# Recycling Wasted Energy for Mobile Charging

Yu Sun*†, Chi Lin*†, Haipeng Dai‡, Pengfei Wang§, Jiankang Ren§, Lei Wang*†, and Guowei Wu*†
*School of Software Technology, Dalian University of Technology, Dalian 116620, China
†Key Laboratory for Ubiquitous Network and Service Software of Liaoning Province, Dalian 116620, China
‡State Key Laboratory for Novel Software Technology, Nanjing University, Nanjing 210024, China
§School of Computer Science and Technology, Dalian University of Technology, Dalian 116024, China.
Email: yusun.dut@gmail.com, c.lin@dlut.edu.cn, haipengdai@nju.edu.cn, wangpf@dlut.edu.cn
rjk@dlut.edu.cn, lei.wang@ieee.org, wgwdut@dlut.edu.cn

***Abstract*—The rapid popularization of wireless power transfer (WPT) technology promotes the wide adoption of wireless rechargeable sensor networks (WRSNs). Traditional methods only focus on how to optimize network performance, and most of them overlook the energy waste issue induced by WPT. In this paper, we explore the potentials of recycling wasted energy when using WPT by means of freeloading. Specifically, with a slight modification on hardware, we expand the functionality of the mobile chargers (MCs), enabling them to harvest and recycle the WPT-induced wasted energy in the air to serve more sensors, which promotes energy efficiency. We model the problem, termed MEFree, as maximizing network energy efficiency by utilizing a limited number of freeloading MCs and scheduling their freeloading behaviors. Through jointly scheduling freeloading and charging tasks, the proposed scheme is able to solve the problem with a $(1 - 1/e)/2$ approximation ratio with a slightly relaxed budget. Extensive simulations are conducted and corresponding numerical results show that our proposed scheme significantly improves network energy efficiency by at least $18.8\%$ and outperforms baseline algorithms by $19.1\%$ on average in various aspects. Our test-bed experiments further demonstrate the practicability of our scheme in actual scenes.**

***Index Terms*—wireless power transfer, freeload charging, mobile charger, energy recycling**

## I. Introduction

Wireless power transfer [1] provides an enabling technology for realizing sensor perpetuation in Wireless Sensor Networks (WSNs), which in turn derives the concept of Wireless Rechargeable Sensor Networks (WRSNs) [2]–[6]. In recent years, considerable research achievements have been proposed on WRSNs. In general, traditional methods can be categorized based on the functionality of wireless charger(s) into two types: stationary chargers (SCs) [7]–[9] and mobile chargers (MCs) [10]–[12]. In these schemes, when performing charging tasks, wireless chargers will emit charging signal in the air, and rechargeable sensors harvest energy through directional antennas, omnidirectional antennas, or coupling coils. However, compared with the huge size of the charging signal coverage area, the size of the energy harvesting antennas is quite small, which is only about $4cm * 20cm$, thus resulting in large amounts of energy waste. Statistically, the transmitting power of a wireless charger is usually two or three orders of magnitudes higher than the receiving power of rechargeable sensors with energy harvesting antenna (*i.e.*, 3W vs. 50mW). Even if multiple rechargeable sensors are simultaneously harvesting from one charger, the energy efficiency can only be as high as $20\%$. In other words, more than $80\%$ of the charging power is wasted in vain [14], [15].

**Chi Lin***† is the corresponding author.

978-1-6654-4131-5/21/$31.00 ©2021 IEEE

This intrinsic defect of WPT hinders the wide adoption of WPT-based applications. Unfortunately, it is overlooked by most previous arts. Hence, it is quite meaningful to explore how to recycle wasted energy to improve the energy efficiency of WRSN. The main goal of this paper is to propose a scheme that reduces excessive energy waste and recycles the ambient wireless signal wasted by chargers. In this work, we make a slight modification on commodity devices where an energy harvesting antenna (or coupling coil) and a small printed circuit board (PCB, *e.g.*, Powercast P2110B [14]) are installed on a UAV (*i.e.*, the MC), which enables it to *freeload* energy. With such modifications, these "freeloading MCs" are able to recycle the ambient charging signals which should have been wasted, and replenish sensors without increasing the energy burdens of the base station.

We formalize the problem as a *Maximizing Network Efficiency via Freeloading Mobile Chargers (MEFree)* problem (see Section III-C), which aims at utilizing a limited number of reasonably scheduled freeloading MCs to recycle the wasted energy to charge sensors. To address the MEFree problem, we face with several technical challenges:

- When determining the behavior of an MC, it is non-trivial to trade-off energy harvesting and charging tasks scheduling in a global view. Moreover, distributing and scheduling the charging tasks for multiple MCs is equivalent to solving multiple interrelated charging scheduling problems simultaneously, leading to great difficulties.
- Since the freeloading spots for mobile chargers to harvest energy is selected from the continuous 2D space, the number of candidate freeloading spots is infinite, which yields an extremely high computational complexity.
- Calculating the traveling path of MCs is similar to solving a traveling salesman problem (TSP), which is proved to be NP-hard. Moreover, the selection of the redundant SCs can be reduced to a variance of the budgeted maximum coverage problem [16], which is also NP-hard. Therefore, the MEFree problem is the combination of several

coupling NP-hard problems, posing great challenges.

To tackle the above-mentioned challenges, we divide the MEFree problem into two subproblems and propose several algorithms to solve them simultaneously. Theoretical analyses are proposed to present some insights for our scheme. Finally, simulations and experiments are conducted to highlight the features of energy recycling. In general, the main contributions of this paper are summarized as follows:

- To the best knowledge of the authors, this is the first work that addresses the energy recycling problem of wireless power transfer in WRSN. Through equipping an energy harvesting antenna (or coupling coil) and a small printed circuit board on each MC, the original MCs are able to recycle the wasted energy, thus reducing energy consumption and saving cost for WRSN. Through reasonable scheduling of the MCs, we are able to replace redundant SCs with freeloading MCs to serve sensors with less energy consumption. Thereby, the energy efficiency of the network is significantly improved.
- With the innovative freeloading MCs, a novel WRSN architecture is constructed. We formalize the MEFree problem, which aims at maximizing the energy efficiency of the WRSN through utilizing freeloading MCs while ensuring energy supply of sensors. Afterwards, we propose area discretization techniques and several algorithms to solve the MEFree problem with a $\frac{1}{2}(1-\frac{1}{e})$ approximation ratio.
- Extensive simulation results indicate that our proposed scheme achieves effective recycling of wasted energy in the network, which significantly improves network energy efficiency by 18.8% and excels with other baseline algorithms by 19.1% on average. Moreover, test-bed experiments demonstrate that our scheme is suitable for practical applications and show merits in recycling wasted energy.

## II. Related Work

In recent years, much effort has been devoted to WRSNs. According to different functionalities of chargers, traditional methods are three-folds: stationary chargers scheduling [7], [8], [17], [18] and mobile chargers scheduling [10], [19]–[23].

For the stationary charger scheduling issue, the chargers transmit wireless signals into the surrounding environment to charge sensors in a one-to-many pattern. Rechargeable sensors harvest the ambient wireless signals and convert them into DC power to replenish themselves. Zhang *et al.* [18] aimed at optimizing charging quality in a 2D target area. They proposed a $(1-\frac{1}{e})$-approximation algorithm to schedule chargers placement and power allocation. Yu *et al.* [8] focused on maximizing overall charging utility by determining the placement position and orientation angle for each charger under connectivity constraint. Dai *et al.* [17] considered the potential risk of electromagnetic radiation from charging signals. They explored how to adjust the power of chargers to maximize the charging utility while ensuring that the radiation does not exceed a given threshold. In addition, they also considered

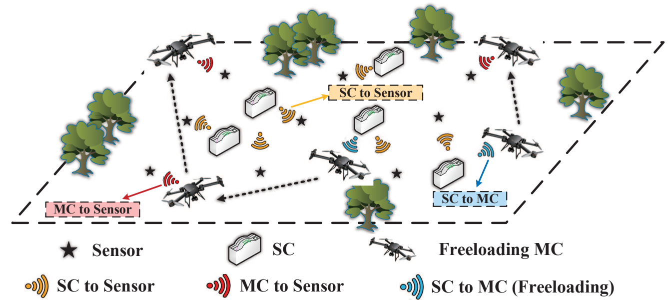



Fig. 1. Network model.

the case where the electromagnetic radiation is floating [7]. Wang *et al.* [23] aimed at maximizing the overall expected charging utility through determining the orientations of the wireless chargers while taking the charging power fluctuation problem into consideration.

