$ can be derived from the P_* tours $C_1^*, C_2^*, \ldots, C_{P_*}^*$, as the base station r is contained in each of the P_* tours, then,

$$w(C^*) \leq w(C) \leq \sum_{i=1}^{P_*} w(C_i^*) \leq P_* \cdot IE. \tag{17}$$

Therefore, $P_* \geq \frac{w(C^*)}{IE}$. Since P_* is a positive integer, we know

$$P_* \geq \lceil \frac{w(C^*)}{IE} \rceil. \tag{18}$$

In the following, we analyze the number of obtained charging tours by algorithm Appro. It first finds an approximate shortest tour C for visiting nodes in $V \cup \{r\}$, following [4],

$$w(C) \leq 1.5w(C^*). \tag{19}$$

For each obtained tour C_k by the proposed algorithm Appro, let $C_k : r \to v_i \to v_{i+1} \cdots \to v_j \to r$. Following the construction of tour C_k, we have

$$w'(r \to v_i \to v_{i+1} \cdots \to v_j \to r) \leq IE, \tag{20}$$

and

$$w'(r \to v_i \to v_{i+1} \cdots \to v_j \to v_{j+1} \to r) > IE, \tag{21}$$

see Fig. 4.

On the other hand, recall that $A = \max_{v \in V}\{2w'(v, r)\}$, then,

$$w'(r, v_i) \leq \frac{A}{2}, \quad w'(v_{j+1}, r) \leq \frac{A}{2} \tag{22}$$

Therefore, the length of path $v_i \to v_{i+1} \cdots \to v_j \to v_{j+1}$ is

$$\begin{aligned} & w'(v_i \to v_{i+1} \cdots \to v_j \to v_{j+1}) \\ & = w'(r \to v_i \to v_{i+1} \cdots \to v_j \to v_{j+1} \to r) \\ & \quad - w'(r \to v_i) - w'(v_{j+1} \to r) \\ & \geq IE - \frac{A}{2} - \frac{A}{2} = IE - A \end{aligned} \tag{23}$$

We thus obtain an upper bound on the number P of obtained tours,

$$P \leq \lceil \frac{w(C)}{IE - A} \rceil \leq \lceil \frac{1.5w(C^*)}{IE - A} \rceil \leq \frac{1.5w(C^*)}{IE - A} + 1. \tag{24}$$

The approximation ratio of algorithm Appro is

$$\begin{aligned} \frac{P}{P_*} & \leq \frac{\frac{1.5w(C^*)}{IE-A} + 1}{P_*} \leq \frac{\frac{1.5w(C^*)}{IE-A}}{P_*} + 1, \ \text{as}\ P_* \geq 1 \\ & \leq \frac{\frac{1.5w(C^*)}{IE-A}}{\lceil \frac{w(C^*)}{IE} \rceil} + 1, \quad \text{following Eq. (18), as}\ P_* \geq \lceil \frac{w(C^*)}{IE} \rceil \\ & \leq \frac{\frac{1.5w(C^*)}{IE-A}}{\frac{w(C^*)}{IE}} + 1 = \frac{1.5}{1 - \frac{A}{IE}} + 1. \end{aligned} \tag{25}$$

