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Energy Constrained Monitoring-Driven Mobile Charging in Wireless Rechargeable Sensor Networks

Zhiqiang Wang[1], Jun Fu[1], Lei Han[2, *]

[1]Beijing C&W ELECTRONICS (GROUP) Limited Company, Beijing, China
[2]School of Computer Science, Nanjing University of Posts and Telecommunications, Nanjing, China

Email address:
wangzhqbj@gmail.com (Zhiqiang Wang), abc-2535@163.com (Jun Fu), hanlei@njupt.edu.cn (Lei Han)
[*]Corresponding author

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Abstract: With the development of Wireless Power Transfer (WPT) technology, Wireless Rechargeable Sensor Networks (WRSNs) have become the focus of researchers. Although many researchers have studied the problems of mobile charging in WRSN, they often neglect the differences between sensors. In the actual situation, the utility of different sensors may be different even when they receive the same energy. In this paper, we consider that there are many initial subareas need to be monitored. The different initial subareas have different monitoring utility per unit area, and each sensor covers a circular area. Thus, the entire region can be further divided into more final subareas. The total monitoring utility is the sum of the monitoring utility of the final subareas monitored by sensors. This is the first work to study monitoring-driven mobile charging problem, which considers the differences between different subareas. We model the monitoring-driven mobile charging system and formalize the Monitoring-driven Mobile Charging (MMC) problem. Our goal is to find a traveling loop that does not exceed the energy capacity of the mobile charger, to maximize total monitoring utility. Through area discretization and auxiliary graph construction, we simplify the problem and provide a greedy algorithm to solve it. The simulation results show that the proposed algorithm can outperform comparison algorithms by at most 189.11% in terms of monitoring utility.

Keywords: Wireless Charging, Mobile Charging, Monitoring-Driven, Area Discretization, Auxiliary Graph Construction

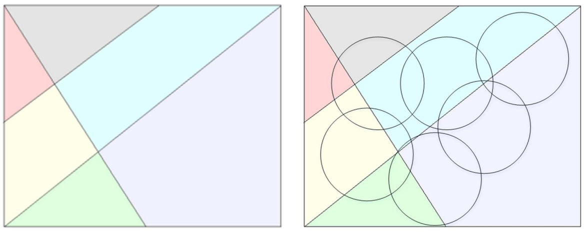
1. Introduction

Wireless Sensor Network (WSN) is a network system composed of a large number of wireless sensors those have sensing, computing and communication capabilities. Due to the advantages of flexible deployment, wide coverage, high real-time performance, and low cost, WSN has been widely used in many fields, such as military surveillance, disaster prediction, biomedical health monitoring, and hazardous environment exploration [1]. In a large number of researches related to WSN, the energy replenishment has always been the focus of industry and academia. Because of the advantage of providing continuous and reliable power supply, Wireless Power Transfer (WPT) technology has been widely used in WSN [2, 3]. With the further development of WPT technology, Wireless Rechargeable Sensor Networks (WRSNs) have been extensively developed in real life, such as unmanned aerial vehicles (UAVs) [4, 5], rechargeable robots [6, 7], and RFID systems [8].

There have also been many researches based on WRSNs [9-13]. From the types of chargers, they can be divided into static charging [9, 10] and mobile charging [11-13]. In the case of a limited number of chargers in a large-scale network, mobile charging is a more suitable choice. In this paper, we study the mobile charging scenario.

However, the above researches in mobile charging only consider how to charge the sensors, but do not involve the impact of the specific monitored objective on the monitoring utility. In previous researches, only the energy is used to judge the utility. In such a case, every sensor is roughly regarded as equivalent. However, in the actual situation, the utility of different sensors may be different even when they receive the same energy. Therefore, in order to be more practical, we need to consider the differences of sensors.

In this paper, as shown in Figure 1(a), we assume that there are many initial subareas need to be monitored. The different initial subareas have different monitoring utility per unit area, and each sensor covers a circular area. As shown in Figure 1(b), the entire region can be further divided into more final subareas. The total monitoring utility is the sum of the monitoring utility of the final subareas monitored by sensors. In particular, even if a final subarea is monitored repeatedly, the monitoring utility can only be obtained once.



(a) (b)