For the mobile charger scheduling issue, mobile chargers are employed to travel around the network and stop at specific spots near sensors to perform charging tasks. Wu *et al.* [10] studied the collaborated tasks-driven mobile charging and scheduling to deal with the energy requirement diversity. Lin *et al.* [20] introduced both temporal and spatial factors to prioritize charging requests, and investigated the issue of multiple WCVs online collaborative charging scheduling. Liang *et al.* [21] studied the deployment of the minimum number of mobile charging vehicles to charge sensors in a large-scale WRSN while enabling network perpetuation. Chen *et al.* [19] developed a class of generic optimization problems on charging scheduling. They designed a quasi-polynomial time algorithm that achieves poly-logarithmic approximation to the optimal charging path. Zhang *et al.* [22] considered how to efficiently provide flexible wireless charging using preplanned charging itineraries where the energy consumption of rechargeable devices fluctuates overtime.

The common problem of previous arts is that they overlooked the recycling of the energy waste induced by WPT, which yields a considerable amount of energy delivered in the air and wasted in vain. To solve this problem, in this work, we focus on utilizing hybrid chargers and use freeloading MCs to recycle the wasted energy, and thereby improve the energy efficiency of the whole network.

## III. Model and Problem Statement

### A. Network Model

As shown in Figure 1, we consider $n$ stationary sensors (denoted as $S = \{s_1, s_2, ..., s_n\}$) deployed in a 2D plane network (with side length $L$) uniformly to conduct monitoring tasks and they are configured with certain protocols [27], [28]. Each sensor is equipped with a rechargeable battery and an energy harvesting module, which can be used to capture the RF signals in the surrounding environment and convert them into DC power to replenish the onboard rechargeable battery.

To provide energy supply for rechargeable sensors, similar to [13], we utilize both SCs and MCs to achieve higher network energy efficiency. Specifically, $m$ SCs (denoted as $O =$

$\{o_1, o_2, ..., o_m\}$) are distributed in the network, which can emit RF signals continuously into the surrounding environment, forming a *sector* charging area with charging radius $r_o$ and charging angle $A_o$ (see Figure 2(a)). Accordingly, rechargeable sensors harvest these RF signals to recharge themselves to sustain normal operation perpetually. Nevertheless, after taking a deep investigation, we found that SCs have rather low energy efficiency since they provide energy supply for quite a few sensors while consuming a large amount of energy to transmit charging signals into the surrounding environment. As reported in [14], [15], in the charging process, more than 80% energy will be wasted.

To address the energy waste issue and enhance the energy efficiency (*i.e.*, reduce the energy consumption) of the whole network, *we make a slight modification on existing commodity MCs (*i.e.*, UAVs in this work) where an energy harvesting antenna (or coupling coil) and a small PCB (Powercast P2110B [14]) are attached to the rechargeable battery (see Figure 9) of an MC.* With this modification, an MC is able to emit RF signals for replenishing sensors and harvest wasted energy by receiving ambient RF signals. Afterwards, to recycle the wasted energy, an MC can travel towards an SC and stay close to it to take a *freeload charging*. Thereby, introducing freeloading MCs will not increase energy consumption. It will enable us to *replace some of the SCs with freeloading MCs, thereby reducing the energy consumption of the network.*

We consider that there are $k$ available MCs (denoted as $U = \{u_1, u_2, ..., u_k\}$), which can harvest energy from ambient RF signals from SCs and charge sensors. With freeloading MCs, some redundant SCs can be removed to save network energy consumption.

Rechargeable sensors perform sensing tasks, data transmission, and data relaying, which are energy-consuming. The energy consumption rate of sensor $s_i$ is denoted as $\eta_i$, which consists of sensing consumption rate $\eta_{i,s}$ and transmission consumption rate $\eta_{i,t}$. As a result, the energy consumption rate for a sensor is no less than $\eta_{i,s}$.

Sensors are able to harvest energy by receiving RF signals transmitted by nearby SCs. The transmitting power of an SC is denoted as $P_o$. The corresponding charging radius is denoted as $r_o$. The charging power from charger $o_i$ to sensor $s_j$ decreases as their distance increases (see Equation (1)). Whenever the distance exceeds $r_o$ or the sensor is out of the sector charging area, it cannot capture any energy. Thus we define the coverage set of SC $o_i$ as the set of sensors within its charging area, and it is denoted as $S_{o_i} = \{s_j \in S | \ l(o_i, s_j) \leq r_o, \ \overrightarrow{o_i, x} \cdot \overrightarrow{a_{o_i}} - l(o_i, x)cos(A_o/2) \geq 0\}$.

### B. Freeloading MC

Different from SCs, freeloading MCs work in a different pattern. During the working process, freeloading MCs will first stay at selected freeloading spots and harvest energy from nearby SCs, and then depart to charge panic sensors. Such process is performed in every time period $T$. Referring to [29], compared with the time period $T$, the charging scheduling time (traveling towards sensors and charging them) is negligible.

A Freeloading MC is implemented based on a UAV equipped with a low-cost energy harvesting antenna (or coupling coil) and a small PCB (see Figure 9), which enables it to harvest RF signals. Here, such additional components are cheap and small in size, which will not cost burdens to the MC.

When a freeloading MC stays at a freeloading spot to harvest energy, its receiving power can be calculated as the same as that of sensors:

$$P_{u_i}(x) = \begin{cases} P_o \cdot \frac{\alpha}{(\beta + l(o_i, x))^2}, & 0 \leq l(o_i, x) \leq r_o, \\ & and \ \overrightarrow{o_i, x} \cdot \overrightarrow{a_{o_i}} - l(o_i, x)cos(A_o/2) \geq 0, \\ 0, & otherwise. \end{cases} \tag{1}$$

Here, $x$ is the freeloading spot, $P_{u_i}(x)$ is the receiving power of $u_i$ when it is staying at freeloading spot $x$. $\alpha$ and $\beta$ are energy transfer constants configured by hardware and environment. $o_i$ denotes the SC from which MC $u_i$ receives energy. $\overrightarrow{a_{o_i}}$ is the unit vector in the orientation of $o_i$. $l(o_i, x)$ is the distance between $o_i$ and $x$.

WPT requires tight alignment between charging and receiving antennas (or coils). When an MC is moving, the displacement between transceivers is likely to occur at anytime. Hence, such received energy can be negligible. Due to the intrinsic feature of the energy management module, when MC performs charging tasks, it cannot harvest ambient energy either, as the energy harvesting module will be blocked when its battery is discharging [14], [15], [30].

Since the energy source of freeloading MCs is the wasted energy in the air, we believe such MCs will not bring in extra energy consumption in the network. In essence, the role of MC is to *convert the wasted charging signals into their own energy and transfer it to sensors*. Thus, they can be considered as energy-saving alternatives to SCs. With freeloading MCs, some of the SCs can be removed to save energy.

Let $O' \subseteq O$ be the set of selected SCs to be removed, and $U' \subseteq U$ be the set of scheduled freeloading MCs. Once SCs in $O'$ are removed, some of the sensors may suffer from insufficient energy supply. To keep the network perpetual, the energy received by a sensor over a time period $T$ should be no less than the energy it consumes. Since each sensor has its own charging deadline, in order to serve the most panic sensor timely, MCs have different scheduling cycles of time $T_1, T_2, ..., T_m$. MCs in $U'$ should provide energy supply for these sensors to compensate for their power loss:

$$e(u_i, s_j) \geq \eta_i \cdot T, \ \forall u_i \in U', \ \forall s_j \in S_{u_i}, \tag{2}$$

where $e(u_i, s_j)$ is the energy transmitted from $u_i$ to $s_j$, and $S_{u_i}$ is defined as the set of sensors to be charged by $u_i$.

Let $S'$ denote the set of sensors that lack energy supply after removing chargers in $O'$, *i.e.* $S' = \bigcup_{o_i \in O'} S_{o_i}$. Thus we have

$$S' = \bigcup_{u_i \in U'} S_{u_i}. \tag{3}$$

Let $\delta$ be the energy consumed by MC on transmitting per unit energy to the sensor and $\sigma$ be the energy consumed on traveling a unit length. The energy cost $C_i$ of MC $u_i$ to finish the whole charging task is composed of two parts: charging cost $C_{i,e}$ and traveling cost $C_{i,t}$, which can be calculated by

$$C_i = C_{i,e} + C_{i,t} = \sum_{s_j \in S_{u_i}} e(u_i, s_j) \cdot \delta + \mathcal{L}_i \cdot \sigma, \quad (4)$$

where $\mathcal{L}_i$ is the length of the shortest Hamiltonian cycle including all sensors in $S_{u_i}$ and the freeloading spot. The calculation problem of $\mathcal{L}_i$ is similar to the traveling salesman problem (TSP), which is NP-Hard and can be approximately solved using the nearest neighbor strategy [31].