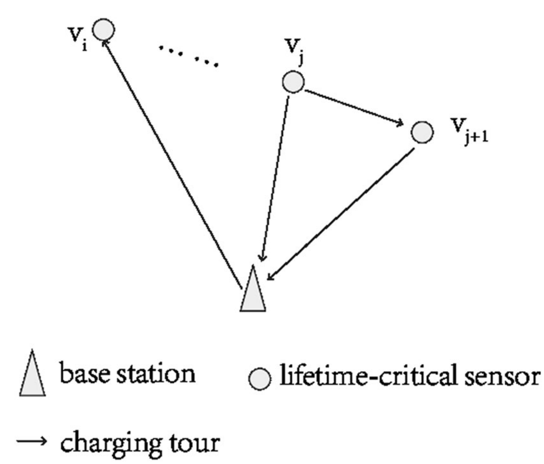

Fig. 4 The procedure of decomposing a long charging tour

On the other hand, the approximation ratio in [15] is $\frac{4}{1-\frac{A}{IE}}$, where $0 \leq \frac{A}{IE} < 1$. It can be seen from Fig. 5 that the value of the approximation ratio for each of the two algorithms increases with the increase of $\frac{A}{IE}$, and the approximation ratio of algorithm `Appro` is smaller than that in [15]. Specially, when $\frac{A}{IE} = 0$, the approximation ratio of algorithm `Appro` is $\frac{1.5}{1-\frac{A}{IE}} + 1 = 2.5$, which is at least 1.5 smaller than the ratio $\frac{4}{1-\frac{A}{IE}} = 4$.

The rest is to analyzed the time complexity of algorithm `Appro`. It takes $O(n^2)$ time to transform graph G into G', where $n = |V|$. Then, it takes $O(n^3)$ to obtain an approximate shortest tour C for visiting sensors in G', by invoking Christofides algorithm [4]. Finally, it takes $O(n)$ time to decompose tour C into shorter tours. Therefore, the time complexity of algorithm `Appro` is $O(n^2) + O(n^3) + O(n) = O(n^3)$. $\square$

5 Performance evaluation

In this section, we evaluate the performance of the proposed algorithm through simulation experiments.

5.1 Simulation environment

Consider a sensor network deployed in a $500\,\text{m} \times 500\,\text{m}$ square area. A base station is located at the center of the area. The network consists of from 100 to 400 sensors, which are randomly deployed in the area. The battery capacity of each sensor is 10.8 kJ [23] and the battery capacity of each charging vehicle is from 1000 to 5000 kJ. The charging energy rate of charging vehicle for replenishing a sensor is $\mu = 5$ Watts [12, 15], the energy consumption rate of the charging vehicle is $\eta = 0.6$ kJ/m when it travels and its traveling speed is $s = 5\,\text{m/s}$. The experimental period T is one year, that is, $T = 365 \times 24 \times 3600\,\text{s}$.

The sensors consume their energy during data sensing, data transmission, and data receiving. We consider two different distributions of sensor energy consumption rates: linear distribution and random distribution [15]. In the linear distribution, the energy consumption rate ρ_i of a sensor v_i is inversely proportional to the distance between the sensor v_i and the base station r. Since the sensors close to the base station need to relay data for other sensors far away from the base station, the sensors nearby the base station consume their energy quicker than the sensors far from the base station. Then, the energy consumption rates of the sensors decrease linearly. Assume that the sensor nearest to the base station has the maximum energy consumption rate $\rho_{\max} = 10\,\text{mJ/s}$ and the sensor furthest from the base station has the minimum energy consumption rate $\rho_{\min} = 1\,\text{mJ/s}$. On the other hand, in the random distribution, the energy consumption rate ρ_i of sensor v_i is a random value between the minimum energy consumption rate $\rho_{\min} = 1\,\text{mJ/s}$ and the maximum energy consumption rate $\rho_{\max} = 10\,\text{mJ/s}$ [14, 15].

To evaluate the performance of the proposed algorithm `Appro`, we compare it with existing algorithms `LB_optimal` [15], `NMV` [15], `minMCP` [5], `AA` [28], `APS` [8], and `rewardMax` [16], which are briefly described as follows. Algorithm `LB_optimal` [15] delivers a lower bound on the optimal value, where `LB_optimal` $= \lceil \frac{WH(T)}{IE} \rceil$ and $WH(T)$ represents the total energy consumption of the minimum spanning tree T in the graph induced by the lifetime-critical sensors in V. Both the algorithms `NMV` [15] and `minMCP` [5] find approximate solutions to the minimum vehicle deployment problem. Algorithm `AA` [28] schedules vehicles to charge sensors, such that the total amount of charged energy to sensors minus the total vehicle traveling energy is maximized, while ensuring that every vehicle does not deplete its energy in its charging tour. Algorithm `APS` [8] finds each tour to charge the maximum number of sensors in increasing order of their residual energy, such that the total energy consumption of the tour is no more than the vehicle energy capacity. Algorithm `rewardMax` [16] delivers a charging tour for each vehicle, so that the sum of the amounts of energy charged to sensors by the vehicle in the tour is maximized, subject to the vehicle energy capacity.