Figure 1. *Illustration of subareas. (a) Initial subareas. (b) Final subareas.*

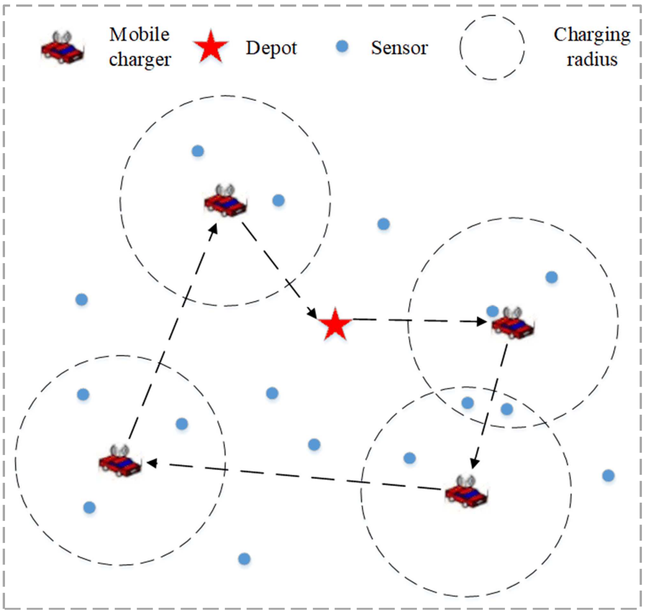


Figure 2. *System model.*

This paper aims to study the Monitoring-driven Mobile Charging (MMC) problem. As shown in Figure 2, the mobile charger moves from the depot and can charge the sensors at any location in the region. The charging mode in this paper is full charging, which means that when the mobile charger charges at a location, the energy demand of all sensors within the charging radius should be fully satisfied. Our goal is to find a traveling loop that does not exceed the energy capacity of the mobile charger, to maximize total monitoring utility.

The MMC problem is very challenging. First, the number of possible charging locations is infinite. Second, when multiple sensors repeatedly monitor the same final subareas, the total monitoring utility is not the direct accumulation of the monitoring utility of these sensors. Therefore, the interaction between sensors cannot be ignored. Third, MMC problem is more difficult than the budgeted maximum coverage problem, which is a well-known NP-hard problem [14].

The main contributions of this paper are outlined as follows:

1. To the best of our knowledge, this is the first work to study monitoring-driven mobile charging problem, which considers the differences between different subareas.
2. We model the monitoring-driven mobile charging system and formalize the Monitoring-driven Mobile Charging (MMC) problem. Through area discretization and auxiliary graph construction, we simplify the problem and provide a greedy algorithm to solve it.
3. Through extensive simulations and experiments, we demonstrate that the proposed algorithm can improve monitoring utility by at most 189.11%, compared with the benchmark algorithms.

The rest of the paper is organized as follows. *Section II* presents the brief review on the previous works. *Section III* presents system model and formulates MMC problem. *Section IV* presents the details of our solution. Experimental results are shown in *Section V*. We conclude this paper in *Section VI*.

2. Related Work

There are many researches on charging scheduling for WRSNs. We briefly review the works on mobile charging, utility driven charging scheduling, utility-charging joint scheduling, and budget constrained charging scheduling, which are closely related to this study.

Mobile charging. Xu et al. [15] used multiple mobile chargers for charging sensors to speed up sensor charging significantly, thereby reducing their expiration durations and improving the monitoring quality of WRSNs. They formulated a novel delay minimization problem and devised the very first approximation algorithm with a provable approximation ratio for the problem. However, in their paper, utility was not the optimization objective. Ma et al. [16] utilized a mobile charger to charge multiple sensors simultaneously under the energy capacity constraint of the mobile charger to maximize the charging utility. Srinivas et al. [17] proposed a mobile charger utility maximization approach through preemptive scheduling (MCUMPS) for WRSNs. In their approach, they mainly focused on the visiting order of the mobile charger by segregating the sensors into two categories called critical nodes and emerging nodes. Critical nodes (CNs) had a higher priority than emerging nodes because the dying of CNs isolated some part of the network. However, whether in [16] or [17], the difference in monitoring utility of different sensors was not involved. Priyadarshani et al. S. Priyadarshani et al. [18] proposed a multi-node charging vehicle scheduling scheme using partial charging model to minimize the travel energy. However, in our paper, the charging model is full charging.

Utility-driven charging scheduling. Sun et al. [19] focused on the charging exclusivity issue in stochastic events monitoring while improving network performance. In specific, they paid close attention to the trade-off between charging and task sensing, and formulated a combinatorial optimization problem with routing constraints. They introduced novel discretization techniques and investigated the routing problem to reformulate the original problem into a submodular function maximization problem. Ren et al. [20] proposed an Intelligent Charging scheme Maximizing the Quality Utility (ICMQU) to design the charging path for the mobile charger. They aimed to maximize the sensing utility for both single mobile charger and multiple mobile chargers with heterogeneous sensors, which had different sensing quality. Compared with the previous studies, they considered not only the utility of the data collected from the environment, but also the impact of sensors with different quality. However, the above works did not consider the differences between subareas.

Utility-charging joint scheduling. Wu et al. [21, 22] respected the energy requirement diversity among sensors to investigate the collaborated and tasks-driven mobile charging problem. Their goal was to maximize the total task utility that concerned sensor selection and task cooperation. However, in their papers, the task utility of sensors was independent of each other. Ding et al. [23] considered a more practical issue of deploying wireless chargers, where their objective was to maximize the total achieved task utility with a limited deployment cost budget. To address this problem, they split it into two sub-problems, where the first sub-problem was about power allocation for sensors, and the second sub-problem was about optimal wireless charger placement. However, Ding et al. [23] did not involve the mobile charging.