Note that, the energy cost $C_i$ of $u_i$ should never exceed its harvested energy. In other words, a mobile charger should head towards a freeloading spot to harvest energy before exhaustion, because it has no energy supply except for the ambient RF signal. Specifically, this energy constraint can be described as

$$P_{u_i}(x) \cdot T \geq C_i. \quad (5)$$

### C. Problem Formalization

Given an existing WRSN in which $n$ rechargeable sensors are distributed in a 2D plane, and $m$ SCs are deployed around rechargeable sensors to provide energy supply for them by transmitting RF signals into the surrounding environment. We consider that there are $k$ freeloading MCs available to dispatch.

The *Maximizing Network Efficiency via Freeloading Mobile Chargers (MEFree)* problem is *to replace some of the stationary chargers with a limited number of freeloading mobile chargers to reduce network energy consumption and maximize the network energy efficiency.* The MEFree problem can be formulated as

$$(\textbf{MEFree}) \quad \max \quad \psi = \frac{\sum_{s_i \in S} \eta_i}{\sum_{o_j \in O \setminus O'} P_{o_j}}$$
$$s.t. \quad |U'| \leq k. \quad (6)$$
$$(1) - (5)$$

Here, $\psi$ represents the energy efficiency of the network, and $P_{o_j}$ is the transmitting power of SC $o_j$. Note that $\psi$ can be calculated as the ratio of the total power consumed by sensors to the total power injected into the network by SCs.

## IV. Proposed Scheme

To solve the MEFree problem, we firstly reformulate the problem into a simplified version. Then we propose area discretization techniques and several algorithms to solve the problem with a specific performance guarantee.

### A. Problem Reformulation

According to the problem formalization, our objective is to maximize the network energy efficiency. Since the energy consumption rate of sensors is fixed, maximizing the network energy efficiency is equivalent to minimizing SCs' energy consumption. Therefore, this problem can be further transformed into *maximizing the reduction of energy consumption caused by SCs*. In other words, our objective is to maximize the total transmitting power (denoted as $E'$) of the removed SCs. Accordingly, the MEFree problem can be reformulated as

$$(\textbf{MEFree-R}) \quad \max \quad E' = |O'| \cdot P_o$$
$$s.t. \quad |U'| \leq k. \quad (7)$$
$$(1) - (5)$$

Through in-depth analysis, we can divide the MEFree-R problem into two subproblems: (1) Selecting the set $O' \in O$ of redundant SCs and removing them while enabling network perpetuation by scheduling a limited number of freeloading MCs; (2) Scheduling freeloading MCs in set $U' \in U$ to compensate for energy loss of sensors caused by removal of SCs while minimizing required number of MCs.

Note that the reformulated MEFree-R problem is NP-hard (see proofs in Section V-A). In the following, we propose a series of methods to address this problem.

### B. Area Discretization

After problem reformulation, we still face another difficulty that the freeloading spots of mobile chargers are in the continuous space, which means that the candidate locations are infinite. Enumerating all possible spots to select an appropriate one will induce extremely high computational complexity.

To reduce the computational complexity of selecting freeloading spots for MCs, an area discretization technique is required, which can partition the continuous network area into discrete subareas. We apply the grid area discretization method which fits well with our network model and has rather low computational complexity. The related discretization-induced error will be explored in Section V-B.

As shown in Figure 2(b), we divide the 2D plane into uniform grids $\{\Gamma_1, \Gamma_2, ..., \Gamma_g\}$ with side length $\theta$. The number of grids is $g = \lceil \frac{\Phi}{\theta^2} \rceil$, where $\Phi$ is the area of the network. Similar to [11], the receiving power at each spot within a grid is considered as uniform. Therefore, any point within it can be regarded as the candidate freeloading spot for MCs, and we randomly choose one in every grid as a candidate for MC to harvest energy.

Note that, the uniform receiving power in a grid is approximated as the minimum receiving power within it. When a grid $\Gamma_i$ is covered by SC $o_i$, the minimum/uniform receiving power (denoted as $p(o_i, \Gamma_i)$) is identical with the spot that has the longest distance to $o_i$. When a grid is partially covered by a single SC, it will be divided into two sub-grids: covered sub-grid $\Gamma_i'$ and uncovered sub-grid $\Gamma_i''$ (see Figure 2 (b)). We calculate $p(o_i, \Gamma_i')$ as the minimum/uniform receiving power in $\Gamma_i'$ while $p(o_i, \Gamma_i'')$ is naturally considered as 0.

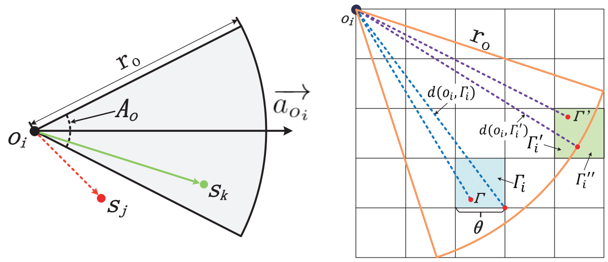
Let $\theta = \frac{\sqrt{2}}{2}\beta(\frac{1}{\sqrt{1-\zeta}} - 1)$, where $\zeta$ is a given error threshold ($0 \leq \zeta < 1$). For each spot $x$ within grid $\Gamma_i$, we have the following bounded approximation error:

$$p(o_i, \Gamma_i) \geq (1 - \zeta) p(o_i, x), \ \forall x \in \Gamma_i. \quad (8)$$

The detailed proof for (8) is given in Section V-B. Thereby, the second challenge introduced in Section I is tackled.

### C. Scheduling Freeloading MCs

We propose two algorithms named MCS and CMN to solve one of the above-mentioned subproblems: charge sensors with




(a) (b)

Fig. 2. (a) Charging model: SC can only charge the sensors within its sector charging area (*e.g.*, $s_k$) rather than outside sensors (*e.g.*, $s_j$). (b) Area discretization.

the minimized number of freeloading MCs. Note that the key difference from existing mobile charging schemes is the uncertainty of freeloading spots and sensor allocation.

*1) Status of MC:* First, we introduce the two statuses of a freeloading MC: *busy* and *available*. An MC harvests energy at a freeloading spot for battery replenishment to support it to perform charging tasks later. For an MC $u_i$, after serving all sensors, if there is still free time for it before the next scheduling cycle, we consider that $u_i$ is *available* and is not *busy* enough. Apparently, serving more sensors and increasing the traveling distance will also increase the energy consumption of $u_i$, thus making it spend more harvested energy, in other words, making it busier.

For an MC $u_i$ in a network, if it has to spend all the harvested energy to fulfill charging tasks, or adding any other sensor to $S_{u_i}$ will make it fail to complete all charging tasks (*i.e.*, cause node exhaustion), we consider that it is *busy*. In other words, for a *busy* MC, there is no spare time within a scheduling cycle besides harvesting energy and performing charging tasks.

To minimize the number of the required freeloading MCs, a straightforward method is to make full use of the MCs in $U'$. For a freeloading MC $u_i$, we tend to add sensors to $S_{u_i}$ until it is busy so that $u_i$ can serve as many sensors as possible.

*2) Duty Ratio:* For a freeloading MC $u_i$, we define its busy degree as the ratio of its consumed energy (traveling cost and charging cost) to its total harvested energy in one time period $T$, which is denoted as duty ratio $d_i$, *i.e.*,

$$d_i = \frac{C_i}{P_{u_i}(x) \cdot T}. \tag{9}$$

Obviously, a larger duty ratio indicates that the corresponding MC has heavier charging tasks. If there is no charging task for MC $u_i$, we have $d_i = 0$. In contrast, $d_i = 1$ means $u_i$ is busy since all the harvested energy will be used for charging tasks.

For a more accurate description, we use the total duty ratio $D$ to represent the number of scheduled freeloading MCs to charge sensors in $S'$. Specifically, $D$ is calculated as

$$D = \sum_{u_i \in U'} d_i. \tag{10}$$

Naturally, we have $D \leq |U'|$ since $d_i \leq 1$ for each $u_i$.

*3) Single MC Scheduling:* We introduce an algorithm named Maximizing Coverage with Single mobile charger (MCS for short), and its objective is to schedule charging tasks and construct the corresponding traveling path for a single MC.