5.2 Algorithm evaluation and performance

We first study the performance of the seven algorithms `Appro`, `LB_optimal`, `NMV`, `minMCP`, `AA`, `APS`, and `rewardMax`, by increasing the network size from 100 to 400. Figure 6(a) shows that the number of charging vehicles

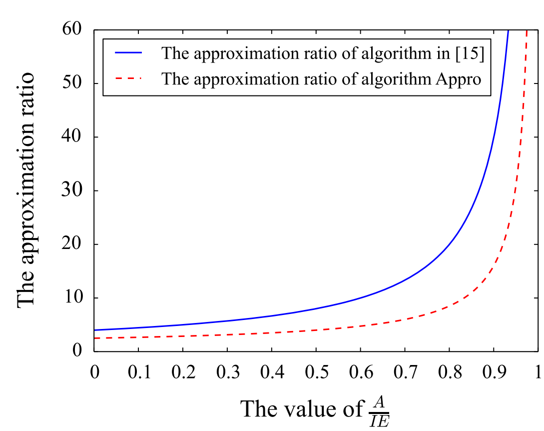

Fig. 5 The approximation ratios of algorithm `Appro` and the algorithm in [15]

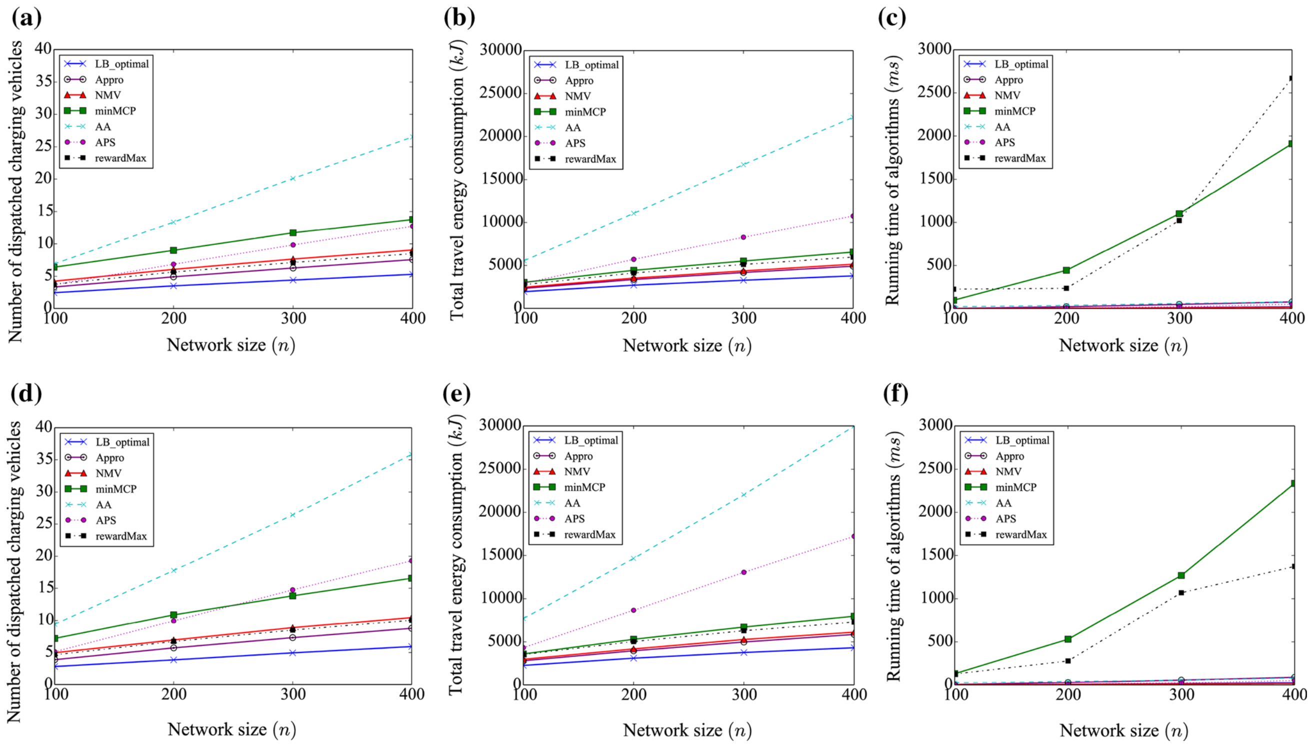

Fig. 6 Performance of algorithms `LB_optimal`, `Appro`, `minMCP`, `minMCP`, `AA`, `APS`, and `rewardMax` by increasing the network size n from 100 to 400, when $IE = 1,000\,\text{kJ}, \rho_{\min} = 1\,\text{mJ}$, and $\rho_{\max} = 10\,\text{mJ}$. **a** Number of dispatched charging vehicles with the linear distribution. **b** Total travel energy consumption with the linear distribution. **c** Running time with the linear distribution. **d** Number of dispatched charging vehicles with the random distribution. **e** Total travel energy consumption with the random distribution. **f** Running time with the random distribution

dispatched by algorithm `Appro` is the smallest one among the algorithms except `LB_optimal`, and is at least 11% smaller than that by algorithm `rewardMax`. For example, the numbers of scheduled vehicles by algorithms `Appro`, `NMV`, `minMCP`, `AA`, `APS`, and `rewardMax` are 7.5, 16.5, 10.5, 26.5, 12.8, and 8.5, respectively, when the network size $n = 400$. On the other hand, compared to the lower bound `LB_optimal` on the optimal value, the algorithm `Appro` delivers only 0.8 more charging vehicles than algorithm `LB_optimal` when the network size $n = 100$, and dispatches 2.29 more vehicles when the network size $n = 400$. Then, Fig. 6(a) validates the claim that the approximation ratio of algorithm `Appro` is smaller than that by the state-of-the-art algorithm `NMV`, see Theorem 1.