Budget constrained charging scheduling. Dai et al. [24] studied the problem of Placing directional wIreless chargers with Limited mObiliTy (PILOT) to maximize the overall charging utility for a set of static rechargeable devices on a 2D plane by determining deployment positions, stop positions and orientations, and portions of time for all deployed chargers that could move in a limited area after their deployment. Then they proposed an approximation algorithm to address PILOT. However, their budget constraints did not include the mobile costs. Zhang et al. [25] considered wireless charging service provision in a two-dimensional target area and focused on optimizing charging quality. They first considered the charger placement and power allocation problem with stationary rechargeable devices: Given a set of stationary devices and a set of candidate locations for placing chargers, they aimed to find a charger placement and a corresponding power allocation to maximize the charging quality, subject to a power budget. Then they proposed an approximation algorithm to solve it. They also considered how to deal with mobile rechargeable devices, cost-constrained power reconfiguration, and optimization with more candidate locations. Although they considered mobility, in their paper, the movable objects were the rechargeable devices, but not the chargers. Wu et al. [26] considered the multi-UAV wireless charging scheme in large scale wireless sensor networks, where sensors could be charged by the UAV with wireless energy transfer. They studied how to optimize the route association to maximize the overall charging coverage utility, when charging routes and associated sensors should be jointly selected. They cast it as maximizing a monotone submodular function subject to matroid constraints and proposed an approximation algorithm to solve it. Lin et al. [27] addressed the issue that how to serve a 3-D WRSN with the UAV. Their main concern was to maximize the charged energy for sensors supplied by the UAV with the energy constraint. They designed a spatial discretization scheme to construct a finite feasible set of charging spots and a temporal discretization scheme to determine the appropriate charging duration for each charging spot. A cost-efficient algorithm (CEA) with a provable approximation ratio was proposed to solve it. However, both of Wu et al. [26] and Lin et al. [27] did not involve the differences of subareas.

Overall, although there are many existing works on charging scheduling, there is no monitoring-driven mobile charging which involves the differences of subareas.

3. System Model and Problem Formulation

3.1. Network Model

Let $O = \{o_1, o_2, ..., o_n\}$ be the set of n sensors distributed in a two-dimensional region R. The sensor $o_j \in O$ can monitor a circular area with monitoring radius d_j. It has the energy demand $c(o_j)$, which is necessary for completing the monitoring task. Suppose that all the sensors' batteries are empty at the beginning. We use $\Gamma = \{\varphi_1, \varphi_2, ..., \varphi_{m_0}\}$ to denote the set of all initial subareas. For each $\varphi_z \in \Gamma$, it has monitoring utility per unit area w_z. Referring to Figure 1, combining the initial subareas with the monitoring circle areas of all sensors, final subareas can be obtained. We use $\Phi = \{\phi_1, \phi_2, ..., \phi_m\}$ to denote the set of all final subareas, and each $\phi_l \in \Phi$ has the area a_l. Obviously, any final subarea must belong to an initial subarea. Therefore, according to the monitoring utility per unit area of initial subareas, we can obtain the monitoring utility per unit area of each final subarea, and use w_l to denote the monitoring utility per unit area of final subarea ϕ_l. Therefore, the final subarea ϕ_l has the monitoring utility $a_l w_l$.

A mobile charger starts at the depot s_0 and tries to charge some sensors. The mobile charger can charge at any location in the region and it has the energy capacity E.

3.2. Energy Consumption Model

In our paper, there are two types of energy consumption, the charging energy consumption and the traveling energy consumption. Firstly, we show how to calculate the charging energy consumption. The charging power that sensor $o_j \in O$ receives from mobile charger at charger location $s_i \in R$ can be expressed by the following empirical formula [28]:

$$\Pr(s_i,o_j)=\begin{cases}\frac{\alpha}{(d(s_i,o_j)+\beta)^2}, & d(s_i,o_j)\le D\\ 0, & d(s_i,o_j)>D,\end{cases} \tag{1}$$

where $d(s_i,o_j)$ is the distance between o_j and s_i, D is the maximum charging distance, α and β are the constants that are determined by the hardware and environment.

When the mobile charger arrives at the charging location s_i, it must satisfy the energy demands of all sensors within its maximum charging distance. We define the set of these sensors as $\Lambda(s_i)=\{o_j \mid d(s_i,o_j)\le D\}$. Therefore, the charging time at the charging location s_i is:

$$t(s_i)=\max_{o_j\in\Lambda(s_i)}\frac{c(o_j)}{\Pr(s_i,o_j)} \tag{2}$$

The transmitting power of the mobile charger is γ. Therefore, the energy consumed at charging location s_i is $\gamma t(s_i)$. However, if a sensor o_j belongs to multiple $\Lambda(s_i)$, when it has been charged once, its energy demand will become zero. In addition, the depot s_0 is not considered as a charging location, therefore its charging time is zero. Even if there is a charging location that completely overlaps with s_0, the two locations are still considered different.

Then, we consider the traveling energy consumption. We use $L=<s_0,s_1,...,s_q,s_0>$ to denote the traveling loop. The traveling energy consumption per unit distance of the mobile charger is μ. The energy cost from s_i to $s_{i'}$ is $\mu d(s_i,s_{i'})$, where $d(s_i,s_{i'})$ is the distance between s_i and $s_{i'}$. Therefore, the traveling energy consumption of L is $\sum_{x=0}^{q-1}\mu d(s_x,s_{x+1})+\mu d(s_q,s_0)$.