**Algorithm 1** Maximizing Coverage with Single Mobile Charger (MCS)

1: **Input**: The set $S'$ of sensors to be charged, candidate freeloading spots $\Gamma_1, \Gamma_2, ..., \Gamma_g$, and freeloading MC $u_i$.
2: **Output**: Charging set $S_{u_i}$, freeloading spot $\Gamma_{u_i}$, traveling path $\mathcal{L}$, and duty ratio $d_i$.
3: **Initialization**: $S_{u_i} \leftarrow \varnothing$, $\mathcal{L} \leftarrow \varnothing$, $k \leftarrow 1$.
4: Select the freeloading spot $\Gamma_{u_i}$ with the maximum energy receiving power;
5: **while** $S' \neq \varnothing$ **do**
6:   **for** $\forall s \in S'$ **do**
7:     Calculate the traveling path $\mathcal{L}_i$ consisting of $S_{u_i} \cup \{s\} \cup \{\Gamma_{u_i}\}$ through the nearest neighbor strategy [31];
8:     **if** (1)-(5) hold for $S_{u_i} \cup \{s\}$ **then**
9:       Compute $d_i'$ with $S_{u_i} \cup \{s\}$;
10:     **else**
11:       Continue;
12:     **end if**
13:   **end for**
14:   $s_k \leftarrow \arg\max_{s \in S'} \{d_i' | d_i' \leq 1\}$;
15:   $S_{u_i} \leftarrow S_{u_i} \cup \{s_k\}$;
16:   $S' \leftarrow S' \backslash \{s_k\}$;
17:   $\Gamma_{u_i} \leftarrow \arg\min_{\Gamma} d_i$;
18:   Recalculate $\mathcal{L}_i$;
19:   $k \leftarrow k+1$;
20: **end while**
21: Output $S_{u_i}$, $\Gamma_{u_i}$, $\mathcal{L}_i$, and $d_i$.

To remove SCs from $O'$ and compensate charging service for sensors in $S'$, as shown in Algorithm 1, we present the detailed process of scheduling an MC to serve sensors.

Algorithm 1 works as follows. In the initial state, $S_{u_i} = \varnothing$ and $d_i = 0$ (Line 3). To ensure the network perpetuation, the energy received by a sensor should be no less than the energy it consumes in time period $T$. Hence, a straightforward method is to let MC harvest as much energy as possible. Thereby, we select the freeloading spot with the maximum energy receiving power as the initial freeloading spot (Line 4).

Afterwards, we iteratively select sensors until all sensors in $S'$ are added into $S_{u_i}$, or $u_i$ is busy and cannot serve more sensors. Specifically, in an iteration, for each sensor in $S'$, we add it to $S_{u_i}$ and rebuild the traveling path through the nearest neighbor strategy. If (1)-(5) hold for $S_{u_i} \cup \{s\}$, which means that $u_i$ is able to serve all the sensors in $S_{u_i} \cup \{s\}$, the corresponding duty ratio $d_i'$ will be calculated. Otherwise, such a sensor will be excluded (Lines 5-13). The sensor with the maximum value of $d_i'$ will be added to $S_{u_i}$. Once $S_{u_i}$ is modified, we assign the MC to harvest energy from different freeloading spots separately and obtain the corresponding duty ratio. The spot with the minimum duty ratio will be selected as the new freeloading spot $\Gamma_{u_i}$ for $u_i$. After that, $\mathcal{L}_i$ will be recalculated (Lines 14-18).

With the MCS algorithm, we can obtain the sensor set $S_{u_i}$ which will be charged by $u_i$, the corresponding freeloading spot $\Gamma_{u_i}$, traveling path $\mathcal{L}_i$, and $u_i$'s duty ratio $d_i$.

*4) Scheduling Multiple Mobile Chargers:* Since the charging capability of a single MC is limited, we hereby explore how to schedule multiple MCs to serve the network.

Based on MCS algorithm, we introduce an algorithm named

**Algorithm 2** Coverage with Minimum Number of Mobile Chargers (CMN)

1: **Input**: The set of sensors to be charged $S'$, candidate freeloading spots $\Gamma_1, \Gamma_2, ..., \Gamma_g$, and freeloading MC set $U$.
2: **Output**: Deployed mobile charger set $U'$, total duty ratio $D$, and number of mobile chargers $i$.
3: **Initialization**: $i \leftarrow 1$.
4: **while** $S' \neq \bigcup_{u_j \in U'} S_{u_j}$ **do**
5: Use the k-means clustering algorithm to partition the sensor set $S'$ into $i$ subsets $\{S'_1, S'_2, ..., S'_i\}$;
6: **for** each $S'_j$ **do**
7: Schedule mobile charger $u_j$ to cover sensors in $S'_j$ using MCS algorithm;
8: Compute $S_{u_j}$, $\Gamma_{u_j}$, and $d_j$;
9: $U' \leftarrow U' \cup \{u_j\}$;
10: **end for**
11: **if** $S' \leftarrow \bigcup_{u_j \in U'} S_{u_j}$ **then**
12: Break;
13: **else**
14: $S_r \leftarrow S' \backslash \bigcup_{u_j \in U'} S_{u_j}$;
15: **while** $S_r \neq \varnothing$ **do**
16: $s^* \leftarrow \arg\max_{s_i \in S_r} \eta_i$;
17: Distribute $s^*$ to the MC that has the minimum duty ratio increment and update its freeloading spot and traveling path;
18: **end while**
19: **end if**
20: **if** $S' \leftarrow \bigcup_{u_j \in U'} S_{u_j}$ **then**
21: Break;
22: **else**
23: $i \leftarrow i + 1$;
24: **end if**
25: **end while**
26: $D \leftarrow \sum_{u_j \in U'} d_j$;
27: Output $U'$, $D$, and $i$.

Coverage with Minimum Number of mobile chargers (CMN for short) to *coordinate multiple freeloading MCs to charge all the sensors in sensor set $S'$ while minimizing the number of required MCs*. The detailed process is given in Algorithm 2.

The algorithm is to cover all sensors in $S'$ with the minimum number of freeloading MCs. Firstly, the classic k-means clustering algorithm is applied to partition the sensor set $S'$ into subsets $\{S'_1, S'_2, ..., S'_k\}$. For each subset $S'_j$, we dispatch a freeloading MC to serve the sensors in it and obtain the corresponding charging set $S_{u_j}$, freeloading spot $\Gamma_{u_j}$, and duty ratio $d_j$ (Lines 5-10). If all subsets are covered, then the sensor set $S'$ is covered by $i$ freeloading MCs. We calculate the total duty ratio $D$ of all mobile chargers in $U'$ and output corresponding results (Lines 11-12 and Lines 26-27).

Otherwise, MCs will try to coordinate charging tasks with each other. We denote the set of uncovered sensors as $S_r$. If $S_r \neq \varnothing$, we search for the sensor with the largest energy consumption rate in $S_r$. Then, the algorithm tries to add it to each $u_i$ in $U'$ and calculate the corresponding duty ratio after adding it. If no mobile charger can serve this sensor, the algorithm will increase the number of MCs to divide $S'$ into more subsets and repeat the above process (Lines 22-24). If one or more MCs are able to serve this sensor, we select the one with the minimum duty ratio increment and recalculate the freeloading spot as well as the traveling path (Lines 13-19). The algorithm iteratively adds uncovered sensors in $S_r$ to charging sets until all uncovered sensors are covered. With this method, we can ensure the energy supply of all sensors with the minimum number of freeloading MCs.

The algorithm will eventually output freeloading MCs set $U'$, total duty ratio $D$, and the number of MCs $i$. Thereby, we have solved the first subproblem of MEFree, and the first challenge introduced in Section I is tackled.

**Algorithm 3** Global Algorithm for MEFree-R Problem

1: **Input**: Stationary chargers set $O$, sensor set $S$, mobile charger set $U$.
2: **Output**: Minimized network energy consumption $E$, selected stationary chargers set $O'$.
3: **Initialization**: $E \leftarrow |O| \cdot P_o$, $O' \leftarrow \varnothing$, $U' \leftarrow \varnothing$.
4: **while** $O \neq null$ **do**
5: **for** $\forall o_i \in O$ **do**
6: For $O'$ and $O' \cup \{o_i\}$, compute the reduced network energy consumption, denoted as $E'(O')$ and $E'(O' \cup \{o_i\})$;
7: Calculate the total duty ratio $D(O')$, $D(O' \cup \{o_i\})$ and number of mobile chargers $N(O')$, $N(O' \cup \{o_i\})$ with $O'$ and $O' \cup \{o_i\}$ through CMN algorithm (Algorithm 2);
8: **end for**
9: $o^* \leftarrow \arg\max_{o_i \in O} \frac{E'(O' \cup \{o_i\}) - E'(O')}{D(O' \cup \{o_i\}) - D(O')}$;
10: **if** $N(O' \cup \{o_i\}) \leq |U|$ **then**
11: $O' \leftarrow O' \cup \{o^*\}$;
12: **end if**
13: $O \leftarrow O \backslash \{o^*\}$;
14: **end while**
15: $E \leftarrow E - E'(O')$;
16: Output $E, O'$;

### *D. Replacing Stationary Chargers*

Another underlying problem is to select the set $O' \in O$ of redundant SCs and replace them with a limited number of freeloading MCs while guaranteeing network perpetuation. Here, we propose an algorithm based on the CMN algorithm to solve this problem with a bounded approximation ratio.