Figure 6(b) plots the total travel energy consumptions of charging vehicles by the seven different algorithms. It can be seen that the total energy consumption by algorithm `Appro` is smaller than those by the five algorithms `NMV`, `minMCP`, `AA`, `APS`, and `rewardMax`. Specially, on average, the total travel energy consumption by algorithm `Appro` is at least 5% less than that by each of the five algorithms.

Figure 6(c) demonstrates the running times of different algorithms, from which it can be seen that the running times by the five algorithms `Appro`, `LB_optimal`, `NMV`, `AA`, and `APS` are no longer than 0.1 second, and are much shorter than that by both algorithms `minMCP` and `rewardMax`.

On the other hand, Fig. 6(d–f) demonstrate the performance of the seven algorithms when the energy consumption rates follow the random distribution. It can be seen that the number of dispatched vehicles by algorithm `Appro` is 17, 45, 60, 25, and 13% less than those by algorithms `NMV`, `minMCP`, `AA`, `APS`, and `rewardMax`, respectively, when the network size n increases from $n = 100$ to $n = 400$. Also, the total energy consumption by algorithm `Appro` is about at least 8% less than those by the other six algorithms except `LB_optimal`, respectively.

We then investigate the algorithm performance by increasing the battery capacity IE from 1000 to 4000 kJ. Figure 7(a) shows that the number of deployed charging vehicles by each of the seven algorithms decreases with the increase of the vehicle battery capacity IE. Figure 7(a) also shows that the number of vehicles by algorithm `Appro` is about 21% smaller than that by algorithm `NMV` when IE increases from 1000 to 3000 kJ and it is about 12% less than that by algorithm `NMV` when $IE = 4000\,\text{kJ}$. Moreover,

