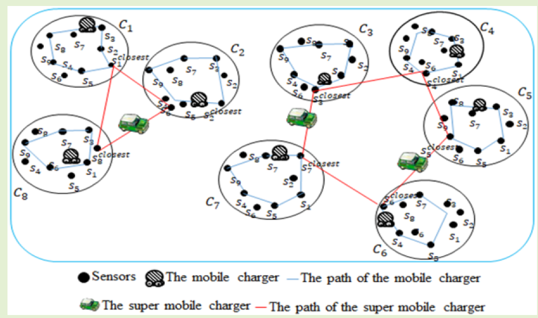
# PLPR: Joint Perpetual Lifetime and Path Reduction for Energy Recharging Using Multiple Mobile Chargers in WRSNs

Weimin Wen, Chih-Yung Chang, *Member, IEEE*, Qiaoyun Zhang, and Diptendu Sinha Roy




***Abstract*—Energy recharging is one of the most important issues in wireless rechargeable sensor networks (WRSNs). Many energy recharging algorithms have been proposed using multiple mobile chargers (MCs). However, the number of MCs that significantly impact the network lifetime of the given WRSNs still can be improved. This article proposes an energy recharging algorithm, called joint perpetual lifetime and path reduction algorithm (PLPR), which uses the MC to recharge the sensors and uses the super MC to recharge the MCs, aiming at minimizing the number of MCs and super MCs while achieving the purpose of sustainable survival of all sensors. Initially, the proposed PLPR determines the number of MCs, clusters the sensors into several groups, and constructs the initial path for each MC in each cluster. Based on these paths, the proposed PLPR further reduces the path length in each cluster and improves the recharging efficiency of the MC. To satisfy the perpetual lifetime of the MCs, the PLPR further constructs an initial path, reduces the path length, and schedules the recharging task of super MCs. Performance evaluations reveal that the proposed PLPR outperforms existing energy recharging algorithms in terms of average energy consumption, total recharging time, charging efficiency, traveling distance of MC, fairness indices, standard deviation (SD) of recharging efficiency, and average waiting time for a given WRSN.**

***Index Terms*— Energy recharging, mobile charger (MC), path reduction, perpetual lifetime, wireless rechargeable sensor network (WRSN).**

## I. INTRODUCTION

WIRELESS sensor networks (WSNs) are composed of numerous sensors that have found extensive applications across a variety of fields. One notable example is their use in traffic monitoring systems, where a diverse range of sensors are attached to trains to collect valuable information [1], [2]. WSNs have also found significant applications in industrial internet of things (IoTs), where sensor-based intelligent devices [3], [4] are interconnected to detect conditions in production lines and industrial environments, ultimately enhancing operational efficiency and environmental quality. In the domains of smart agriculture [5] and smart cities, a multitude of sensors are deployed to monitor agricultural growth and facilitate efficient irrigation of greenbelts. Moreover, sensors play a pivotal role in healthcare [7] and smart automation applications [8], as they are strategically deployed in patients and smart living spaces to detect and analyze human behavior, thereby improving overall quality of life. These sensors typically rely on battery power and are constrained by limited energy resources, making the recharging of sensors a critical challenge in WSNs. The academic community has introduced a range of strategies for recharging sensors to extend the operational lifespan of wireless rechargeable sensor networks (WRSNs), broadly categorizing these approaches into two types: a single mobile charger (MC) and multiple MCs.

In scenarios involving a single MC, research [9], [10], [11], [12], [13], [14] has focused on utilizing an MC for creating a recharging circuit that encompasses all sensor nodes. This

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Weimin Wen is with the School of Computer and Information Engineering, Chuzhou University, Chuzhou, Anhui 239000, China (e-mail: wenweim@chzu.edu.cn).

Chih-Yung Chang is with the Department of Computer Science and Information Engineering, Tamkang University, New Taipei City 25137, Taiwan (e-mail: cychang@mail.tku.edu.tw).

Qiaoyun Zhang is with the Department of Computer Science and Information Engineering, Tamkang University, New Taipei City 25137, Taiwan, and also with the School of Computer and Information Engineering, Chuzhou University, Chuzhou, Anhui 239000, China (e-mail: zqyun@chzu.edu.cn).

Diptendu Sinha Roy is with the Department of Computer Science and Engineering, National Institute of Technology, Shillong 793003, India (e-mail: diptendu.sr@nitm.ac.in).

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method ensures a systematic charging schedule with restricted movement for the MC, aiming to evenly distribute energy among all sensor nodes. However, this strategy often results in excessively long charging routes, which can cause energy depletion and failure of nodes in large-scale deployments.

In studies [15], [16], [17], [18], [19], [20], and [21], which examined scenarios involving multiple MCs, researchers partitioned the sensors into distinct clusters, with each being allocated an MC tasked with recharging the sensors within its cluster. Following this setup, each charger constructed a path passing through all sensors and recharged them in its assigned cluster. However, these studies did not tackle the issues of cluster balancing or optimizing the charging paths for efficiency. Moreover, the potential for collaboration among the MCs was overlooked.

Given multiple MCs and a set of deployed sensors, this article proposes a joint perpetual lifetime and path reduction algorithm, called PLPR, for energy recharging. The proposed PLPR explores the cooperation opportunities of multiple of MCs and super MCs, aiming to minimize the number of the MCs and super MCs while achieving the purpose of sustainable survival of all sensors. Initially, the PLPR partitions the sensors into several clusters according to the number of MCs and constructs an initial path for each MC in each cluster. To reduce the path length in each cluster, the proposed PLPR further explores a path reduction mechanism to help improve the recharging efficiency of the MCs. Then the PLPR further estimates the number of super MCs and constructs an initial path for them. Finally, the PLPR reduces the path length and dispatches the super MCs to different paths to improve the charging efficiency of the super MCs. The following highlights the contributions and key features of this article.

1) Improve the recharging efficiency: the proposed PLPR method introduces both local and global path optimization strategies for mobile and super MCs, respectively. This approach significantly enhances the charging performance of both types of chargers compared to previous studies, such as the one mentioned in [19]. As a result, it effectively extends the overall lifespan of the network.
2) Considering path reduction for overlapped sensors: this article presents a path reduction mechanism that effectively shortens the length of recharging paths while ensuring the continuous operation of WRSNs.
3) Hierarchical recharging cooperation aimed at minimizing the number of MCs and super MCs while ensuring the sustainable survival of all sensors. This article partitions the sensors into several clusters and assigns MCs to each cluster, charging cooperatively all static sensors to maintain their perpetual lifetime. The super MCs will cooperatively charge those MCs to maintain their perpetual lifetime.

The remaining parts of this article are organized as follows. Section II reviews the related works and compares them with our work. Section III presents the network environment, assumptions, and problem formulation of this article. Section IV presents the designing concepts and details of the proposed PLPR. Section V presents the performance improvement of the proposed mechanism against the existing studies. Finally, Section VI presents the conclusions.

## II. Related Work

In the academic literature, numerous studies have explored the use of MCs for recharging sensors, which can broadly be categorized into two approaches: employing a single MC or utilizing multiple MCs. Below is a brief overview of the research in these areas.

### A. Single MC

Several studies have utilized an MC to recharge all sensor nodes. For instance, Yu et al. [9] introduced a recharging path construction (RPC) mechanism designed to reduce the recharging path's length and enhance charging efficiency. The RPC mechanism starts by creating an initial path that includes all sensors. Subsequently, it partitions the sensors into groups based on their order and optimizes the path for each group. However, as the network expands, the length of the MC's path also increases, leading to the depletion of sensor node.

Feng et al. [10] proposed an efficient mobile energy replenishment scheme (MERSH) based on hybrid mode, aiming to reduce the charging duration of the sensors to minimize the charging latency and waiting time. The MERSH optimized the path of the MC and adjusted the energy consumption of the sensors in online mode.

Lyu et al. [11] proposed a hybrid particle swarm optimization genetic algorithm (HPSOGA) to cope with the problem of periodic charging plans with limited travel for MCs, aiming to maximize the docking time ratio (i.e., the ratio of charging time to total time) while ensuring the continuous operation of the sensor network and avoiding node death due to energy depletion. However, the article mentions the path optimization but does not specifically describe how to implement the path optimization shortening mechanism.

Liu et al. [12] proposed the multinode temporal special partial-charging (MTSPC) algorithm, aiming to optimize the energy usage effectiveness and the number of dead sensors. The MTSPC constructed an original path for the MC and then selected those sensors with the shortest deadline to join the path. Then the MTSPC adjusted the charging path to rescue the dropped sensors. However, the MTSPC did not consider the length of the path from the current charging sensor position to the next one. The path length can be further improved.