Through Algorithm 2, we can obtain the number of required MCs and corresponding duty ratio to charge a given sensor set $S'$. Therefore, for any $O' \in O$, we can obtain the corresponding sensor set $S'$ and calculate the corresponding duty ratio $D$ of freeloading MCs to charge the sensors in $S'$, which is considered as the cost of replacing SCs in $O'$. Following this idea, we iteratively add SCs to $O'$ and calculate the corresponding cost. The detailed process is described in Algorithm 3.

For each $o_i \in O$, we calculate the reduced network energy consumption $E'$ when we remove this SC, and calculate the corresponding cost of this removal, which is represented by the increase of total duty ratio $D$ of freeloading MCs (Lines 5-8). We define the cost-benefit ratio as the ratio of increased $E'$ and increased $D$ when adding a new SC $o_i$ to $O'$. In each iteration, an SC $o^*$ is selected and added to $O'$ such that the cost-benefit ratio is maximized (Lines 9-12), *i.e.*,

$$o^* = \arg\max_{o_i \in O} \frac{E'(O' \cup \{o_i\}) - E'(O')}{D(O' \cup \{o_i\}) - D(O')}. \quad (11)$$

The iteration process will be repeated until the number of required MCs exceeds $|U|$. Finally, the network energy consumption is calculated as $E = E - E'(O')$ (Line 15).

Thereby, the third challenge introduced in Section I is tackled.

## V. Theoretical Analysis

Related theoretical analyses are provided here. We prove the NP-hardness of MEFree-R problem and the approximation error of area discretization. In addition, we analyze the approximation ratio of CMN algorithm and global algorithm.

### A. NP-Hardness

***Theorem 1:*** The MEFree-R problem is NP-hard.

*Proof:* For the MEFree-R problem, the number of MCs can be considered as the cost of removing SCs while the objective is to maximize the total weight (transmitting power) of selected SCs. Thereby, it can be reduced to a variance of the budgeted maximum coverage problem [16], which is proved to be NP-hard. Moreover, when scheduling MCs and calculating the required number of MCs, we need to obtain their traveling path through solving a traveling salesman problem (TSP), which is also NP-hard. Similar to [10], we note that the two problems mentioned above are both NP-hard and are coupled with each other. Thus the MEFree-R problem is the combination of two mutual coupling NP-hard problems, which is also NP-hard. ■

### B. Approximation Error of Area Discretization

***Theorem 2:*** The approximation error introduced in area discretization (see Section IV-B) is bounded to

$$p(o_i,\Gamma_i) \geq (1-\zeta)p(o_i,x),\ \forall x \in \Gamma_i. \tag{12}$$

*Proof:* We let $l(o_i,\Gamma_i)$ denote the longest distance between SC $o_i$ and all locations in grid $\Gamma_i$. For any spot $x$ in $\Gamma_i$, we have $l(o_i,\Gamma_i) \leq l(o_i,x)+\sqrt{2}\theta$. By comparing $p(o_i,\Gamma_i)$ with $p(o_i,x)$, we have

$$\begin{aligned}
&\frac{p(o_i,\Gamma_i)}{p(o_i,x)} = (\frac{l(o_i,x)+\beta}{l(o_i,\Gamma_i)+\beta})^2 \geq (\frac{l(o_i,x)+\beta}{l(o_i,x)+\sqrt{2}\theta+\beta})^2 \\
&= (\frac{l(o_i,x)+\beta}{l(o_i,x)+\frac{\beta}{\sqrt{1-\zeta}}})^2 = (1-\zeta)(\frac{l(o_i,x)+\beta}{\sqrt{1-\zeta}l(o_i,x)+\beta})^2 \\
&\geq 1-\zeta.
\end{aligned}$$

Thus, we have proved Theorem 2. ■

### C. Approximation Ratio of CMN Algorithm

***Theorem 3:*** The CMN algorithm has a $\frac{\sqrt{2}\alpha P_o n}{\beta^2 \eta_s^i(\sqrt{n}-1)}$ approximation ratio to the optimal solution.

Firstly, we analyze the relationship between energy consumption and energy supplement of the whole network. For the optimal solution, we have

$$E^r_{OPT} \geq \sum_{u_i \in U} C^i_{OPT}, \tag{13}$$

where $E^r_{OPT}$ is the total received energy of freeloading MCs in the optimal solution.

Suppose that the total received energy is evenly distributed to each MC, and the average received energy is denoted as $E^{avg}_{OPT}$. We have the following equation:

$$N^* \cdot E^{avg}_{OPT} \geq \sum_{u_i \in U} C^{(e,i)}_{OPT} + C^{(t,i)}_{OPT}, \tag{14}$$

where $N^*$ is the number of required MCs in optimal solution.

Similarly, for the approximated solution, we have

$$E^r_{APPR} \geq \sum_{u_i \in U} C^i_{APPR}, \tag{15}$$

where $E^r_{APPR}$ is the total received energy in an approximated solution. By evenly distributing the total received energy to each freeloading MC, we can get

$$N' \cdot E^{avg}_{APPR} \geq \sum_{u_i \in U} C^{(e,i)}_{APPR} + C^{(t,i)}_{APPR}, \tag{16}$$

where $N'$ is the number of required MCs in the approximated solution, which is the output of CMN algorithm.

For the optimal solution, we replace the average energy $E^{avg}_{OPT}$ by the *maximum received energy* of a single MC (denoted as $E^{max}_{OPT}$). For the approximated solution, we replace $E^{avg}_{APPR}$ by the *minimum used energy* of a single MC (denoted as $E^{min}_{APPR}$). Thus we have

$$N^* \cdot E^{max}_{OPT} \geq \sum_{u_i \in U} C^{(e,i)}_{OPT} + C^{(t,i)}_{OPT}, \tag{17}$$

$$N' \cdot E^{min}_{APPR} \leq \sum_{u_i \in U} C^{(e,i)}_{APPR} + C^{(t,i)}_{APPR}. \tag{18}$$

By combining (17) and (18), we have

$$\frac{N'}{N^*} \leq \frac{E^{max}_{OPT}}{E^{min}_{APPR}} \cdot \frac{\sum_{u_i \in U}(C^{(e,i)}_{APPR} + C^{(t,i)}_{APPR})}{\sum_{u_i \in U}(C^{(e,i)}_{OPT} + C^{(t,i)}_{OPT})}. \tag{19}$$

We calculate the maximum received energy in optimal solution by $E^{max}_{OPT} = \frac{\alpha \cdot P_o}{\beta^2} \cdot T$. For the minimum used energy in approximated solution, we have $E^{min}_{APPR} = \eta_{i,s} \cdot T$, where a freeloading MC serves a single sensor in a scheduling period.

The charging cost of the optimal solution and approximated solution are the same, because the sensors' energy consumption in the two solutions are identical. For the traveling cost, we replace the traveling cost in the optimal solution by the minimum traveling cost of visiting each sensor. The traveling cost in approximated solution is no more than $\sqrt{2}nL \cdot \sigma$, which is larger than the maximum traveling cost for visiting each sensor. Thus, we can reformulate Equation (19) as

$$\begin{aligned}
\frac{N'}{N^*} &\leq \frac{\frac{\alpha \cdot P_o}{\beta^2} \cdot T}{\eta_{i,s} \cdot T} \cdot \frac{\sqrt{2}nL \cdot \sigma + \sum_{u_i \in U} C^{(t,i)}_{APPR}}{\frac{nL}{\lceil \sqrt{n} \rceil} \cdot \sigma + \sum_{u_i \in U} C^{(t,i)}_{OPT}} \\
&\leq \frac{\frac{\alpha \cdot P_o}{\beta^2} \cdot T}{\eta_{i,s} \cdot T} \cdot \frac{\sqrt{2}nL \cdot \sigma}{(\sqrt{n}-1)L \cdot \sigma} = \frac{\sqrt{2}\alpha P_o n}{\beta^2 \eta_{i,s}(\sqrt{n}-1)},
\end{aligned} \tag{20}$$

where $\frac{L}{\lceil \sqrt{n} \rceil}$ is the uniform interval of adjacent sensors.