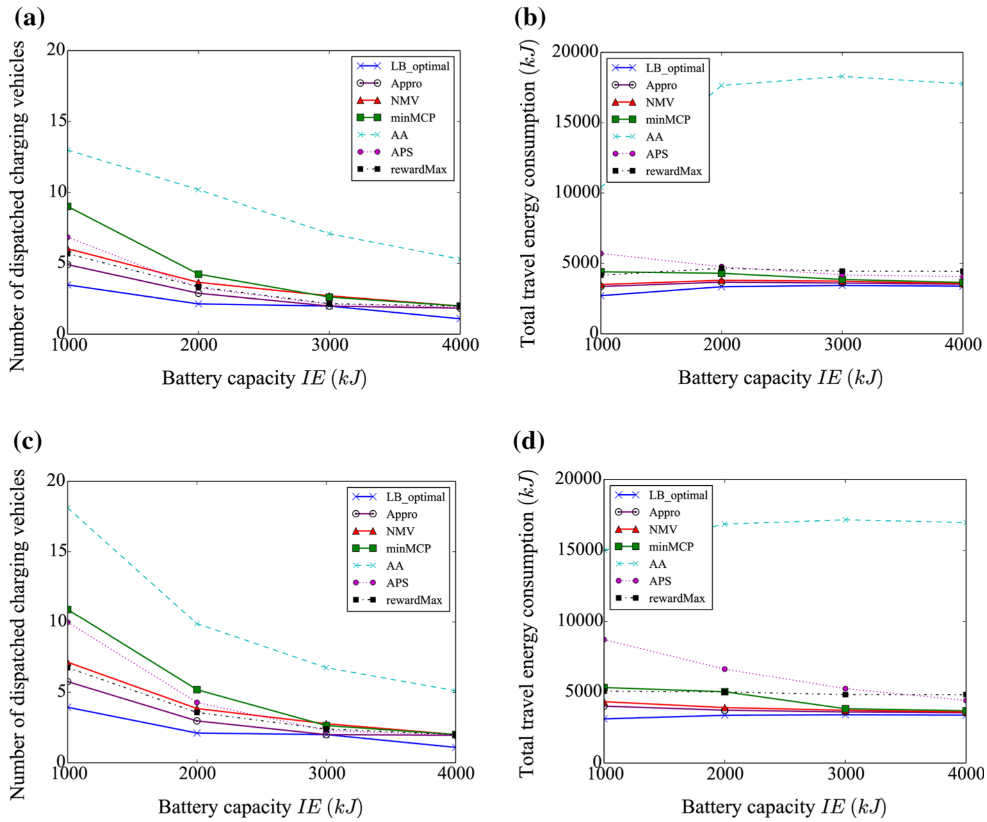

Fig. 7 Performance of algorithms LB_optimal, Appro, minMCP, minMCP, AA, APS, and rewardMax by increasing the battery capacity IE from 1000 kJ to 4000 kJ, when $n = 200$, $\rho_{\min} = 1$ mJ, and $\rho_{\max} = 10\,mJ$. **a** Number of dispatched charging vehicles with the linear distribution. **b** Total travel energy consumption with the linear distribution. **c** Number of dispatched charging vehicles with the random distribution. **d** Total travel energy consumption with the random distribution

the number of vehicles by algorithm Appro is about 47% smaller than that by algorithm minMCP when $IE = 1000\,$kJ. Figure 7(b) shows that the total travel energy consumption by algorithm Appro is less than those by algorithms minMCP and NMV, which is about 8% less than that by algorithm NMV. Figure 7(c, d) plot similar curves when the energy consumption rate follows the random distribution.

We finally evaluate the algorithm performance by increasing the maximum energy consumption rate $\rho_{\max}$ of the sensors from $\rho_{\max} = 1$ mJ to $\rho_{\max} = 10$ mJ while fixing $\rho_{\min}$ at 1 mJ. It can be seen from Fig. 8(a, c) that the number of dispatched vehicles by algorithm Appro is about 20% less than that by algorithm NMV and about 38% more than that by algorithm LB_optimal. Figure 8(b, d) show that the total travel energy consumption by algorithm Appro is about 24% and 7% less than the consumptions by the two algorithms minMCP and NMV.