Ma et al. [13] proposed a multinode full-charging approximation algorithm, aiming to maximize the energy utility and minimize both the number of dead sensors and the charging path length. However, the path length of the MC increased with the network size.

Gharaei et al. [14] proposed an energy-efficient charging path optimization scheme aiming to minimize energy consumption while ensuring efficient mobility. In the scheme, it initiated the initial position and charging range of the charger. Then, it calculated the energy demand of each node based on its initial energy state and the required charging amount. After that, the scheme estimated the energy of each node and constructed the charging path. Finally, according to the constructed charging path, the charger moved along the path and charged the nodes. However, the scheme did not consider the path length from the current charging sensor position to the next one. The path length could be further improved.

### B. Multiple MCs

Lee et al. [15] proposed an energy-efficient adaptive directional charging (EEADC) algorithm, aiming to minimize energy consumption. The EEADC used the mean-shift algorithm to divide clusters according to the density of sensor nodes. Then the clusters were divided into single-charger or multicharger clusters depending on the number of sensors in each cluster. The EEADC used directional antennas to improve energy efficiency and identified the charging points and beam directions. However, EEADC did not consider reducing the charging path.

Nguyen et al. [16] proposed an MC scheduling algorithm (MCSA), aiming to minimize the number of MCs and ensure that all sensors work properly. The MCSA evaluated the average energy consumption ratio of the sensor per distance and then iteratively selected those sensors with the maximal value to charge. Then, MCSA built multiple paths and assigned them to multiple MCs. However, MCSA did not consider the reduction of path length.

Han et al. [17] proposed a mobile charging algorithm based on multicharger cooperation (MCCA), aiming to minimize the number of nonfunctional nodes. The MCCA divided the whole network into multiple uneven clusters and scheduled the collaborative charging for multiple chargers. However, MCCA did not consider the path reduction for each MC.

Madhja et al. [18] proposed an efficient hierarchical collaborative wireless charging algorithm, aiming to design efficient protocols for the coordination and charging procedure of MCs. However, the protocols did not consider the sensor waiting time and path trajectory optimization.

Almagrabi [19] proposed a fair energy division scheme (FEDS). In the FEDS, two types of MCs (WMCs) are employed to charge cluster heads and member nodes, separately. The objective of FEDS is to achieve a perpetual lifetime for member nodes and cluster heads during the cycle. However, it did not consider optimizing paths of inter-cluster and intra-cluster for a large-scale WRSN.

Tomar et al. [20] proposed an optimal and dynamic scheduling of multiple MCs, aiming to achieve efficient charging of the network's sensor nodes. This article was divided into three stages. Firstly, a threshold was determined for each sensor node. Then, the network was partitioned into different regions based on the energy distribution. Each region consisted of a varying number of sensor nodes and an MC. Finally, the sensor nodes were ranked and charged according to the ranking.

Goyal and Tomar [21] proposed a novel scheduling scheme for on-demand charging in WRSNs. Firstly, an efficient network partitioning method was introduced to distribute the MCs and balance their workload. Then, an adaptive charging threshold for the nodes was calculated using a mathematical formula. Fuzzy logic was employed to consider various network attributes and determine the charging schedule for the MCs.

The latest research trends and advancements in the field suggest that researchers are exploring more efficient path planning and energy management approaches for single MCs. This includes the distribution of sensor nodes and energy consumption models to optimize the charger's path. To achieve this, heuristic algorithms, genetic algorithms, and fuzzy logic techniques are being employed to enhance path planning and energy allocation strategies, with the goal of improving charging efficiency and extending network lifetime.

In addition, researchers are also focusing on the use of multiple MCs to further enhance charging efficiency and coverage. They are investigating coordination and cooperation among these chargers to optimize charging paths and ensure balanced charging of sensor nodes. Communication and scheduling issues are also being addressed to ensure efficient and coordinated charging.

Furthermore, there is a growing interest in exploring energy sources and conversion technologies for chargers that are more sustainable and environmentally friendly. This includes researching novel energy harvesting and conversion technologies such as solar power, vibration energy, and wireless energy transfer. The aim is to reduce reliance on traditional power grids and enhance the autonomy and reliability of chargers.

In summary, the latest research trends indicate that researchers are dedicated to improving path planning, energy management, and charger design for both single and multiple MCs. The goal is to enhance charging efficiency and prolong network lifespan, achieving more sustainable and environmentally friendly charging solutions for WSNs. This article aims to capture these trends by exploring sustainable lifecycle charging technologies for sensors and MCs, as well as attempting to shorten charging paths to improve lifecycle and charging efficiency.

While existing algorithms have focused on improving recharging efficiency and addressing energy consumption issues, they have faced challenges in large-scale scenarios. Single MC algorithms have taken a long time for each round of charging, leading to some nodes dying due to lack of energy. On the other hand, algorithms that use multiple MCs have not developed a path reduction policy. In contrast, the proposed cooperative charging algorithm, called PLPR, partitions sensors into multiple clusters and constructs initial paths for each MC in each cluster. This algorithm aims to reduce path length and improve recharging efficiency. Additionally, PLPR dispatches super MCs to different paths to further enhance charging efficiency. Table I provides a comparison between the proposed algorithm and related works.

TABLE I
COMPARISON BETWEEN PROPOSED AND RELATED WORKS

| Related works | Path reduction | Multi-node charging | Charging workload balancing | Multiple Mobile Chargers | Hierarchical recharging cooperation |
|---|---|---|---|---|---|
| [9] | ○ | × | × | × | × |
| [10] | ○ | × | × | × | × |
| [11] | ○ | × | × | × | × |
| [12] | ○ | ○ | × | × | × |
| [13] | ○ | ○ | × | × | × |
| [14] | × | × | × | × | × |
| [15] | × | × | ○ | ○ | × |
| [16] | × | ○ | × | ○ | × |
| [17] | × | ○ | ○ | ○ | × |
| [18] | × | ○ | ○ | ○ | ○ |
| [19] | × | ○ | ○ | ○ | ○ |
| [20] | × | ○ | ○ | ○ | × |
| [21] | ○ | ○ | ○ | ○ | × |
| Proposed *PLPR* | ○ | ○ | ○ | ○ | ○ |

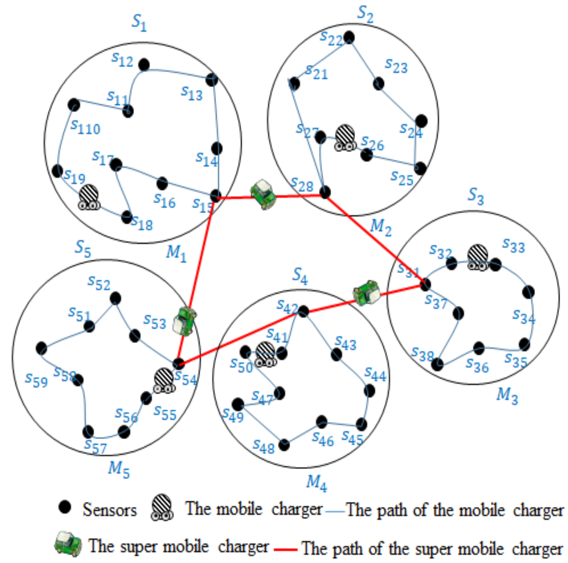



Fig. 1. WRSN model with mobile and super MCs.

## III. NETWORK ENVIRONMENT AND PROBLEM FORMULATION

This section presents the network environment and the assumptions of the given WSNs. The problem formulation is subsequently presented.

### A. Network Environment

This article assumes that a set of $n$ static sensors $S = \{s_1, s_2, \ldots, s_n\}$ is randomly deployed in an $l \times l$ monitoring region $R$. Each static sensor is powered by a rechargeable battery. Assume that $m$ is the minimal number of MCs that perform energy replenishment such that all the sensors in $S$ can maintain their perpetual lifetime. Let $M = (M_1, M_2, \ldots, M_m)$, where $m$ is to be minimized in this article. The $m$ MCs will cooperatively charge all static sensors to maintain their perpetual lifetime. Let $S_i = \{s_{i,1}, s_{i,2}, \ldots, s_{i,|S_i|}\}$ denote the set of sensors, which are charged by MC $M_i$. It is obvious that

$$S = \bigcup_{i=1}^{m} S_i.$$

Let $P_i = (s_{i,1}, s_{i,2}, \ldots, s_{i,1})$ denote the path of the MC $M_i$. The MC $M_i$ moves along the path $P_i$ to charge all sensors $s_{i,j} \in S_i$. Let $l_{i,j} = d(s_{i,j}, s_{i,(j+1)\bmod|S_i|})$ denote the distance between sensor nodes $s_{i,j}$ and $s_{i,j+1}$. Let $|P_i| = \sum_{j=1}^{|S_i|} l_{i,j}$ denote the path length of a charging cycle of mobile charge $M_i$. To support the energy requirements of $m$ MCs, this article introduces $p$ super MCs $\phi = \{\phi_1, \phi_2, \ldots, \phi_p\}$. These $p$ super MCs work collaboratively to charge the $m$ MCs, ensuring their continuous operations. To simplify the charging policy, it is assumed that the $p$ super MCs move along the same path to charge the $m$ MCs. Let $P_{\text{super}} = (\xi_1, \xi_2, \ldots, \xi_m, \xi_1)$ denote the common path of the $p$ super MCs, where $\xi_i$ denotes the stop location for recharging MC $M_i$.