Therefore, the total energy consumption for any charging loop L can be expressed as:

$$\sum_{x=1}^{q}\gamma t(s_x)+\sum_{x=0}^{q-1}\mu d(s_x,s_{x+1})+\mu d(s_q,s_0) \tag{3}$$

3.3. Monitoring Utility Model

We use $\mathrm{H}(o_j)$ to denote the set of final subareas within the monitoring circle area of o_j. The monitor utility of sensor o_j is:

$$u(o_j)=\sum_{\phi_l\in\mathrm{H}(o_j)}a_l w_l \tag{4}$$

We use S to denote the set of charging locations in L. After the mobile charger completes all charging tasks, the set of final subareas those can be monitored is $\Omega(S)=\bigcup_{s_i\in S}\bigcup_{o_j\in\Lambda(s_i)}\mathrm{H}(o_j)$. The total monitoring utility is defined as:

$$U(S)=\sum_{\phi_l\in\Omega(S)}a_l w_l \tag{5}$$

3.4. Problem Formulation

The problem is to find a traveling loop for the mobile charger to maximize the total monitoring utility in the network. We refer to this problem as the Monitoring-driven Mobile Charging (MMC) problem:

$$(MMC):\quad \max U(S) \tag{6}$$

$$s.t.\sum_{x=1}^{q}\gamma t(s_x)+\sum_{x=0}^{q-1}\mu d(s_x,s_{x+1})+\mu d(s_q,s_0)\le E \tag{7}$$

$$s_i\in R,\forall s_i\in S \tag{8}$$

The constraint (7) ensures that the total energy consumption does not exceed the energy capacity. The constraint (8) ensures that the charging locations in S all belong to R.

We list the frequently used notations in Table 1.

Table 1. *Frequently Used Notations.*

Symbol	Description
R	Continuous two-dimensional space region
r	Monitoring radius of all sensors
Γ, m_0	Set of initial subareas, Number of initial subareas
Φ, m	Set of final subareas, Number of final subareas
O, n	Set of sensors, Number of sensors
a_l, w_l	Area of final subarea ϕ_l, Monitoring utility per unit area of final subarea ϕ_l
E	Energy capacity of mobile charger
D	Maximum charging distance of mobile charger
$c(o_j)$	Energy demand of sensor o_j
$\mathrm{H}(o_j)$	Set of final subareas within the monitoring radius of sensor o_j
$\Pr(s_i,o_j)$	Charging power from s_i to o_j
$t(s_i)$	Charging time at the charging location s_i
γ	Transmitting power of the mobile charger
μ	Traveling energy consumption per unit distance of the mobile charger
L, S	Traveling loop, Set of charging locations in L
$u(o_j)$, $U(S)$	Monitoring utility of o_j, Total monitoring utility of S
δ, ε	Side length of uniform grids, Discretization error

4. Solution of MMC Problem

In this section, we present the algorithm of the MMC problem. We first show the hardness of MMC problem. Next, we introduce an area discretization method to reduce the number of the candidate charging locations in MMC from infinite to finite. Then, we introduce the auxiliary graph construction to remove the constraint of charging energy consumption. At last, we solve the problem with a simple but efficient algorithm and give the details of algorithm and analysis.

4.1. Hardness

First, we attempt to find an optimal algorithm for the MMC problem. Unfortunately, as the following theorem shows, the MMC problem is NP-hard.

Theorem 1. *The MMC problem is NP-hard.*

Proof: We first introduce the following budgeted maximum coverage problem: A collection of sets $R=\{s_1,s_2,...,s_q\}$ with associated costs $\gamma t(s_i)$ is defined over a domain of elements $O=\{o_1,o_2,...,o_n\}$ with associated weights $u(o_j)$. The goal is to find a collection of sets S, such that the total cost of elements in S does not exceed a given budget E, and the total weight of elements covered by S is maximized.

If the traveling energy consumption of the mobile charger is zero and there are limited charging locations, the simplified MMC problem is equivalent to the budgeted maximum coverage problem. If MMC problem can obtain the optimal solution in polynomial time, the budgeted maximum coverage problem can also obtain the optimal solution in polynomial time. However, this contradicts the fact that the budgeted maximum coverage problem is NP-hard. Therefore, MMC problem is NP-hard.

Since the MMC problem is NP-hard, it is impossible to compute the optimal solution in polynomial time unless P=NP. Therefore, we try to use the heuristic algorithm to solve it. However, before presenting our algorithm, we need to execute area discretization and auxiliary graph construction to simplify the problem.

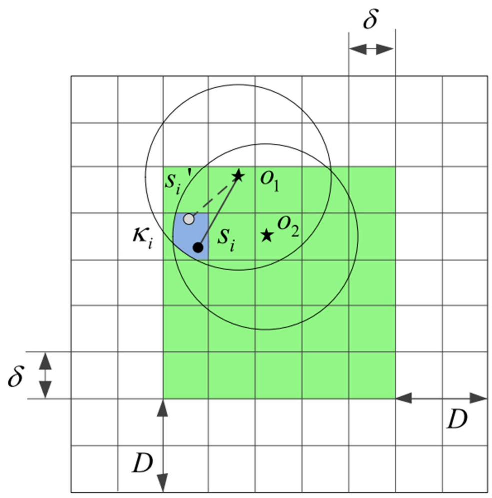


***Figure 3.** Illustration of area discretization [29].*

4.2. Area Discretization

At first, we discrete region R into uniform grids with side length δ, and then further divide the discretized subareas by drawing circles with radius D for each sensor. The distances from each charging location in the same discretized subareas to sensors are approximated accordingly. For example, as shown in Figure 3, there are 81 discretized subareas after gridding and 33 more after drawing circles. Suppose we obtain χ effective discretized subareas those cover at least one sensor, and then randomly choose a location in each discretized subarea as the candidate charging location. We denote the set of the charging locations by $K=\{k_1,k_2,...,k_\chi\}$.