6 Related work

The scheduling of charging vehicles for sensor networks has drawn a lot of attentions and existing studies can be divided into two categories. In the first category, one charging vehicle is assumed to have sufficient energy to charge all lifetime-critical sensors [8, 16, 24, 33–35]. For example, given a set of energy-critical sensors, Guo et al. [8] found a tour to charge the maximum number of sensors in increasing order of their residual energy, such that the length of the tour is no longer than a threshold L_{tsp}. Liang et al. [16] studied the problem of finding a charging tour for a vehicle, so that the sum of the amounts of energy charged to the sensors in the tour by the vehicle is maximized, subject to the energy capacity of the vehicle. The also proposed a constant approximation algorithm for the problem. However, this assumption is only valid for small-scale WSNs. In large-scale WSNs, some researchers argued that it is necessary to consider the battery capacity of one charging vehicle [5, 10, 15, 28], and schedule multiple charging vehicles to replenish sensor energy.

Given a weighted graph and a tour length constraint D, assume that the edge weights in the graph satisfy the triangle inequality. In order to find the minimum number of closed tours to cover all the nodes in the graph and ensure that the total length of each tour is no longer than D, Nagarajan et al. [18] proposed a double standard approximation algorithm with $(O(\log\frac{1}{\varepsilon}), 1+\varepsilon)$, which means that the length of each tour found by the algorithm does not exceed $(1+\varepsilon)D$ while the number of found tour is no more than $O(\log\frac{1}{\varepsilon})$ times of the optimal value, where ε is a constant with $0 < \varepsilon < 1$. Dai et al. [5] designed an algorithm for the minimum vehicle deployment problem, by utilizing

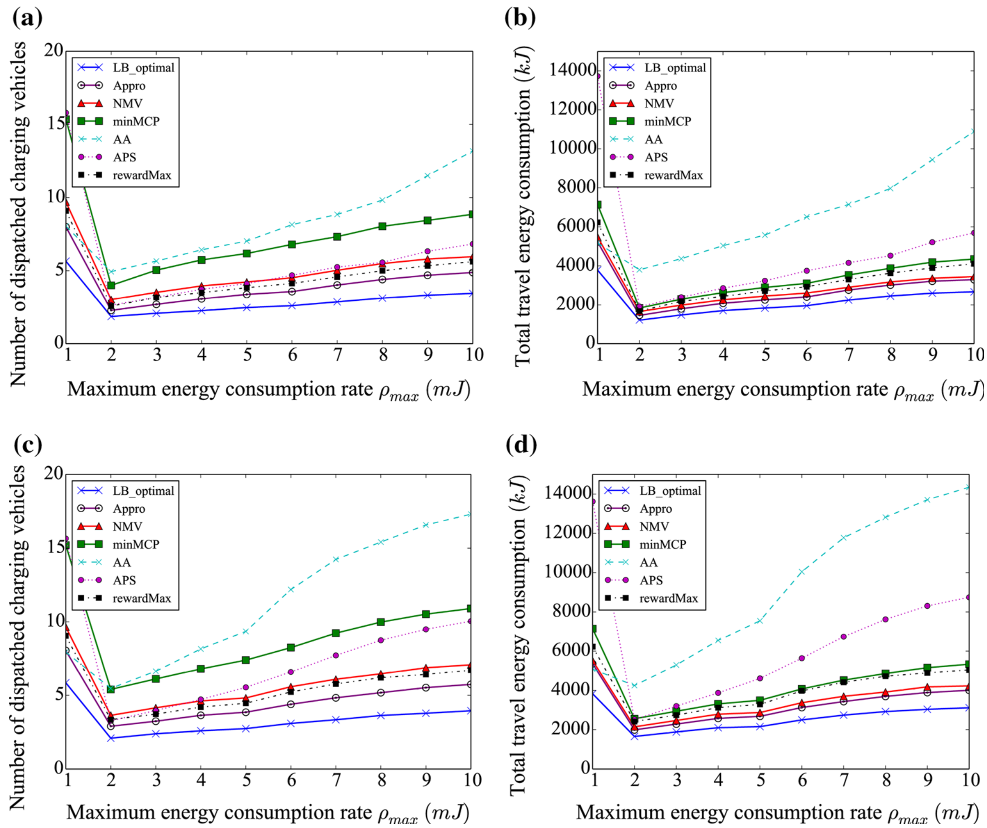

Fig. 8 Performance of algorithms `LB_optimal`, `Appro`, `minMCP`, `minMCP`, `AA`, `APS`, and `rewardMax` by increasing the maximum energy consumption rate $\rho_{\max}$ from 1 to 10 mJ, when $n = 200, IE = 1000\,\mathrm{kJ}$, and $\rho_{\min} = 1$ mJ. **a** Number of dispatched charging vehicles with the linear distribution. **b** Total travel energy consumption with the linear distribution. **c** Number of dispatched charging vehicles with the random distribution. **d** Total travel energy consumption with the random distribution