Considering the varying forwarding loads of different sensors, each sensor $s_{i,j}$ has its unique energy consumption rate. To ensure efficient recharging, each MC is required to move at a constant velocity and recharge the sensors it visits. Additionally, each super MC is expected to move at a constant velocity and come to a stop at location $\xi_i$ to recharge the MC $M_i$.

Fig. 1 gives an example to illustrate the scenario considered in this article. As shown in Fig. 1, there are five MCs and three super MCs. The sensors are partitioned into five sets $\{S_1, S_2, S_3, S_4,$ and $S_5\}$. The MCs $M_1, M_2, M_3, M_4,$ and $M_5$ are dispatched to sensor sets $S_1, S_2, S_3, S_4,$ and $S_5$ along paths $P_1, P_2, P_3, P_4,$ and $P_5$, respectively. The super MCs $\phi_1, \phi_2,$ and $\phi_3$ will move along path $P_{\text{super}} = (s_{15}, s_{28}, s_{31}, s_{42},$ and $s_{54})$ and stop at locations $s_{15}, s_{28}, s_{31}, s_{42},$ and $s_{54}$ to recharge MCs $M_1, M_2, M_3, M_4,$ and $M_5$.

### B. Recharging Model

The following presents the recharging model of this article. Let $P_i$ denote the path along which the MC $M_i$ moves and then stops for charging all sensors $s_{i,j} \in S_i$. The MC $M_i$ should guarantee that the battery of each sensor in the cluster $S_i$ is fully recharged. Let $d$ be the distance between $M_i$ and $s_{i,j}$. The obtained energy of sensor $s_{i,j}$ is decreased with $d$. Let $P^t_{M_i}$ denote the recharging power applied by the MC $M_i$ at time $t$. Let $G^s$ denote the energy transmission gains between $M_i$ and $s_{i,j}$, and $G^r$ denote the energy receiving gains between $M_i$ and $s_{i,j}$. Let $L^P$ denote the energy loss, $P^r_{s_{i,j}}$ denote the energy received by $s_{i,j}$, and $\lambda$ denote the amplitude. According to Friis's free space equation [22], the recharging power obtained by $s_j$ from the MC $M_i$ can be formulated as the following equation:

$$P^r_{s_{i,j}} = \frac{G^r G^s \eta}{L^P}\left(\frac{\lambda}{4\pi\,(d+\beta)}\right)^2 P^t_{M_i} \tag{1}$$

where $\eta$ is referred to as rectifier efficiency and $\beta$ is a parameter to adjust the Friis transmission equation for the short distance transmission. Equation (1) is a cornerstone in antenna theory for radio communications. It relates the transmitted power, antenna gains, distance, wavelength, and received power, allowing us to calculate the power received by an antenna from another antenna at a given distance. However, when applied to the domain of WSN charging, the Friis equation has some limitations. Firstly, it assumes ideal conditions, such as free-space propagation with no obstacles or obstructions. In real-world WSNs, the environment is often complex, with obstacles such as walls, furniture, and other objects that can attenuate or reflect the wireless signals. These factors can significantly reduce the actual received power compared to the predictions made using the Friis equation.

### C. Problem Description

This article essentially studies the cooperation of multiple MCs and super MCs aiming to minimize the number of the MCs and super MCs while achieving sustainable survival for all sensors. Equation (1) reflects the goal of this article.

The objective

$$\text{Min}\,(m+p)\,. \tag{2}$$

The following are some constraints that should be satisfied when achieving the objectives outlined in (2).

Let $\mathcal{L}_{i,j}$ denote the survival time of sensor $s_{i,j}$ in the cluster $S_i$. The value of $\mathcal{L}_{i,j}$ can be measured by

$$\mathcal{L}_{i,j} = \frac{B_{\text{sensor}}}{e_{i,j}^{\text{consume}}} \tag{3}$$

where $B_{\text{sensor}}$ denotes the battery capacity of each sensor and $e_{i,j}^{\text{consume}}$ is the energy consumption rate of sensor $s_{i,j}$ in different working time. Let $T_{\text{car},i}^{\text{round}}$ denote the total time length of each round of MC $M_i$. This includes the movement time along path $P_i$, the time to recharge all sensors $s_{i,j} \in S_i$, and the time to recharge the MC itself. Let $e_{s_{i,j},t_j}^{\text{rem}}$ denote the residual energy of $s_{i,j}$ in cluster $S_i$ at time $t_j$. Let $e_{\text{sensor}}^{\text{charge}}$ denote the recharging rate, which is the energy obtained by the sensor per unit of time. Let $B_{\text{car}}$ denote the battery capacity of each MC. Let $e_{M_i,t_i}^{\text{rem}}$ denote the remaining energy of the MC $M_i$ at time $t_i$. Let $e_{\text{car}}^{\text{charge}}$ denote the recharged energy obtained by the MC per unit of time from the super MC. The value $T_{\text{car},i}^{\text{round}}$ is expressed as

$$T_{\text{car},i}^{\text{round}} = \frac{|P_i|}{v} + \left(\sum_{j=1}^{|S_i|} \frac{B_{\text{sensor}} - e_{s_{i,j},t_{\text{sensor},t_j}^{\text{rech}}}^{\text{rem}}}{e_{\text{sensor}}^{\text{charge}}}\right) + \frac{B_{\text{car}} - e_{M_i,t_{\text{car},i}^{\text{rech}}}^{\text{rem}}}{e_{\text{car}}^{\text{charge}}} \tag{4}$$

where $t_{\text{sensor},t_j}^{\text{rech}}$ denotes the starting time point of sensor $s_{i,j}$ to be recharged, $t_{\text{car},i}^{\text{rech}}$ denotes the starting time point of MC $M_i$ to be recharged, and $v$ is the traveling speed of MC. Equation (4) depicts that the round time length $T_{\text{car},i}^{\text{round}}$ of MC $M_i$ consists of its traveling time on path $P_i$, the time for recharging all sensors $s_{i,j} \in S_i$, and its own recharging time from the super MC.

To guarantee that the sensor $s_{i,j}$ can be charged by the MC $M_i$ before it runs out of energy, the following time constraint of the MC should be satisfied.

Time constraint of the MC

$$\min\nolimits_{1\le j\le |S_i|} \mathcal{L}_j \ge T_{\text{car},i}^{\text{round}}\,. \tag{5}$$

Let $E_{\text{car}}^{\text{round}}$ denote the energy consumption of MC $M_i$ for each round. Let $e_i^{\text{move}}$ denote the energy consumption of MC $M_i$ for moving on path $P_i$ per unit length. Let $e_{\text{car}}^{\text{consume}}$ denote the energy consumption of MC $M_i$ for recharging the sensor per unit time. Let $\alpha_{\text{car,sensor}}$ denote the charging conversion rate of MC to sensor. The value of $E_{\text{car}}^{\text{round}}$ is measured by

$$E_{\text{car}}^{\text{round}} = |P_i| * e_i^{\text{move}} + \sum_{j=1}^{|S_i|} \frac{B_{\text{sensor}} - e_{s_{i,j},t_j^{\text{rech}}}^{\text{rem}}}{\alpha_{\text{car,sensor}}} * e_{\text{car}}^{\text{consume}} \tag{6}$$

where $t_j^{\text{rech}}$ denotes the time point that the MC arrives at sensor $s_{i,j}$ and $e_{s_{i,j},t_j^{\text{rech}}}^{\text{rem}}$ is the residual energy of $s_{ij}$ at time $t_j^{\text{rech}}$.

Let $B_{\text{car}}$ denote the battery capacity of the MC. To ensure that the energy consumption of each MC $M_i$ for charging all sensors in path $P_i$ is less than or equal to the battery capacity, the following constraint should be satisfied.