Thereby, the number of required MCs obtained by the CMN algorithm is smaller than $\frac{\sqrt{2}\alpha P_o n}{\beta^2 \eta_{i,s}(\sqrt{n}-1)}$ of the optimal solution, and Theorem 3 is proved. ■

### D. Approximation Ratio of Global Algorithm

***Theorem 4:*** Our scheme achieves the approximation ratio of $\frac{1}{2}(1-\frac{1}{e})$ with a slightly relaxed budget, and its total time complexity is $O(n^4k^3m^2)$.

In area discretization, we randomly choose a spot within every uniform grid as candidate freeloading spots for MCs, which probably increases the traveling path of MCs. However, the increased path length for each MC will not exceed $2\sqrt{2}\theta = 2\beta(\frac{1}{\sqrt{1-\zeta}}-1)$, which is twice the longest distance within a grid. As a result, according to [32], a slightly relaxed budget is required to achieve the approximated solution, and it has a bounded approximation ratio if the objective function of the problem is *nonnegative, monotone, and submodular*.

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

- $f(\varnothing) = 0$ and $f(A) \geq 0$ for all $A \subseteq \mathcal{V}$ *(nonnegative)*;
- $f(A) \leq f(B)$ for all $A \subseteq B \subseteq \mathcal{V}$ or equivalently: $f(A \cup \{e\}) - f(A) > 0$ for all $A \subseteq \mathcal{V}$ and $e \in \mathcal{V} \backslash A$ *(monotone)*;
- $f(A) + f(B) \geq f(A \cup B) + f(A \cap B)$, for any $A, B \subseteq \mathcal{V}$ or equivalently: $f(A \cup \{e\}) - f(A) \geq f(B \cup \{e\}) - f(B)$, $A \subseteq B \subseteq \mathcal{V}$, $e \in \mathcal{V} \backslash B$ *(submodular)*;

*Proof:* It is obvious that the objective function $E' = 0$ when the result set is empty, since network consumption will not be reduced if no SC is removed. Meanwhile, once the result set is not an empty set, the objective function $E'$ will be greater than 0. Thereby, $E'$ is nonnegative.

We note that adding an SC into the result set (replacing this charger by freeloading MCs) will certainly increase the value of objective function $E'$. Thus, $E'$ is monotone.

Since the energy consumption rate of SCs (transmitting power) is a uniform constant, we note that the increment of objective function when an SC is newly added will not be influenced by the size of the result set. In any case, adding the same SC to the result set will produce a constant increment of the objective function value. Hence, $E'$ is submodular. ■

Since $E$ is nonnegative, monotone, and submodular, the global algorithm can achieve at least $\frac{1}{2}(1 - \frac{1}{e})$ of the optimal solution with a slightly relaxed budget [32].

For the time complexity, the MCS algorithm has a $O(n^4)$ time complexity, and the CMN algorithm achieves the time complexity of $O(n^4k^3)$. The global algorithm has at most $m$ iterations, within which $m$ calculations and $m$ calls of CMN algorithm are conducted. As a result, the total time complexity is $O(n^4k^3m^2)$.

## VI. Simulation Analysis

We carry out extensive simulations to evaluate the performance of our proposed algorithm from several aspects: error threshold of area discretization, number of available MCs, number of sensors, and the number of SCs.

### A. Simulation Setup

In our simulation, 100 rechargeable sensors are uniformly deployed in a $100m * 100m$ 2D network to perform sensing tasks continuously. To provide energy supply, 40 stationary wireless chargers are deployed in the network to serve the sensors around them with the help of WPT technology. The sensors receive energy from the chargers to support their sensing tasks, thus guaranteeing the perpetual functionality of the network.

It should be mentioned that in most previous studies, electromagnetic induction is applied for wireless charging. However, influenced by the intrinsic feature of electromagnetic induction, the receiver can only harvest milliwatts of power [14], leading to a long period of charging time for freeloading. In our work, *magnetic resonance coupling* approach is utilized to realize the WPT. The transmission distance can be up to 1 meter and the energy efficiency is around $60\%$ [33], [34], thus ensuring the energy supply for freeloading MCs.

Our proposed scheme aims at replacing several redundant SCs with freeloading MCs to save network energy consumption as much as possible. Referring to [35], related parameters are set as: $\alpha = 15$, $\beta = 10$, $\delta = 1.4$, and $\sigma = 4$, which are similar to the settings in actual situations.

### B. Baseline Setup

As far as we know, there is no existing scheme that applies the notion of freeloading MCs to reduce energy consumption. Thereby, we choose several baseline algorithms for comparison: maximum duty ratio algorithm (MDR), maximum MC energy algorithm (MME), and random algorithm (RAN).

MDR algorithm seeks for maximizing the duty ratio of each mobile charger. MME algorithm tries to maximize the energy received by freeloading MCs during the scheduling process. RAN algorithm randomly replaces SCs. Moreover, we use *Ours* to represent our proposed scheme for short.

### C. Simulation Results and Analysis

Generally, we compare the simulations with theoretical analysis (see Figure 11). The numerical results indicate that the theoretical result is approximately $3\%$ higher than the simulation result, and their variation trends are identical. This demonstrates that our simulation results are consistent with the theoretical analysis. The detailed simulation analyses are given in the following.

Firstly, we analyze the influence of the error threshold $\zeta$. As shown in Figure 3, when $\zeta$ increases from 0.1 to 0.6, the saved network energy consumption of the four algorithms decreases gradually. We note that in area discretization, the grid side length $\theta = \frac{\sqrt{2}}{2}\beta(\frac{1}{\sqrt{1-\zeta}} - 1)$ becomes larger when $\zeta$ increases. Larger grids will reduce the approximation accuracy of charging power, leading to degradation of algorithm performance. Generally, our proposed scheme outperforms other algorithms by $16.8\%$ on average in saving wasted energy.

Then, we analyze the influence of the number of available MCs. As shown in Figure 4, when the number of MCs increases from 30 to 80, the saved network energy consumption of Ours, MDR, and MME algorithms increases significantly at the beginning and gradually become stable. With more available MCs provided, it is feasible to replace more SCs with freeloading MCs to save energy. Nevertheless, when more SCs are removed, the opportunities for MCs to freeload will be fewer as well. It should be noted that when the number of remaining SCs reduces to a certain extent (when MC number reaches 70), the number increase of available MCs will not evidently improve the performance of the network. We conclude that in the aspect of available MCs, our proposed scheme outperforms other algorithms by $10.1\%$ at least and $17.4\%$ on average.

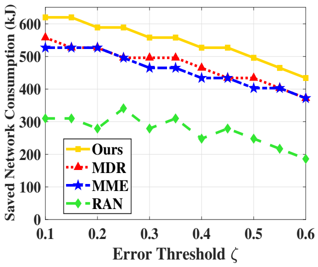



Fig. 3. Saved network consumption vs. Error threshold $\zeta$.

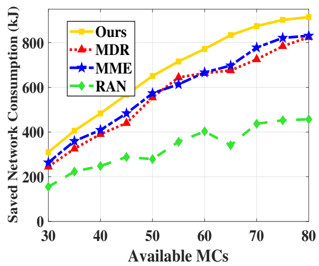



Fig. 4. Saved network consumption vs. Available MCs.

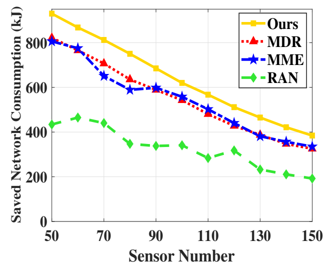



Fig. 5. Saved network consumption vs. Sensor number.

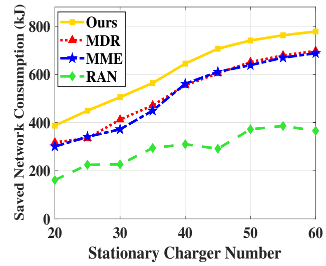



Fig. 6. Saved network consumption vs. Stationary charger number.

Thirdly, we analyze the influence of sensor number $n$. As shown in Figure 5, when the number of sensors increases from 50 to 150, the saved network energy consumption of Ours, MDR, and MME algorithms reduces accordingly, because a higher sensor density will lead to more charging tasks and a heavier scheduling burden after removing several SCs. In the scheduling process, more freeloading MCs are needed to serve sensors. Meanwhile, a higher sensor density will also shorten the distance between adjacent sensors, which reduces the burden of freeloading MCs on traveling. As a result, with the increase of sensor number, the decreasing trend of the saved energy gradually slows down. We conclude that our proposed scheme outperforms other algorithms by $17.1\%$ on average.