According to [29], we have the following two theorems.

Theorem 2. *The obtained number of subareas after area discretization is* $O(\frac{|R|}{\delta^2}+\frac{nD}{\delta}+n^2)$, *where* $|R|$ *is the size of* R.

Theorem 3. *Let* $\Pr(s_i,o_j)$ *be the maximum charging power from the charging location in the same subarea as* $k_h\in K$ *to sensor* o_j, $\Pr(k_h,o_j)$ *be the charging power from* k_h *to sensor* o_j. *Setting* $\delta=\frac{\sqrt{2}}{2}\beta(\frac{1}{\sqrt{1-\varepsilon}}-1)$, *where* ε *is the discretization error and* $\varepsilon\in(0,1)$, *we have* $(1-\varepsilon)\Pr(s_i,o_j)\le\Pr(k_h,o_j)\le\Pr(s_i,o_j)$.

According to (2), we can have $t(s_i)\le t(k_h)\le\frac{1}{1-\varepsilon}t(s_i)$.

Now, we can simplify MMC to $P1$, where the number of charging locations is limited.

$$P1:\qquad \max U(S) \tag{9}$$

$$s.t.\sum_{x=1}^{q}\gamma t(s_x)+\sum_{x=0}^{q-1}\mu d(s_x,s_{x+1})+\mu d(s_q,s_0)\le E \tag{10}$$

$$s_i\in K,\forall s_i\in S \tag{11}$$

4.3. Auxiliary Graph Construction

In order to reduce the constraints in MMC from the combination of charging energy consumption and traveling energy consumption to the constraint of traveling energy consumption, we need to construct an auxiliary graph G. The intuition behind the construction of G is as follow. As the charging energy consumed at the charging location s_i is $\gamma t(s_i)$. Each edge that is connected with the charging location s_i is assigned the identical weight $\frac{1}{2}\gamma t(s_i)$. Therefore, the weight of the edge $(s_i,s_{i'})$ is $W(s_i,s_{i'})=\mu d(s_i,s_{i'})+\frac{1}{2}\gamma t(s_i)+\frac{1}{2}\gamma t(s_{i'})$, and the weight of s_i and $s_{i'}$ is zero. Then we can reduce the constraint from the combination of the charging energy consumption and traveling energy consumption to the constraint of the traveling energy consumption.

Theorem 4. *The total energy consumed by the mobile charger in graph* G *is equal to that consumed in realistic situation.*

Proof: Given a traveling loop $L=<s_0,s_1,...,s_q,s_0>$, its total energy consumption is

$\sum_{x=0}^{q}\gamma t(s_x)+\sum_{x=0}^{q-1}\mu d(s_x,s_{x+1})+\mu d(s_q,s_0)$. In auxiliary graph G, the total energy consumption is as follow:

$$
\begin{aligned}
&\sum_{(s_i,s_{i'})\in L} W(s_i,s_{i'}) = \sum_{x=0}^{q-1} W(s_x,s_{x+1}) + W(s_q,s_0) \\
&= \sum_{x=0}^{q-1}(\mu d(s_x,s_{x+1}) + \frac{1}{2}\gamma t(s_x) + \frac{1}{2}\gamma t(s_{x+1})) + \mu d(s_q,s_0) \\
&+ \frac{1}{2}\gamma t(s_q) + \frac{1}{2}\gamma t(s_0) \\
&= \sum_{x=0}^{q-1}\mu d(s_x,s_{x+1}) + \mu d(s_q,s_0) + (\frac{1}{2}\gamma t(s_0) + \frac{1}{2}\gamma t(s_1) + \frac{1}{2}\gamma t(s_1) \\
&+ \frac{1}{2}\gamma t(s_2) + \ldots + \frac{1}{2}\gamma t(s_{q-1}) + \frac{1}{2}\gamma t(s_q)) + \frac{1}{2}\gamma t(s_q) + \frac{1}{2}\gamma t(s_0) \\
&= \sum_{x=0}^{q-1}\mu d(s_x,s_{x+1}) + \mu d(s_q,s_0) + \sum_{x=0}^{q}\gamma t(s_i) \\
&= \sum_{x=0}^{q-1}\mu d(s_x,s_{x+1}) + \mu d(s_q,s_0) + \sum_{x=1}^{q}\gamma t(s_i)
\end{aligned}
\quad (12)
$$

Therefore, we obtain the theorem.

Then we can reformulate the problem $P1$ to $P2$.

$$P2: \quad \max U(S) \quad (13)$$

$$s.t. \sum_{(s_i,s_{i'})\in L} W(s_i,s_{i'}) \le E \quad (14)$$

$$s_i \in K, \forall s_i \in S \quad (15)$$

Remark: When a new charging location is added into the loop, the auxiliary graph should be updated, because the energy demand of some sensors may become zero.

4.4. Algorithm Design

In this subsection, we will provide a simple but efficient algorithm to solve the problem $P2$.