Energy consumption constraint of the MC

$$E_{\text{car}}^{\text{round}} \le B_{\text{car}}. \tag{7}$$

In this article, another important constraint is that the MC $M_i$ can be charged by the super MC before it runs out of energy. Let $T_{\text{super}}^{\text{round}}$ denote the time length of each round of the super MC. Let $|P_{\text{super}}|$ denote the path length of the super MC. Let $T_{\text{super}}$ denote the time length required for the super MC to travel a unit distance. The $T_{\text{super}}^{\text{round}}$ can be expressed as

$$T_{\text{super}}^{\text{round}} = |P_{\text{super}}| * T_{\text{super}} + \sum_{i=1}^{m} \frac{\left(B_{\text{car}} - e_{M_i,t_{\text{car},i}^{\text{rech}}}^{\text{rem}}\right)}{e_{\text{car}}^{\text{charge}}} \tag{8}$$

where $t_{\text{car},i}^{\text{rech}}$ denotes the starting time point of MC $M_i$ to be recharged.

To ensure that each MC $M_i$ can be charged at the designated stop location before it runs out of energy. Notation $T_{\text{car},i}^{\text{round}}$ should satisfy the following constraint.

Time constraint of the super MC

$$\min_{1\le i\le m} T_{\text{car},i}^{\text{round}} \ge T_{\text{super}}^{\text{round}}. \tag{9}$$

Let $e_{\text{super}}^{\text{move}}$ denote the energy consumption of the super MC for moving on path $P_{\text{super}}$ per unit length. Let $\alpha_{\text{super,car}}^{\text{charge}}$ denote the loss rate of charging from super MC to MC. Let $e_{\text{super}}^{\text{consume}}$ denote the energy consumption of the super MC for recharging each MC per unit time. Let $B_{\text{super}}$ denote the battery capacity of each super MC. To guarantee that the energy consumption of each super MC for each round must be less than or equal to its battery capacity, the following constraint should be satisfied.

Energy consumption constraint of the super MC

$$|P_{\text{super}}| * e_{\text{super}}^{\text{move}} + \sum\nolimits_{i=1}^{m} \frac{B_{\text{car}} - e_{M_i,t_{\text{car},i}^{\text{rech}}}^{\text{rem}}}{\alpha_{\text{super,car}}^{\text{charge}}} * e_{\text{super}}^{\text{consume}} \le B_{\text{super}}. \tag{10}$$

## IV. Joint Energy Conservation and Collision Avoidance for Paths Construction

The proposed PLPR algorithm is composed of four phases. Firstly, the initialization phase aims to determine the minimal number of MCs, partition the sensors into multiple clusters, and finally construct an initial path for each MC in each cluster. Then the second phase, called local path reduction phase, aims to reduce the path length in each cluster. This helps improve the recharging efficiency of the MC. The third phase, called super MC phase, aims to determine the number of super MCs and construct an initial path for them. Finally, the global path reduction phase aims to reduce the path length and dispatch the super MCs to different paths for improving the charging efficiency of the super MCs.

### A. Initialization Phase

This phase aims to determine the minimal number of MCs and construct an initial path for them. To achieve this goal, there are three tasks designed in this phase. The first task aims to estimate the minimal number of MCs in an $l \times l$ monitoring region $R$. Then the second task aims to partition the WSN $S$ into multiple clusters. Finally, the last task aims to construct an initial path for each MC to recharge the sensors in each cluster. Next, the following presents the design of each task.

*1) Task 1 Estimating the Number of MCs:* This task aims to estimate the number of MCs. Assume that $m$ is the minimum number of MCs which can support the perpetual lifetime of $S$. This task aims to estimate the value of $m$. To balance the recharging workloads, each MC will be responsible for recharging $(n/m)$ sensors. Let $S_i = \{s_{i,1}, \ldots, s_{i,n/m}\}$ be the set of assigned $(n/m)$ sensors. Assuming that there are $n$ static sensors regularly deployed in a monitoring region $R$ with size $l \times l$, the $n$ sensors equally partition the monitoring region. Each partition with size $(l \times l/n)$ will have one static sensor node on average. Therefore, the average distance between two adjacent sensor nodes is $\sqrt{(l \times l/n)}$. Let $P_i$ be the shortest path which passes through all sensors $s_{i,j} \in S_i$. The total length of path $P_i$, denoted by $|P_i|$, is $\sqrt{(l \times l/n)} \times (n/m)$. Recall that $e_i^{\text{move}}$ denotes the energy consumption of MC $M_i$ to move on path $P_i$ for a unit length. Let $E_i^{\text{move}}$ denote the total energy consumption of MC $M_i$ for moving the whole path $P_i$. It is calculated as follows:

$$E_i^{\text{move}}(m) = \sqrt{\frac{l \times l}{n}} \times \frac{n}{m} \times e_i^{\text{move}} + \vartheta \tag{11}$$

where $E_i^{\text{move}}$ is a function of $m$ and $\vartheta$ is the efficiency factor of MCs, including friction loss, air resistance, and other losses during mechanical transmission.

In addition to moving on path $P_i$, the other source of energy consumption of MC $M_i$ is to recharge the sensors $s_{i,j} \in S_i$. Let $E_i^{\text{recharge}}$ denote the total energy consumption of MC $M_i$ for recharging all the sensors $s_{i,j} \in S_i$. The $E_i^{\text{recharge}}$ can be derived by

$$E_i^{\text{recharge}}(m) = \sum_{j=1}^{\frac{n}{m}} e_{\text{car}}^{\text{consume}} \times \frac{B_{\text{sensor}} - e^{\text{rem}}_{s_{i,j}, t_j^{\text{rech}}}}{\alpha_{\text{car,sensor}}}. \tag{12}$$

Recall that $E_{\text{car},i}^{\text{round}}$ denotes the total energy consumption of $M_i$ for recharging all the sensors $s_{i,j} \in S_i$. For each round, the MC $M_i$ requires energy to travel along path $P_i$, recharge $(n/m)$ sensors, and account for the efficiency factor $\vartheta$. The $E_{\text{car},i}^{\text{round}}$ can be expressed as

$$E_{\text{car},i}^{\text{round}}(m) = E_i^{\text{move}}(m) + E_i^{\text{recharge}}(m) + \vartheta \tag{13}$$

which is a function of $m$ where all the other parameters are known. According to the constraint (7), we have

$$E_{\text{car},i}^{\text{round}}(m) \le B_{\text{car}}. \tag{14}$$

Let $o_{\min}$ be the smallest value of $o$ which satisfies (15). Let $m_1$ be the value of $E_{\text{car},i}^{\text{round}}(o_{\min})$. That is,

$$m_1 = E_{\text{car},i}^{\text{round}}(o_{\min}). \tag{15}$$

Let $T_i^{\text{move}}$ denote the time for MC $M_i$ to move the whole path $P_i$. The value of $T_i^{\text{move}}$ can be derived by

$$T_i^{\text{move}}(m) = \frac{\sqrt{\frac{l \times l}{n}} \times \frac{n}{m}}{v} \tag{16}$$

where $T_i^{\text{move}}$ is a function of $m$.

Let $T_i^{\text{recharge}}$ denote the total time for MC $M_i$ to recharge all the sensors $s_{i,j} \in S_i$. The $T_i^{\text{recharge}}$ can be derived by

$$T_i^{\text{recharge}}(m) = \sum_{j=1}^{\frac{n}{m}} \frac{B_{\text{sensor}} - e^{\text{rem}}_{s_{i,j}, t^{\text{rech}}_{\text{sensor},j}}}{e_{\text{sensor}}^{\text{charge}}} \tag{17}$$

where $t_{\text{sensor},j}^{\text{rech}}$ denotes the starting time point of sensor $s_{i,j}$ to be recharged.

Recall that $T_{\text{car},i}^{\text{round}}$ denotes the time length of each round for MC $M_i$ to recharge all the sensors $s_{i,j} \in S_i$. The $T_{\text{car},i}^{\text{round}}$ can be expressed as

$$T_{\text{car},i}^{\text{round}} = T_i^{\text{move}}(m) + T_i^{\text{recharge}}(m) + \frac{B_{\text{car}} - e^{\text{rem}}_{M_i t^{\text{rech}}_{\text{car},i}}}{e_{\text{car}}^{\text{charge}}} \tag{18}$$

where $t_{\text{car},i}^{\text{rech}}$ denotes the starting time point of MC $M_i$ to start recharging.