Fourthly, we analyze the influence of the number of SCs. As shown in Figure 6, when the number of SCs increases from 20 to 60, the saved network energy consumption of Ours, MDR, and MME algorithms increases continuously, because more SCs also increases the redundancy. Therefore, more SCs can be removed to save energy. Meanwhile, a higher SC density will optimize the SC deployment structure. Thus, the reduction of network energy consumption increases accordingly. After the SC number exceeds a certain value, the newly added chargers will contribute less to charging sensors. Thereby the increasing trend gradually stabilizes. Our proposed scheme outperforms other algorithms by $20.3\%$ on average in recycling wasted energy.

To demonstrate the performance of our scheme in recycling the wasted energy, we record the energy harvested by MCs in a period of time while setting different network parameters. As shown in Figure 7, MCs harvest a large amount of wasted energy and effectively recycle the energy for charging sensors. When the number of available MCs increases from 35 to 75, the recycled energy of MDR, MME, and Ours increases apparently. We note that our scheme effectively recycles the wasted energy and outperforms other baseline algorithms by $15.7\%$ on average.

The comparison of network energy efficiency between *with* and *without* freeloading is depicted in Figure 8. We form six different WRSNs according to the parameters in Section VI-A, marked $A$, $B$, $C$, $D$, $E$, and $F$. In each WRSN ($A$ to $F$), SCs and MCs are both utilized to charge sensors in these networks, following different deployment strategies without freeloading. Afterwards, we additionally perform freeloading schemes (Ours, MDR, and MME) in these six WRSNs and record the increased network efficiency accordingly. We conclude that Ours outperforms other baseline algorithms apparently in terms of energy efficiency. The numerical results in different networks indicate that with a slight modification of MC (enabling its freeloading ability), we can effectively improve the network efficiency by $18.8\%$ on average, compared with the case without freeloading.

## VII. Test-Bed Experiments

To highlight the outperformed feature of the proposed scheme in realistic scenes, test-bed experiments are conducted.

Firstly, to build our test-bed, we utilize COTS (Commercial-Off-The-Shelf) wireless power transmitters and install an energy harvesting module on COTS sensors. Through a slight modification, they are applied as SCs and rechargeable sensors, correspondingly. Moreover, we also equip each UAV with an energy harvesting module, which enables it to capture charging signals from the ambient environment and convert them into DC power. When an MC lands at the freeloading spot, it rotates itself to find the orientation of the antenna with the maximum energy receiving power. Moreover, each of the available UAVs (DJI Phantom 4 is adopted in our test-bed) carries a wireless power transmitter to perform charging tasks for sensors (see Figure 9) with a limited energy budget of $292.7kJ$.

Magnetic resonance coupling is also applied in our realistic deployment scenarios. Specifically, coupling coils are equipped on SCs, MCs, and sensors. The energy transmission efficiency can achieve over $70\%$ when they are close to each other [33], [34]. Thereby, the “freeloading ability” of MC is significantly enhanced and the proposed energy-recycling scheme can be conducted effectively in real scenes.

The experimental scenario is shown in Figure 10, we utilize 36 rechargeable sensors to perform sensing tasks in an open area. 15 SCs are deployed around sensors, and they send wireless signals into the surrounding environment. Afterwards, we select several SCs and replace them with UAVs, which are utilized as freeloading MCs, while ensuring all the sensors' energy supply. A UAV first chooses a freeloading spot at which it harvests energy for the following charging tour, and then travels within the network to perform charging tasks. After fulfilling all the tasks, it returns to its freeloading spot to wait for the next scheduling cycle. The color of grids indicates the frequency of MCs' appearance, showing that freeloading MCs frequently appear in the grids where panic sensors, freeloading

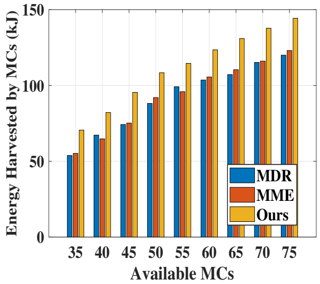



Fig. 7. The energy recycled by MCs from environment.

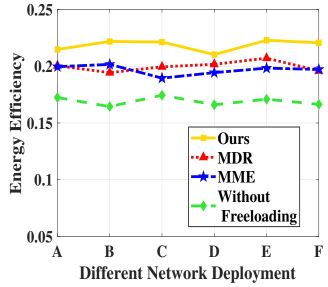



Fig. 8. Network energy efficiency: Freeloading vs. Without freeloading.


Fig. 9. Test-bed in realistic scenario: SC, freeloading MC, and sensors.

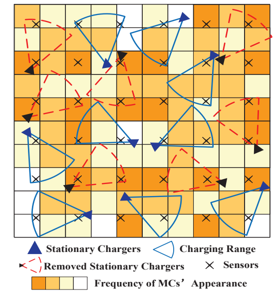



Fig. 10. Deployment of test-bed experiments.

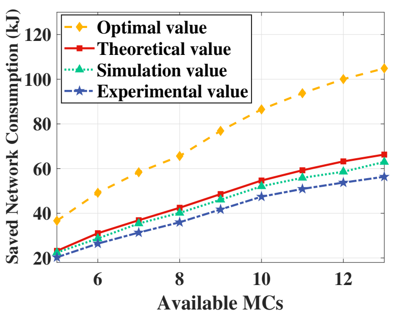



Fig. 11. Comparison among theoretical results, simulation results, and experimental results.

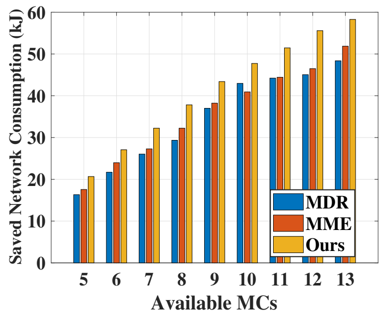



Fig. 12. Saved network consumption vs. Available MCs in test-bed experiments.

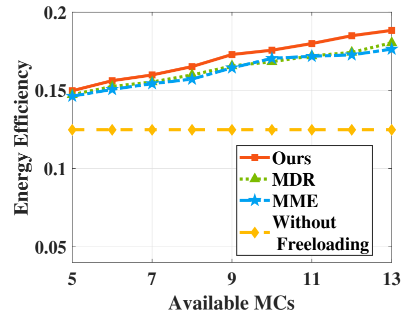



Fig. 13. Energy Efficiency vs. Available MCs in test-bed experiments.

spots, and the path between them are located (grids with a darker color).

Firstly, to demonstrate the rationality of our experiments, we compare the experimental results with theoretical results in Figure 11. The theoretical result is approximately $10\%$ higher than the experimental result, and the trends of the three curves are basically consistent. We conclude that the experimental result fits well with the theoretical analysis. The only slight gap is due to environmental disturbance and hardware noise of experimental parameters.

In Figure 11, we also depict the optimal value of the objective function. It is noted that the optimal value is obtained through the brute-force search, which is time-consuming and only applicable to small-scale networks. Through comparison, the theoretical value, simulation value, and experimental value achieve better than $\frac{1}{2}(1-\frac{1}{e})$ of the optimal value, which indicates that the approximation ratio is basically correct.

The experiments are carried out several times. Each time we change the number of available MCs and record the corresponding value of the objective function. Meanwhile, in each case, we additionally apply MDR and MME algorithms for comparison.

The experimental results of three different algorithms (Ours, MDR, and MME) with different numbers of available MCs are shown in Figure 12. When the number of available MCs changes from 5 to 13, our proposed algorithm always outperforms the other two algorithms (MDR and MME). Benefited from the recycling of wasted energy, the network energy efficiency achieves an obvious upward trend with the increase of available MCs (see Figure 13). Compared to the without-freeloading scheme, our scheme can achieve at least $17.3\%$ increment of energy efficiency.

## VIII. Conclusions

Aiming at the key problems of energy waste and low energy efficiency induced by stationary chargers in WRSN applications, this paper arms the mobile charger with an energy harvesting module to enable it to recycle wasted energy of WPT in a freeloading manner without investing extra burdens to the MC. We formulate the MEFree problem and propose several algorithms to schedule freeloading MCs reasonably while removing several redundant stationary chargers, which effectively recycles a lot of wasted energy and significantly improves the energy efficiency of the network. Theoretical analysis indicates that our scheme can achieve $\frac{1}{2}(1-\frac{1}{e})$ of the optimal solution with a slightly relaxed budget. Through extensive simulations, numerical results show the proposed scheme achieves at least $18.8\%$ energy efficiency increment while outperforming baseline algorithms by $19.1\%$ on average. Moreover, test-bed experiments demonstrate the feasibility of our scheme in realistic scenarios.