The lower level optimization in MMC involves finding a shortest traveling loop including some sensors which ensures the total energy consumption not exceed the energy capacity. Optimizing this energy consumption is more difficult than solving Traveling Salesman Problem (TSP) [30], which is also a NP-hard problem. However, we could use a nearest neighbor method to obtain the loop which can reduce energy consumption as much as possible.

Algorithm 1: Monitoring-driven Mobile Charging Algorithm (MMCA)

Input: $\forall o_j \in O$, s_0, E, μ, γ, $\forall \phi_l \in \Gamma$, K, G

Output: L, S

1: $K^* \leftarrow K$, $S \leftarrow \varnothing$;

2: while $K^* \neq \varnothing$ do

3: according to $S \bigcup \{s_0\}$, use the nearest neighbor method to obtain L;

4: for each $k_h \in K^*$ do

5: $S(k_h) \leftarrow S \bigcup \{k_h\}$;

6: according to $S(k_h) \bigcup \{s_0\}$, use the nearest neighbor method to obtain $L(k_h)$;

7: end

8: $k_h \leftarrow \arg\max_{k_{h'}\in K} \dfrac{U(S(k_{h'})) - U(S)}{\sum_{(s_i,s_{i'})\in L(k_{h'})} W(s_i,s_{i'}) - \sum_{(s_i,s_{i'})\in L} W(s_i,s_{i'})}$;

9: if $\sum_{(s_i,s_{i'})\in L(k_h)} W(s_i,s_{i'}) \le E$ then

10: $S \leftarrow S(k_h)$;

11: end

12: $K^* \leftarrow K^* \backslash \{k_h\}$;

13: end

14: according to $S \bigcup \{s_0\}$, use the nearest neighbor method to a path L;

As illustrated in Algorithm 1, let K^* be the residual candidate location set, we initialize K^* and S (Line 1). If there are candidate locations in K^* (Line 2), we traverse all locations in K^* and add each location k_h to a temporary set $S(k_h)$ (Line 4). According to $S(k_h) \bigcup \{s_0\}$, we use the nearest neighbor method to find a loop $L(k_h)$ (Line 6). Then we find the location with the maximum utility-consumption ratio (Line 8). If the energy constraint is satisfied, we update S to $S(k_h)$ (Line 9-11). Update K^* (Line 12) and continue traversing until the K^* is empty. Finally, according to $S \bigcup \{s_0\}$, we obtain the loop (Line 14).

4.5. Theoretical Analysis

In this subsection, we give a series of theoretical analysis about MMCA. Firstly, we need to provide a definition.

Definition 1. *(Nonnegative, monotone, and submodular function): Given a finite ground set V, a real-valued set function defined as $f: 2^V \leftarrow \mathbb{R}$, f is called nonnegative, monotone, and submodular if and only if it satisfies following conditions, respectively:*

1) $f(\varnothing) = 0$ and $f(A) \ge 0$ for all $A \in V$;

2) $f(A) \le f(B)$ for all $A \subseteq B \subseteq V$;

3) $f(A) + f(B) \ge f(A \bigcup B) + f(A \bigcap B)$ for any $A, B \subseteq V$ or equivalently: $f(A \bigcup \{v\}) - f(A) \ge f(B \bigcup \{v\}) - f(B)$, $A \subseteq B \subseteq V$, $v \in V \setminus B$.

Then, we have the following theorem.

Theorem 5. *The monitoring utility function is nonnegative, monotone and submodular.*

Proof: According to the definition of our monitoring utility function, obviously, it is nonnegative and monotone. Then we prove that it is submodular. To prove the submodularity, we only need to show that the following inequality holds for any $A \subseteq B \subseteq V$ and $v \in V \setminus B$:

$$U(A \bigcup \{v\}) - U(A) \ge U(B \bigcup \{v\}) - U(B) \quad (16)$$

We consider the following three cases:

(Case 1) If $\mathrm{H}(v)\bigcap\Omega(B)=\varnothing$, obviously, we have

$$U(B\bigcup\{v\})-U(B)=\sum_{\phi_l\in\mathrm{H}(v)}a_l w_l=U(A\bigcup\{v\})-U(A) \quad (17)$$

(Case 2) If $\mathrm{H}(v)\bigcap\Omega(B)\neq\varnothing$, $\mathrm{H}(v)\bigcap\Omega(A)=\varnothing$, we have

$$\begin{aligned}U(B\bigcup\{v\})-U(B)&=\sum_{\phi_l\in\mathrm{H}(v)}a_l w_l-\sum_{\phi_l\in\mathrm{H}(v)\bigcap\Omega(B)}a_l w_l\\&\leq\sum_{\phi_l\in\mathrm{H}(v)}a_l w_l\\&=U(A\bigcup\{v\})-U(A)\end{aligned} \quad (18)$$

(Case 3) If $\mathrm{H}(v)\bigcap\Omega(B)\neq\varnothing$, $\mathrm{H}(v)\bigcap\Omega(A)\neq\varnothing$, because $A\subseteq B$, assume $C=B\setminus A$. We have

$$\begin{aligned}U(B\bigcup\{v\})-U(B)&=\sum_{\phi_l\in\mathrm{H}(v)}a_l w_l-\sum_{\phi_l\in\mathrm{H}(v)\bigcap\Omega(A)\bigcap\Omega(C)}a_l w_l\\&\leq\sum_{\phi_l\in\mathrm{H}(v)}a_l w_l-\sum_{\phi_l\in\mathrm{H}(v)\bigcap\Omega(A)}a_l w_l\\&=U(A\bigcup\{v\})-U(A)\end{aligned} \quad (19)$$

Based on (17), (18) and (19), we obtain the theorem.