Similarly, according to the time constraint of the MC, we have

$$T_{\text{car},i}^{\text{round}}(m) \le \min_{s_{i,j} \in S_i} \mathcal{L}_j. \tag{19}$$

Let $\mathcal{L}_{\text{sensor}}^{\min}$ denote the minimum survival time of all sensors $s_{i,j} \in S_i$. The value of $\mathcal{L}_{\text{sensor}}^{\min}$ can be measured by

$$\mathcal{L}_{\text{sensor}}^{\min} = \min_{s_{i,j} \in S_i} \mathcal{L}_j. \tag{20}$$

Let $\varsigma_{\min}$ be the smallest value of $\varsigma$ which satisfies the following equation:

$$T_{\text{car},i}^{\text{round}}(m) \le \mathcal{L}_{\text{sensor}}^{\min}. \tag{21}$$

Let $m_2$ denote be the value of $T_{\text{car},i}^{\text{round}}(\varsigma_{\min})$. That is,

$$m_2 = T_{\text{car},i}^{\text{round}}(\varsigma_{\min}).$$

The number $m$ of MCs can be obtained by

$$m = \max(m_1, m_2). \tag{22}$$

*2) Task 2 Cluster Partition:* The first task estimates the number of MCs. In the second task, the machine learning algorithm, hierarchical clustering (HC), will be applied to partition the sensors in $S$ into $m$ clusters $C = \bigcup_{1\le i\le m} C_i$ such that each MC can be assigned to recharge the sensors in each cluster. The HC algorithm will perform the following steps. Initially, each sensor in $C$ will form an individual cluster. In each round, the two nearest clusters are merged into one. All sensors in the monitoring region will be merged round by round until $m$ clusters are formed. In the process of cluster merging, the distance is used to measure whether or not two clusters should be merged. Let $w_x$ and $w_y$ denote two clusters. Let $d(w_x, w_y)$ denote the minimal distance between sensors $s_i \in w_x$ and $s_j \in w_y$, that is,

$$d\left(w_x, w_y\right) = \min\nolimits_{\forall s_i\in w_x, \forall s_j \in w_y} d\left(s_i, s_j\right). \tag{23}$$

The two clusters $w_x$ and $w_y$ that have minimal distance among all possible pairs will be merged into a new cluster $w_{h=(x,y)}$ in each round. Let $w_x^{\text{best}}$ and $w_y^{\text{best}}$ denote the two clusters which satisfy (16)

$$\left(w_x^{\text{best}}, w_y^{\text{best}}\right) = \arg\min_{w_x, w_y \in R} d\left(w_x, w_y\right). \tag{24}$$

Then clusters $w_x^{\text{best}}$ and $w_y^{\text{best}}$ will be merged into a larger one, say $w_{h=(x,y)}$. The merging process will be repeatedly applied until the number of clusters is $m$.

*3) Task 3 Initial Path Construction for Each MC:* This task aims to construct an initial path for each cluster. The path will pass through all sensors in each cluster so that the MC can recharge all sensors in the cluster along this path. Let $C_i = \{s_{i,1}, \ldots, s_{i,\lfloor \frac{n}{m} \rfloor}\}$ denote the set of sensors and $\Psi = \{e_1, e_2, \ldots e_{\lfloor \frac{n}{m} \rfloor -1}\}$ denote the set of edges between sensors. Let $s_{i,1}$ denote the initial node. According to [23], the *Dijkstra*'s algorithm is applied to construct the shortest path for the MC $M_i$.

| | |
|---|---|
| | ***/* Initialization Phase */*** |
| | **Inputs: A set of *n* static sensors and the size of the monitoring region *R*** **Output: The initial recharging path of all mobile chargers** |
| **1** | Assume that $n$ sensors equally partition the monitoring region. Each partition with size $\frac{l\times l}{n}$ will have one static sensor node in average. |
| **2** | Calculate the path length of each mobile charger $\lvert P_i \rvert$ |
| **3** | Calculate $E_i^{move}(m)$ according to Exp. (11) |
| **4** | Calculate $E_i^{recharge}(m)$ according to Exp. (12) |
| **5** | Calculate $E_{car,i}^{round}(m)$ according to Exp. (13) |
| **6** | If $(E_{car,i}^{round}(m) \le B_{car})$ |
| **7** | $\{\, m_1 = E_{car,i}^{round}(\, o_{min}) \,\}$ |
| **8** | Calculate $T_i^{move}(m)$ according to Exp. (16) |
| **9** | Calculate $T_i^{recharge}(m)$ according to Exp. (17) |
| **10** | Calculate $T_{car,i}^{round}$ according to Exp. (18) |
| **11** | If $(T_{car,i}^{round}(m) \le \mathcal{L}_{sensor}^{min})$ |
| **12** | $\{m_2 = T_{car,i}^{round}(\varsigma_{min})\}$ |
| **13** | Calculate $m$ according to Exp. (22) |
| **14** | Applying the *HC* algorithm to partition the sensors in $S$ into $m$ clusters $C$=$\bigcup_{1\le i\le m} C_i$ |
| **15** | Applying the *Dijkstra*'s algorithm to construct the shortest path $P_i$=$(s_{i,1}, s_{i,2}, \ldots, s_{i,\lvert S_i \rvert})$ for each cluster $C_i$ |

## B. Local Path Reduction Phase

This phase aims to reduce the path length for each MC, improving the recharging efficiency of the MC. To achieve this goal, two cases should be considered. First, if the recharging range of neighboring sensors overlap, the MC can find a point inside the overlapped region. Then, the MC stops at this point to recharge all overlapped sensors. As a result, the MC does not need to visit these overlapped sensors one by one. Second, the path length between three adjacent sensors will be optimized in each cluster. Section IV-B presents the design of each case.

*1) Path Reduction for Overlapped Sensors:* The case considers the overlapped region of the charging ranges of some sensors. Without loss of generality, assume that the charging ranges of $\varrho$ sensors $s_1, s_2, \ldots, s_\varrho$ overlap and the overlapped region is formed by $q$ intersection points $p_1, \ldots, p_q$. Let $\Phi_1, \Phi_2, \ldots, \Phi_\varrho$ denote the charging ranges of those sensors $s_1, s_2, \ldots, s_\varrho$. Let $(x_i, y_i)$ denote the coordinates of point $p_i$. The central point $p_{\text{center}}$ of this region can be derived by

$$p_{\text{center}} = \left(\frac{\sum_{i=1}^{q}(x_i)}{q}, \frac{\sum_{i=1}^{q}(y_i)}{q}\right). \tag{25}$$

The required energy for sensor $s_i$ is as follows:

$$e_{s_i, t_{\text{sensor},i}^{\text{rech}}}^{\text{requir}} = B_{\text{sensor}} - e_{s_i, t_{\text{sensor},i}^{\text{rech}}}^{\text{rem}}. \tag{26}$$

Let vector $v$ consist of $k$ tuples

$$v = \left(e_{s_1, t_{\text{sensor},1}^{\text{rech}}}^{\text{requir}}, \ldots, e_{s_k, t_{\text{sensor},k}^{\text{rech}}}^{\text{requir}}\right).$$

Let $\vec{d_i}$ denote the vector from point $p_{\text{center}}$ to sensor $s_i$. Let the central point have $k$ forces $\vec{f_i} = (\vec{d_i}, \varphi_i)$, $1 \le i \le k$, where $\varphi_i$ denotes the value of force $\vec{f_i}$. Assign the values of $\vec{d_i}$ and $\varphi_i$ by setting

$$\vec{d_i} = \vec{f}_{p_{\text{center}}, s_i}, \varphi_i = e_{s_i, t_{\text{sensor},ik}^{\text{rech}}}^{\text{requir}}.$$

Let $\vec{F} = (x_{\vec{F}}, y_{\vec{F}})$ denote the resultant force. We have

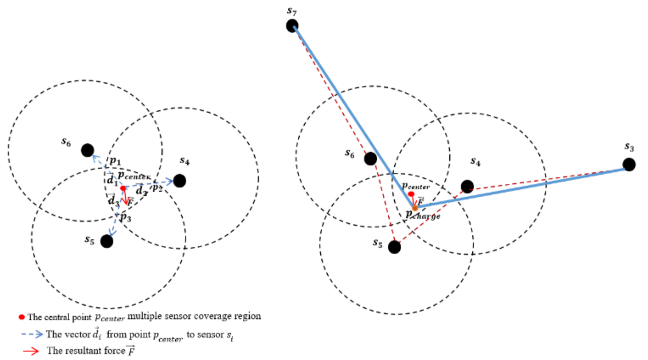
$$\vec{F} = \sum\nolimits_{1\le i\le \varrho} \vec{f}_{i,s_i} \tag{27}$$

Let $p_{\text{charge}} = (x_{\text{charge}}, y_{\text{charge}})$ denote the charging point of the $k$ sensors. The charging location can be derived by

$$x_{\text{charge}} = x_i + x_{\vec{F}}, y_{\text{charge}} = y_i + y_{\vec{F}}. \tag{28}$$

Fig. 2 gives an example to illustrate how to reduce the recharging path of the overlapped sensors.