the algorithm in [18]. However, one disadvantage of [5, 18] is that the energy consumption of a found charging vehicle in its charging tour may exceed the maximum battery capacity of the vehicle with a ratio of ε. Then, the charging vehicle cannot return to the base station to replenish itself. Hu et al. [10] assumed that all sensors in the network have the same energy consumption rate and the charging vehicles replenish the sensors periodically. However, the energy consumption rates of different sensors usually are different, since the sensors near to the base station need to forward data for other sensors far away from the base station. Liang et al. [15] adopted the tree decomposition method and proposed an approximation algorithm to minimize the number of scheduled charging vehicles, by ensuring that the energy consumption of each vehicle in its charging tour does not exceed the battery capacity of the vehicle. In order to minimize the longest charging tour of K charging tours for K charging vehicles, Xu et al. [31, 32] studied the dispatching of K charging vehicles to recharge lifetime-critical sensors and proposed a constant approximation algorithm. He et al. [9] assumed that charging requests of the sensors follows the poisson distribution. They used a Nearest-Job-Next with Preemption (NJNP) discipline for the charging vehicle. However, it does not guarantee that every sensor will be replenished before its energy expiration. Wang et al. [28] first obtained the minimum number K of charging vehicles to maintain the long-term operation of a sensor network, assuming that the data generation rates of different sensors are independent with each other and follow a Poisson distribution. Given a set of lifetime-critical sensors at some time, they then investigated the problem of scheduling the K vehicles to charge sensors, such that the total amount of charged energy to sensors minus the total vehicle traveling energy is maximized, while ensuring that every vehicle does not deplete its energy in its charging tour.

Moreover, note that there are recent pioneering studies for scheduling vehicles in urban transportation networks. For example, Cao et al. [2] considered the routing problem in urban vehicle networks and proposed efficient routing algorithms. Zhu et al. [36] studied the problem of allocating energy-critical electric vehicles to nearby charging stations, such that the total time spent by each electric vehicle (EV) for queuing and charging itself is minimized. They also advocated a new public vehicle system to solve traffic congestion and pollution for smart cities [37–39]. Specifically, they investigated the problem of minimizing the total vehicle travel distance, while ensuring that passenger requests are served [37], and considered the computational efficiency in online ride-sharing for reducing the travel distance with QoS guarantee [38]. Furthermore, they extended the work by jointly considering transportation demands with service guarantee and the cost-effective vehicle charging [39]. However, it is worthy to mention that the proposed algorithms in the aforementioned studies cannot be applied to the problem in this paper.

7 Conclusion and future work

In order to minimize the cost of maintaining the perpetual operations of WSNs, in this paper we studied the problem of scheduling the minimum number of charging vehicles to charge lifetime-critical sensors. By exploring the combinatorial property of the problem, we proposed a novel approximation algorithm. We not only proved that the approximation ratio of the algorithm is better than that by the state-of-the-art, but also showed that the number of dispatched charging vehicles is at least 10% less than those by the existing algorithms by extensive simulation experiments. In addition, we showed that the total energy consumption of the charging vehicles by the proposed algorithm is smaller than those by the existing algorithms.

In the future, we will further optimize the approximation algorithm to reduce the number of deployed charging vehicles, so as to reduce the cost for charging sensors as much as possible.

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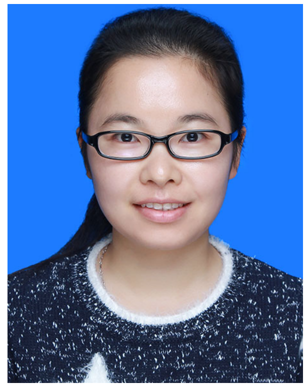

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