Because $U(S)$ is nonnegative, monotone and submodular, according to [31], we have the following theorem.

Theorem 6. *If $U(S)$ is nonnegative, monotone and submodular and shortest traveling loop algorithm can obtain θ- approximation, the algorithm obtains a set such that*

$$U(S)\geq\frac{1}{2}(1-\frac{1}{e})U(S^*)$$

where S^* is the optimal solution of $\max\{U(S)\,|\,T(S)\leq\eta\frac{E(1+\eta(Y_c-1)(1-y_c))}{\theta Y_c}\}$, $T(S)$ is the energy consumption of shortest traveling loop when the input set is S, $\eta=\min_x\min_{A,B:A\subset B}\frac{T(A\bigcup\{x\})-T(A)}{T(B\bigcup\{x\})-T(B)}$, $Y_c=\max\{|S|:T(S)\leq E\}$, $y_c=1-\min_{s\in S}\frac{\mathrm{T}(S)-\mathrm{T}(S\setminus\{s\})}{\mathrm{T}(\{s\})}$.

Theorem 7. *The time complexity of MMCA is $O(\chi^3)$.*

Proof: The running time of MMCA is dominated by finding the traveling loop (Line 6), which takes $O(\chi^2)$. And this operation needs to be performed χ times. Therefore, the time complexity of MMCA is $O(\chi^3)$.

5. Simulation Results

In this section, we perform simulations to verify the performance of our algorithm.

5.1. Simulation Setup

For the simulations, we randomly distribute the sensors in a 2D plane. The default values of parameters are given in Table 2. The unit of power is watt. The settings of parameters refer to the existing work [32]. We will vary the value of the key parameters to explore the impacts on the algorithms. All the simulations are run on a Windows machine with Intel (R) Xeon (R) CPU i7-10750H and 8 GB memory. Each measurement is averaged over 100 instances.

Table 2. *Default Settings of Parameters.*

Parameter	Default value
R	100m * 100m
m	4
n	50
E	2000KJ
$c(o_j)$	[10, 14] KJ
γ	15W
μ	50J/m
δ	2m
α , β	90, 10
D	2m
r	3m

We compare our algorithm with the following two algorithms:

NNA (Nearest Neighbor Algorithm): We modify the Nearest Neighbor Algorithm in [33] to fit the scenario of this paper. In each iteration, NNA traverses all sensors those haven't been visited, and mobile charger chooses the nearest one such that the distance is minimized. The iterations terminate when all sensors are visited or energy capacity is exceeded.

GAD (Greedy Algorithm after Discretization): In each iteration, GAD traverses all candidate charging locations after discretization those haven't been visited, and mobile charger chooses the one which can maximize the total monitoring utility. The iterations terminate when all candidate charging locations are visited or energy capacity is exceeded.

5.2. Monitoring Utility

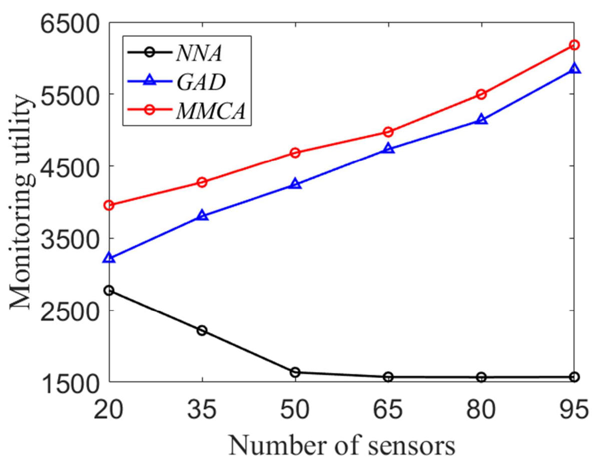


Figure 4. *Monitoring utility vs. n.*

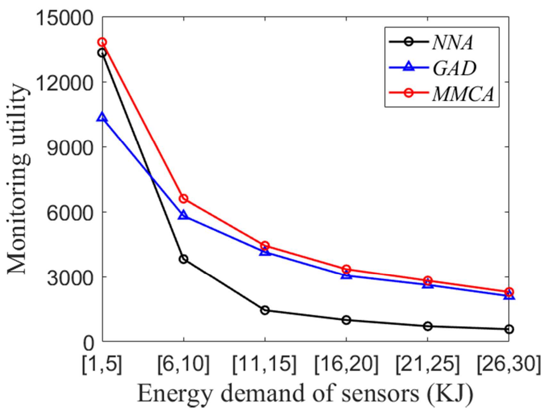


Figure 5. *Monitoring utility vs. c (oj).*

To test the scalability of our algorithm, we increase the number of sensors from 20 to 95. As shown in Figure 4, the monitoring utility of GAD and MMCA increases with the increasing number of sensors. However, the monitoring utility of NNA decreases with the increasing number of sensors. This is because the optimization goal of NNA is not the monitoring utility. There may be more sensors with low monitoring utility in the traveling loop of NNA when the number of sensors increases. Specifically, MMCA increases the monitoring utility by 180.28% and 10.62% on average compared with NNA and GAD, respectively.