## Acknowledgments

This research is sponsored in part by the National Natural Science Foundation of China under Grant 61872052, 61872053, 61872178, 62072067, U1908214, the Xinghai Scholar Program in Dalian University of Technology, Natural Science Foundation of Liaoning Province under Grant No.2019-MS-055, Youth Science and Technology Star of Dalian under Grant 2018RQ45, Fundamental Research Funds for the Central Universities under Grant No. DUT21JC27, DUT20RC(3)039, the CCF-Tencent Open Fund under Grant IAGR20210116.

## References


[1] L. Xie, Y. Shi, Y. T. Hou, and W. Lou, "Wireless power transfer and applications to sensor networks," *IEEE Wireless Communications*, vol. 20, no. 4, pp. 140–145, 2013.

[2] Y. Yang and C. Wang, *Wireless Rechargeable Sensor Networks*. Springer International Publishing, 2015.

[3] P. Zhou, C. Wang, and Y. Yang, "Self-sustainable sensor networks with multi-source energy harvesting and wireless charging," in *IEEE INFOCOM*, 2019, pp. 1828–1836.

[4] W. Xu, W. Liang, H. Kan, Y. Xu, and X. Zhang, "Minimizing the longest charge delay of multiple mobile chargers for wireless rechargeable sensor networks by charging multiple sensors simultaneously," in *IEEE ICDCS*, 2019, pp. 881–890.

[5] T. Liu, B. Wu, S. Zhang, J. Peng, and W. Xu, "An effective multi-node charging scheme for wireless rechargeable sensor networks," in *IEEE INFOCOM*, 2020, pp. 2026–2035.

[6] X. Wang, H. Dai, W. Wang, J. Zheng, N. Yu, G. Chen, W. Dou, and X. Wu, "Practical heterogeneous wireless charger placement with obstacles," *IEEE Transactions on Mobile Computing*, vol. 19, no. 8, pp. 1910–1927, 2020.

[7] H. Dai, Y. Zhao, G. Chen, W. Dou, C. Tian, X. Wu, and T. He, "Robustly safe charging for wireless power transfer," in *IEEE INFOCOM*, 2018, pp. 378–386.

[8] N. Yu, H. Dai, A. X. Liu, and B. Tian, "Placement of connected wireless chargers," in *IEEE INFOCOM*, 2018, pp. 387–395.

[9] H. Dai, C. Wu, X. Wang, W. Dou, and Y. Liu, "Placing wireless chargers with limited mobility," in *IEEE INFOCOM*, 2020, pp. 2056–2065.

[10] T. Wu, P. Yang, H. Dai, W. Xu, and M. Xu, "Collaborated tasks-driven mobile charging and scheduling: A near optimal result," in *IEEE INFOCOM*, 2019, pp. 1810–1818.

[11] ——, "Charging oriented sensor placement and flexible scheduling in rechargeable WSNs," in *IEEE INFOCOM*, 2019, pp. 73–81.

[12] P. Wu, F. Xiao, C. Sha, H. Huang, and L. Sun, "Trajectory optimization for uavs' efficient charging in wireless rechargeable sensor networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 4, pp. 4207–4220, 2020.

[13] C. Lin, C. Guo, W. Du, J. Deng, L. Wang, and G. Wu, "Maximizing energy efficiency of period-area coverage with UAVs for wireless rechargeable sensor networks," in *IEEE SECON*, 2019, pp. 1–9.

[14] "Powercast," http://www.powercastco.com.

[15] J. R. Smith, A. P. Sample, P. S. Powledge, S. Roy, and A. V. Mamishev, "A wirelessly-powered platform for sensing and computation," in *ACM UbiComp*, 2006, pp. 495–506.

[16] S. Khuller, A. Moss, and J. Naor, "The budgeted maximum coverage problem," *Information Processing Letters*, vol. 70, no. 1, pp. 39–45, 1999.

[17] H. Dai, Y. Liu, G. Chen, X. Wu, T. He, A. X. Liu, and Y. Zhao, "SCAPE: safe charging with adjustable power," *IEEE/ACM Transactions on Networking*, vol. 26, no. 1, pp. 520–533, 2018.

[18] S. Zhang, Z. Qian, F. Kong, J. Wu, and S. Lu, "$P^3$: Joint optimization of charger placement and power allocation for wireless power transfer," in *IEEE INFOCOM*, 2015, pp. 2344–2352.

[19] L. Chen, S. Lin, and H. Huang, "Charge me if you can: Charging path optimization and scheduling in mobile networks," in *ACM MobiHoc*, 2016, pp. 101–110.

[20] C. Lin, Z. Wang, J. Deng, L. Wang, J. Ren, and G. Wu, "mTS: Temporal-and spatial-collaborative charging for wireless rechargeable sensor networks with multiple vehicles," in *IEEE INFOCOM*, 2018, pp. 99–107.

[21] W. Liang, W. Xu, X. Ren, X. Jia, and X. Lin, "Maintaining large-scale rechargeable sensor networks perpetually via multiple mobile charging vehicles," *ACM Transactions on Sensor Networks*, vol. 12, no. 2, pp. 14:1–14:26, 2016.

[22] S. Zhang, Z. Qian, J. Wu, F. Kong, and S. Lu, "Optimizing itinerary selection and charging association for mobile chargers," *IEEE Transactions on Mobile Computing*, vol. 16, no. 10, pp. 2833–2846, 2017.

[23] X. Wang, H. Dai, H. Huang, Y. Liu, G. Chen, and W. Dou, "Robust scheduling for wireless charger networks," in *IEEE INFOCOM*, 2019, pp. 2323–2331.

[24] F. Benkhelifa, H. ElSawy, J. A. McCann, and M. Alouini, "Recycling cellular energy for self-sustainable iot networks: A spatiotemporal study," *IEEE Transactions on Wireless Communications*, vol. 19, no. 4, pp. 2699–2712, 2020.

[25] S. Narayanan, M. Shikh-Bahaei, J. Hou, and M. F. Flanagan, "Wireless-powered distributed spatial modulation with energy recycling and finite-energy storage," *IEEE Transactions on Wireless Communications*, vol. 17, no. 10, pp. 6645–6662, 2018.

[26] A. A. Nasir, H. D. Tuan, T. Q. Duong, and H. V. Poor, "MIMO-OFDM-based wireless-powered relaying communication with an energy recycling interface," *IEEE Transactions on Communications*, vol. 68, no. 2, pp. 811–824, 2020.

[27] L. Phan and T. Kim, "Fast consensus-based time synchronization protocol using virtual topology for wireless sensor networks," *IEEE Internet of Things Journal*, vol. 8, no. 9, pp. 7485–7496, 2021.

[28] V. Singh, R. Kumar, and W. Zhao, "Adaptive time-switching and power-splitting protocols for energy harvesting sensor networks with multiple relays," *Comput. Networks*, vol. 179, pp. 107 341:1–10, 2020.

[29] H. Dai, Q. Ma, X. Wu, G. Chen, D. K. Y. Yau, S. Tang, X. Li, and C. Tian, "CHASE: charging and scheduling scheme for stochastic event capture in wireless rechargeable sensor networks," *IEEE Transactions on Mobile Computing*, vol. 19, no. 1, pp. 44–59, 2020.

[30] Y. Sun, C. Lin, H. Dai, Q. Lin, L. Wang, and G. Wu, "Trading off charging and sensing for stochastic events monitoring in wrsns," in *IEEE ICNP*, 2020, pp. 1–11.

[31] D. J. Rosenkrantz, R. E. Stearns, and P. M. L. II, "An analysis of several heuristics for the traveling salesman problem," *SIAM Journal on Computing*, vol. 6, no. 3, pp. 563–581, 1977.

[32] H. Zhang and Y. Vorobeychik, "Submodular optimization with routing constraints," in *AAAI*, vol. 16, 2016, pp. 819–826.

[33] Y. Li, S. Jiang, J. Liu, X. Ni, R. Wang, and J. Ma, "Maximizing transfer distance for WPT via coupled magnetic resonances by coupling coils design and optimization," *IEEE Access*, vol. 8, pp. 74 157–74 166, 2020.

[34] S. Assawaworrarit, X. Yu, and S. Fan, "Robust wireless power transfer using a nonlinear parity-time-symmetric circuit," *Nature*, vol. 546, no. 7658, pp. 387–390, 2017.

[35] C. Lin, C. Guo, H. Dai, L. Wang, and G. Wu, "Near optimal charging scheduling for 3-d wireless rechargeable sensor networks with energy constraints," in *IEEE ICDCS*, 2019, pp. 624–633.