As shown in Fig. 2(a), there are three nodes $s_4$, $s_5$, and $s_6$ whose charging ranges overlap. The intersection points of the overlapped region are $p_1$, $p_2$, and $p_3$. The red dot is the central point $p_{\text{center}}$. The blue arrows $\vec{d_4}, \vec{d_5}$, and $\vec{d_6}$ are the vector from point $p_{\text{center}}$ to sensors $s_4$, $s_5$, and $s_6$, respectively. According to (27), the resultant force $\vec{F}$ is calculated using the red arrow as shown in Fig. 2(a). The charging point of the three sensors $p_{\text{charge}}$ is calculated using the yellow polka dot as shown in Fig. 2(b). Finally, the




(a) (b)

Fig. 2. Example of reducing the recharging path of overlapping sensors. (a) Computing the center point $p_{\text{center}}$ and the resultant force $\vec{F}$ in those overlapping sensor areas. (b) Computing the charging point $p_{\text{charge}}$ and connecting the charging path.

previous sensor $s_7$ and the successive sensor $s_3$ will connect to the charging point $p_{\text{charge}}$ to construct the new path as shown in Fig. 2(b).

Herein, it is noticed that the path reduction operation can be applied repeatedly in case there are more than one charging point. If it is the case, the charging point, which is covered by the largest number of sensors, will be applied path reduction operation first. Then, the covered sensors will be removed. This implies that the covered sensors can be recharged. After that, the path reduction operation will be repeatedly applied to the remaining charging points until there is no charging point.

*2) Case 2: Path Reduction for Every Three Adjacent Sensors:* The path reduction mechanism will be applied to each group $C_i, 1 \leq i \leq m$. The following presents the path reduction operation. Assume that group $C_i$ has $q$ sensors $\{s_{i,1}, s_{i,2}, \ldots, s_{i,q}\}$. Herein, it is noticed that there is a path $P_i = (s_{i,1}, s_{i,2}, \ldots, s_{i,q})$ passing through each sensor in group $C_i$. The goal of this phase is to reduce the path length of $P_i$. To achieve this, the sensors in $C_i$ will be initially partitioned into $q/3$ partitions. Each partition consists of three neighboring sensors. Let $P_{i,j}$ denote $j$th partition, that is,

$$\begin{aligned} P_{i,1} &= \{s_{i,1}, s_{i,2}, s_{i,3}\}, \\ P_{i,2} &= \{s_{i,4}, s_{i,5}, s_{i,6}\}, \ldots, \\ P_{i,q/3} &= \{s_{i,q-2}, s_{i,q-1}, s_{i,q}\}. \end{aligned}$$

The following operations will be applied to each partition. Consider the partition $P_{i,j} = \{\hat{s}_{a-1}, \hat{s}_a, \hat{s}_{a+1}\}$. Let $l(\hat{s}_{a-1}, \hat{s}_{a+1})$ denote the line connecting $\hat{s}_{a-1}$ and $\hat{s}_{a+1}$. Let $p_1$ and $p_2$ denote the intersecting points of the recharging range of sensor $s_a$ and line $l(\hat{s}_{a-1}, \hat{s}_{a+1})$. There are two cases. First, there are intersecting points of recharging sensor $s_a$ and line $l(\hat{s}_{a-1}, \hat{s}_{a+1})$ as shown in Fig. 3. The other case is that there is no intersecting point as shown in Fig. 4.

Consider the first case. Let $\text{len}(l(p_1, p_2))$ denote the length of $l(p_1, p_2)$. Assume that the initial location of MC is $p_1$ and the time is counted starting from $t = 0$. Let $p_{1,2}^t$ denote the point on $l(p_1, p_2)$, which represents the location of MC at time $t$. Let $\pi_t = d(s_a, p_{1,2}^t)$ denote the shortest distance from

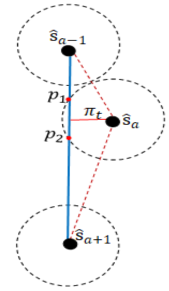
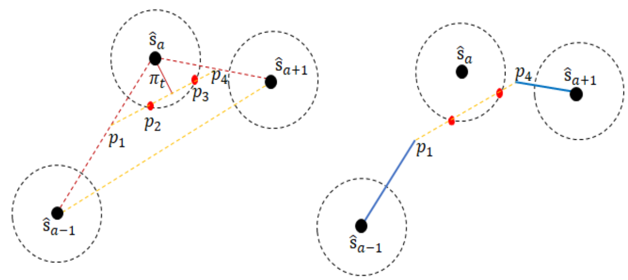


Fig. 3. Example of path reduction with intersection points.



(a) (b)

Fig. 4. Example of initial and reduced recharging paths. (a) Initial recharging path. (b) Reduced recharging path.

$s_a$ to point $p_{1,2}^t$ at time $t$. Let $E^{\text{gain}}$ denote the recharging energy of sensor $\hat{s}_a$ obtained from the MC $M_i$. The $E^{\text{gain}}$ can be expressed as

$$E^{\text{gain}} = \int_0^{\frac{\text{len}(l(p_1,p_2))}{v}} \frac{1 \times P_{\hat{s}_a}^r}{\pi_t^2} dt. \tag{29}$$

To guarantee the full recharge of sensor $\hat{s}_a$, the following equation should be satisfied:

$$B_{\text{sensor}} - e^{\text{rem}}_{\hat{s}_a, t^{\text{rech}}_{\text{sensor},a}} \leq E^{\text{gain}}. \tag{30}$$

In case that constraint (30) is satisfied, the mobile recharger $M_i$ moving along the line $l(\hat{s}_{a-1}, \hat{s}_{a+1})$ with a constant velocity $v$ can fully recharge the batteries of sensors $\hat{s}_{a-1}$, $s_a$ and $\hat{s}_{a+1}$. As a result, the original recharging path

$$P_i = (s_{i,1}, \ldots, \hat{s}_{a-1}, \hat{s}_a, \hat{s}_{a+1}, \ldots, s_{i,q})$$

can be replaced by the new recharging path

$$P_i^{\text{new}} = (s_{i,1}, \ldots, \hat{s}_{a-1}, \hat{s}_{a+1}, \ldots, s_{i,q}).$$

It is obvious that $\text{len}(P_i^{\text{new}}) \leq \text{len}(P_i)$.

The following further discusses the other case in which the line $l(\hat{s}_{a-1}, \hat{s}_{a+1})$ and recharging range do not have two intersection points, as shown in Fig. 4(a). The red dotted line represents the initial recharging path. Let $\hat{s}_a$ be the middle sensor of partition. The path reduction can be achieved by the following operations. Let $l(\hat{s}_{a-1}, \hat{s}_{a+1})$ denote the line connecting $\hat{s}_{a-1}$ and $\hat{s}_{a+1}$. We shift $l(\hat{s}_{a-1}, \hat{s}_{a+1})$ toward $s_a$ until the distance between sensor $s_a$ and the shifted line meets a certain condition. Assume that $p_2$ and $p_3$ denote the intersecting points of sensor $\hat{s}_a$ with $l(\hat{s}_{a-1}, \hat{s}_{a+1})$. Assume that the initial location of MC is $p_2$ and the time is counted

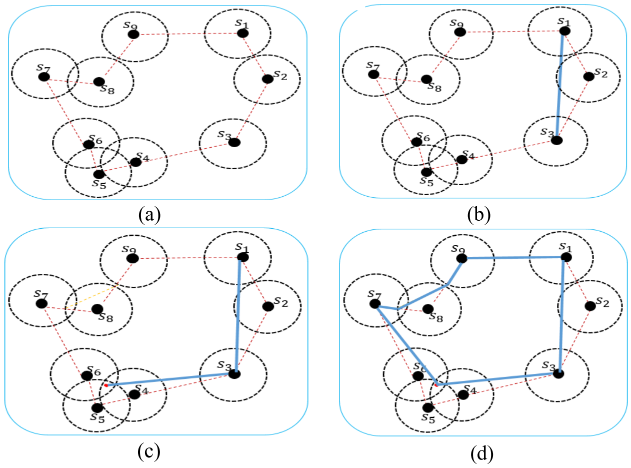


Fig. 5. Example to illustrate the local path reduction algorithm. (a) Initial path $P_i$. (b) Adjusting the subpath ($s_1, s_2$, and $s_3$). (c) Adjusting the subpath ($s_4, s_5$, and $s_6$). (d) Adjusting the subpath ($s_7, s_8$, and $s_9$) and connecting the reduced path $P_i^{\text{new}}$.

starting from $t = 0$. Let $p_{2,3}^t$ denote the point on $l(p_2, p_3)$, which is the location of MC at time $t$. Let $\pi_t = d(s_a, p_{2,3}^t)$ denote the shortest distance from $s_a$ to point $p_{2,3}^t$ at time $t$. Let $E^{\text{gain}}$ denote the recharging energy of sensor $\hat{s}_a$ obtained from the MC $M_i$. The $E^{\text{gain}}$ can be expressed as

$$E^{\text{gain}} = \int_0^{\frac{\text{len}(l(p_2,p_3))}{v}} \frac{1 \times P_{\hat{s}_a}^r}{\pi_t^2} dt. \tag{31}$$

To fully recharge sensor $\hat{s}_a$, the two points $p_2$ and $p_3$ should satisfy constraint (30).