Then, we increase the energy demand of sensors from [1, 5] KJ to [26, 30] KJ. As shown in Figure 5, the monitoring utility of all algorithms decreases with the increasing energy demand of sensors. This is because due to the increasing energy demand of sensors, mobile charger only charge fewer sensors. Averagely, MMCA increases the monitoring utility by 185.03% and 13.45% compared with NNA and GAD, respectively.

Then, we change the energy capacity of mobile charger. With the increasing energy capacity of mobile charger, more sensors can be charged. Therefore, the monitoring utility of all algorithms increases with the increasing energy capacity of mobile charger. As shown in Figure 6, MMCA increases the monitoring utility by 189.11% and 7.76% on average compared with NNA and GAD, respectively.

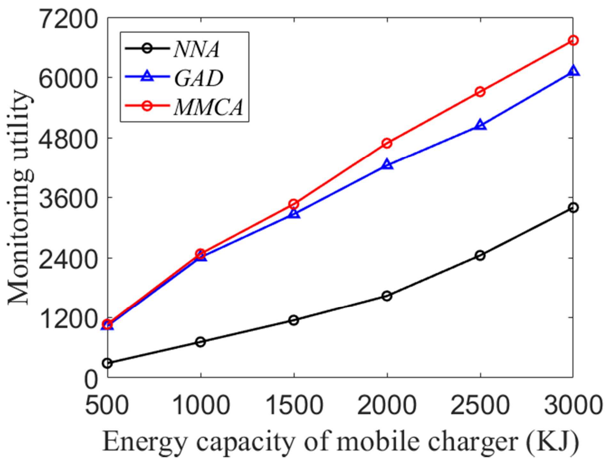


Figure 6. *Monitoring utility vs. E.*

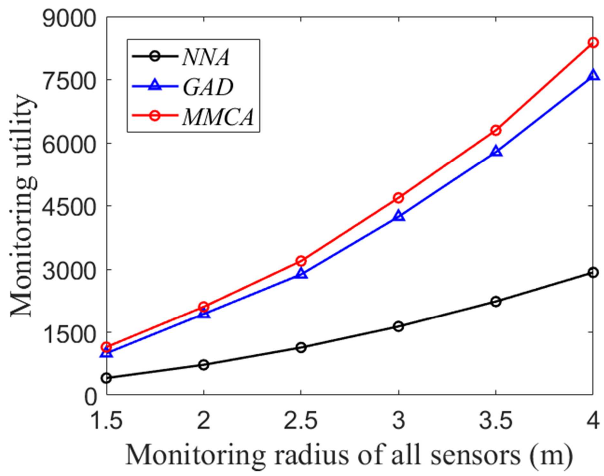


Figure 7. *Monitoring utility vs. r.*

Figure 7 shows the impact of monitoring radius of all sensors on the monitoring utility. The monitoring utility of all algorithms increases with the increasing monitoring radius of all sensors. This is because sensors can achieve more monitoring utility by covering larger area. Averagely, MMCA increases the monitoring utility by 185.06% and 10.80% compared with NNA and GAD, respectively.

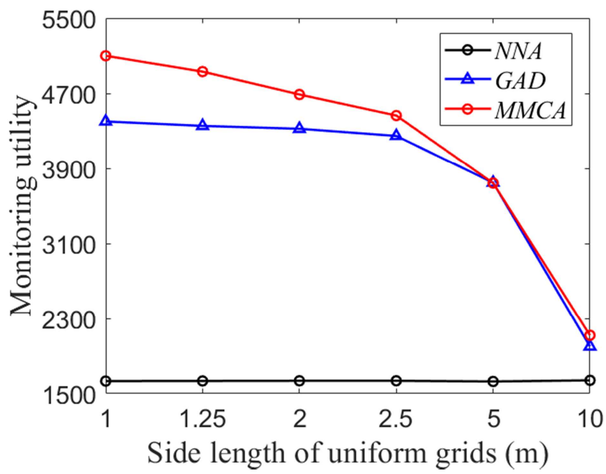


Figure 8. *Monitoring utility vs. δ.*

Figure 8 shows the impact of side length of uniform grids on the monitoring utility. With the increasing side length of grids, the monitoring utility of GAD and MMCA decreases accordingly. However, because NNA is independent of discretization, its monitoring utility remains unchanged. Averagely, MMCA increases the monitoring utility by 155.32% and 8.08% compared with NNA and GAD, respectively.

6. Conclusions

In this paper, we have presented a monitoring-driven mobile charging model, which considers the differences between different subareas, and formulate the Monitoring-driven Mobile Charging (MMC) problem. Through area discretization and auxiliary graph construction, we simplify the problem and provide a greedy algorithm to solve it. The results demonstrate that our algorithm can increase the monitoring utility by at most 189.11% compared with the benchmark algorithms in extensive simulations.

Conflicts of Interest

The authors declare no conflicts of interest.

ORCID

0009-0001-4152-1377 (Zhiqiang Wang)
0009-0006-3664-108X (Jun Fu)
0009-0005-4507-7698 (Lei Han)

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