As a result, the original recharging path

$$P_i = (s_{i,1}, \ldots, \hat{s}_{a-1}, \hat{s}_a, \hat{s}_{a+1}, \ldots, s_{i,q})$$

can be replaced by the new recharging path

$$P_i^{\text{new}} = (s_{i,1}, \ldots, \hat{s}_{a-1}, p_2, p_3, \hat{s}_{a+1}, \ldots, s_{i,q}).$$

It is obvious that $\text{len}(P_i^{\text{new}}) \leq \text{len}(P_i)$.

The abovementioned path reduction mechanism will be applied to each partition to reduce the path length of $P_i$ while ensuring that each sensor can be guaranteed to be fully recharged.

The following gives an example to illustrate the local path reduction algorithm. Fig. 5(a) shows the initial path $P_i$ of MC $M_i$. Then the MC aims to reduce the length of $P_i$. To achieve this, the MC partitions the sensors into three groups. As shown in Fig. 5(b), sensors $s_1, s_2$, and $s_3$ belong to the same group. There are two intersecting points between recharging range of sensor $s_2$ and line $l(s_1, s_3)$. Since the line $l(s_1, s_3)$ passes through the recharging ranges of $s_1, s_2$, and $s_3$, the mobile recharger moving along the line $l(s_1, s_3)$ with a constant velocity $v$ can fully recharge the batteries of sensor $s_1$, $s_2$, and $s_3$. As a result, the original recharging path $P_i = (s_1, s_2, s_3, s_4, \ldots, s_9)$ can be replaced by the new recharging path $P_i^{\text{new}} = (s_1, s_3, s_4, \ldots, s_9)$. It is obvious that $\text{len}(P_i^{\text{new}}) \leq \text{len}(P_i)$. The repetitions of executing the path reduction are shown in Fig. 5(c) and (d), respectively. Finally, the path reduction constructs the new path as shown in Fig. 5(d).

## C. Super MC Phase

This phase aims to determine the minimal number of super MCs and construct an initial path for them. To achieve this, this phase consists of two tasks. The first task aims to estimate the minimal number of super MCs. Then the second task aims to construct an initial path for the super MCs to recharge the MCs. The following presents the details of each task.

*1) Task 1: Estimating the Number of Super MCs:* This task aims to estimate the number of super MCs. Recall that there are $m$ clusters, and each MC can be assigned to recharge the sensors in each cluster. Assume that $p$ is the minimal number of super MCs that can provide the necessary energy supplement to the MCs. This task aims to estimate the value of $p$. The value of $p$ can be derived by considering the time and energy constraints of the super MC. Firstly, consider the time constraint of the super MC. The round time of the super MC should be smaller than each round time of the MC. This ensures that the MCs do not have to wait for the super MC. The following constraint reflects the time constraint of the super MC:

$$T_{\text{super}}^{\text{round}}(p) \leq \min_{M_i \in M} T_{\text{car},i}^{\text{round}} \tag{32}$$

where $T_{\text{super}}^{\text{round}}$ denotes the time length of each round of the super MC. Recall that $T_{\text{car},i}^{\text{round}}$ denotes the time length of each round of MC $M_i$, which includes the time required for moving along path $P_i$ and recharging all sensors $s_{i,j} \in S_i$. Let $T_{\text{car}}^{\text{round}}$ denote the minimum round time of all MCs $M_i \in M$. Let $p_{\min}$ be the smallest value of $p$ which satisfies the following equation

$$T_{\text{car}}^{\text{round}}(p) = \min_{M_i \in M} T_{\text{car},i}^{\text{round}}. \tag{33}$$

Let $p^{\text{min\_time}}$ be the value of $T_{\text{car}}^{\text{round}}(p_{\min})$, which satisfies the time constraint given in (34). We have

$$p^{\text{min\_time}} = T_{\text{car}}^{\text{round}}(p_{\min}). \tag{34}$$

Let $E_{\text{super}}^{\text{round}}$ denote the energy consumption of the super MC for each round. The $E_{\text{super}}^{\text{round}}$ can be expressed as

$$E_{\text{super}}^{\text{round}}(p) = \left( \left| P_{\text{super}} \right| * e_{\text{super}}^{\text{move}} + \sum_{i=1}^{m} \frac{B_{\text{super}} - e_{M_i, t_{\text{car},i}^{\text{rech}}}^{\text{rem}}}{\alpha_{\text{super,car}}^{\text{charge}}} * e_{\text{super}}^{\text{consume}} \right) * p \tag{35}$$

where $E_{\text{super}}^{\text{round}}(p)$ is a function of $p$.

According to the energy constraint given in constraint (10), we have

$$E_{\text{super}}^{\text{round}}(p) \leq p * B_{\text{super}}. \tag{36}$$

Let $p_{\min}$ be the smallest value of $p$ which satisfies (21)

$$E_{\text{super}}^{\text{round}}(p_{\min}) \leq p * B_{\text{super}}.$$

Let $p^{\text{min\_energy}}$ be the minimal value of $p$ which satisfies (37). We have

$$p^{\text{min\_energy}} = E_{\text{super}}^{\text{round}}\left(p_{\min}\right). \quad (37)$$

As a result, the number of super MCs can be obtained by applying the following equation:

$$p = \max\left(p^{\text{min\_time}}, p^{\text{min\_energy}}\right). \quad (38)$$

*2) Task 2: Initial Path Construction for Super MCs:* This task aims to construct an initial path for super MCs. The proposed PLPR algorithm will select one sensor from each cluster and construct a path that passes through the selected sensors. The selected sensor will be the rendezvous point for the MC in that cluster and super MCs. Therefore, the super MCs can recharge each MC along this path. The following describes how to select one sensor from each cluster and then construct a path passing through the selected sensors.

Recall that there are $m$ clusters $C = \{C_1, C_2, \cdots, C_m\}$ and each MC is assigned to one cluster to recharge the sensors in that cluster. Let $c_i(x_i^{\text{center}}, y_i^{\text{center}})$ denote the coordinates of center point in each cluster $C_i$. Let $P_c(x_c^{\text{center}}, y_c^{\text{center}})$ denote coordinates of the center point in the whole monitoring region $R$. The central point $P_c$ can be obtained by the calculation

$$P_c = \left(\frac{\sum_{i=1}^{m} x_i^{\text{center}}}{m}, \frac{\sum_{i=1}^{m} y_i^{\text{center}}}{m}\right). \quad (39)$$

Let $s_i^{\text{closest}}$ denote the minimal distance from sensor node $s_j \in C_i$ to $P_c$ in each cluster $C_i$. The proposed PLPR will select the sensor $s_i^{\text{closest}}$ from cluster $C_i$. The $s_i^{\text{closest}}$ can be expressed as

$$s_i^{\text{closest}} = \arg\min_{s_j \in C_i} d(P_c, s_j). \quad (40)$$

Let $P^{\text{super}}$ denote the shortest path passing through all the selected sensors. Then the *Dijkstra*'s algorithm is applied to connect all the selected sensors to construct the shortest path $P^{\text{super}}=(s_1^{\text{closest}}, s_2^{\text{closest}}, \ldots, s_m^{\text{closest}})$ for the super MC.

The following example illustrates the process of constructing the initial path for super MCs using the proposed PLPR algorithm. Fig. 6(a) depicts the monitoring region $R$ containing $m$ clusters, each denoted by $C_i$. The objective of PLPR is to construct an efficient initial path for the super MCs to traverse.

*Step 1: Cluster Center and Region Center Identification:*

Firstly, the PLPR algorithm computes the coordinates of the center point $c_i$ for each cluster $C_i$, as well as the central point of the entire monitoring region $R$ [Fig. 6(b)]. This step is crucial for determining the relative positions of clusters and identifying potential starting points for the super MCs' path.

*Step 2: Selection of Representative Sensors:*

Subsequently, from each cluster $C_i$, the PLPR algorithm selects a representative sensor $s_i^{\text{closest}}$ that is closest to the cluster's center point $c_i$ [Fig. 6(c)]. By connecting these representative sensors $s_1^{\text{closest}}, s_2^{\text{closest}}, \ldots, s_m^{\text{closest}}$, the algorithm aims to establish a preliminary framework for the shortest possible path that the super MCs will follow.

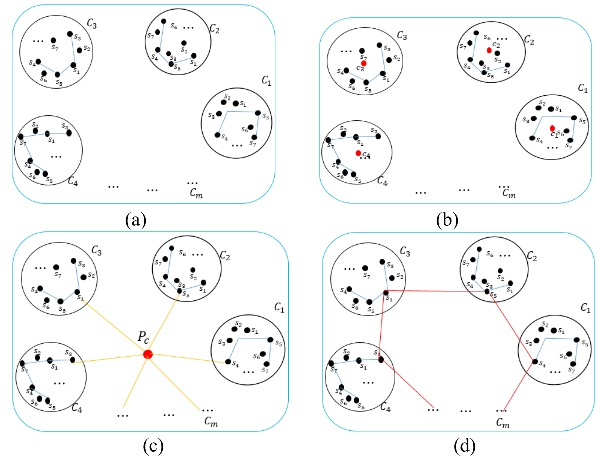


Fig. 6. Example of constructing the initial path for super MCs. (a) Monitoring region $R$. (b) Calculating the central point $c_i$ of each cluster. (c) Selecting all the closest sensor $s_i^{\text{closest}}$ from each cluster to $P_c$. (d) Connecting all the selected sensors to construct the shortest path for super MCs.

*Step 3: Construction of the Initial Path:*

Finally, based on the connected representative sensors, the PLPR algorithm constructs the initial path for the super MCs, as shown in Fig. 6(d). This path is designed to minimize the total travel distance while ensuring that all clusters are visited in an efficient manner. The initial path serves as a starting point for further optimization or refinement, if necessary.

## D. Global Path Reduction Phase

This phase aims to reduce the length of $P^{\text{super}}$, aiming to improve the recharging efficiency of the super MCs. To achieve this goal, there are two tasks designed in this phase. The first one aims to reduce the length of $P^{\text{super}}$. This might break the path $P^{\text{super}}$ into several disjoint cycles such that the longest edge can be removed. Then, the second task aims to assign super MCs to the cycles. The following presents the design of each task.

1) *Task 1: Global Path Reduction of Super MCs:* This task aims to reduce the length of $P^{\text{super}}$. The proposed PLPR algorithm calculates the length of each edge in the path. Then, it finds the longest edge, breaks it, and then reconstructs the path. Recall that $P^{\text{super}} = (s_1^{\text{closest}}, s_2^{\text{closest}}, \ldots, s_m^{\text{closest}})$. Let $L_{\text{initial}}^{\text{super}} = (L_1, L_2, \ldots, L_m)$, where $L_i$ denotes the edge between $s_i^{\text{closest}}$ and $s_{i+1}^{\text{closest}}$, that is, $L_i=(s_i^{\text{closest}}, s_{i+1}^{\text{closest}})$. Let $\text{len}(L_i)$ denote the length of edge $L_i$. Let $L^{\max}$ denote the longest edge in $L_{\text{initial}}^{\text{super}}$, that is,

$$L^{\max} = \max_{Li \in P^{\text{super}}} \text{len}(L_i). \quad (41)$$

As shown in Fig. 7(a) and (b), the edge $L^{\max}$ with maximal length has been identified. This phase aims to break this edge and another edge $L_i$ and then connects the end points of the two edges such that the original path can be partitioned into two paths. In the case that the total length of the two partitioned paths is smaller than the original path length, then the path should be partitioned in this way. However,

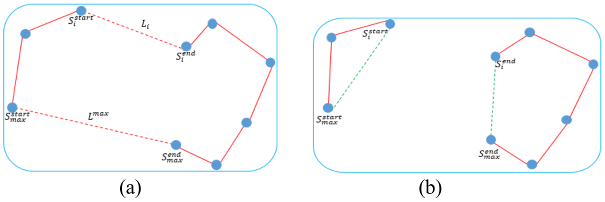



Fig. 7. Example to illustrate the operation pattern of SSEE. (a) Finding the longest edge $L^{\max}$ and selecting the edge $L_j$. (b) Connecting $S_{\max}^{\text{start}}$ to $S_i^{\text{start}}$ and the $S_{\max}^{\text{end}}$ connects to $S_i^{\text{end}}$.

to obtain the minimal length of the two partitioned paths, the edge $L_i$ should be carefully selected. Once the best $L_i$ has been identified, the connection of the end points of the two edges $L^{\max}$. Let $L_i = (S_i^{\text{start}}, S_i^{\text{end}})$. Recall that the $L^{\max} = (S_{\max}^{\text{start}}, S_{\max}^{\text{end}})$. The connection of the two edges can be achieved by SSEE, which denotes start–start + end–end. In the operation of SSEE, the $S_{\max}^{\text{start}}$ connects to $S_i^{\text{start}}$ and the $S_{\max}^{\text{end}}$ connects to $S_i^{\text{end}}$. The following defines connection operation $\odot$, which operates on $L^{\max}$ and $L_i$, aiming to connect the four points $S_i^{\text{start}}$, $S_i^{\text{end}}$, $S_{\max}^{\text{start}}$ and $S_{\max}^{\text{end}}$:

$$L^{\max} \odot L_i = (d\left(S_{\max}^{\text{start}}, S_i^{\text{start}}\right) + d\left(S_{\max}^{\text{end}}, S_i^{\text{end}}\right) - d\left(S_{\max}^{\text{start}}, S_{\max}^{\text{end}}\right) - d\left(S_i^{\text{start}}, S_i^{\text{end}}\right) \tag{42}$$

where $d(S_{\max}^{\text{start}}, S_i^{\text{start}})$ denotes the length of two cluster $S_{\max}^{\text{start}}$ and $S_i^{\text{start}}$.

Let $L^{\text{best}}$ denote the minimum path length for all $L_i \in P_{\text{super}}$, that is,

$$L^{\text{best}} = \arg\min_{Li \in P_{\text{super}}} \left(L^{\max} \odot L_i\right). \tag{43}$$

The best edge that should be broken can be determined by (41). Then, the two edges $L^{\max} = (S_{\max}^{\text{start}}, S_{\max}^{\text{end}})$ and $L^{\text{best}} = (S_{\text{best}}^{\text{start}}, S_{\text{best}}^{\text{end}})$ will be broken, the $S_{\max}^{\text{start}}$ connects to $S_i^{\text{start}}$, and the $S_{\max}^{\text{end}}$ connects to $S_i^{\text{end}}$.

Let $P$ and $P^{\text{partition}}$ denote the original path and the partitioned path, respectively. Let $L_{\text{initial}}^{\text{super}}$ and $L_{\text{adjusted}}^{\text{super}}$ denote the path length of $G$ and $G^{\text{partition}}$, respectively. In the case that the following equation is satisfied, the original path will be partitioned by breaking the two edges $L^{\max}$ and $L^{\text{best}}$:

$$L_{\text{adjusted}}^{\text{super}} < L_{\text{initial}}^{\text{super}}. \tag{44}$$

The path partitioning operation will be applied to each subpath to obtain a shorter path step by step.

2) *Task 2: Assigning Super MCs:* This task aims to assign the super MCs to the partitioned subpaths. Let $p$ be the number of super MCs. Let the number of partitioned subpaths be $q$ and $P^1, \ldots, P^q$ denote the $q$ subpaths. The proposed PLPR algorithm will assign $n^i$ super MCs to subpath $P^i$, where

$$n^i = \left\lfloor |P^i| \Big/ \sum_{k=1}^{q} |P^k| \right\rfloor \times p. \tag{45}$$

The following pseudo-algorithm summarizes the proposed method.

**Algorithm: *PLPR***
**Inputs: A set of $n$ static sensors $S = \{s_1, s_2 \cdots, s_n\}$ and the size of the monitoring region $R$**
**Output: The recharging path of all mobile chargers and super mobile chargers**

/* *Initialization Phase* */
/* Calculate the number of mobile chargers */
Calculate $m$ according to Exp. (22)
Applying the *HC* algorithm to partition the sensors in $S$ into $m$ clusters $C = \bigcup_{1 \le i \le m} C_i$
Applying the *Dijkstra*'s algorithm to construct the shortest path $P_i = (s_{i,1}, s_{i,2}, \ldots, s_{i,|S_i|})$ for each cluster $C_i$
/* *Local Path Reduction Phase* */
For each cluster $C_i \in C$ do{
Case 1: /* Intersection case *
If $(\Phi_1 \cap \Phi_2 \cap \ldots \cap \Phi_k \neq \emptyset)$
/*Calculate the central point in this region */
{Calculate $p_{center}$ according to Equ. (25)
/*Calculate the required energy for each sensor $s_j$ in overlapped region */
For ($j$=1, $j \le |S_i|$, $j$++) {
Calculate $e_{s_j, t_{sensor,j}^{rech}}^{requir}$ according to Equ. (26);}
/* Calculate the resultant force */
Calculates $\vec{F}$ according to Equ. (27);
/*Calculate the coordinates of the charging point*/
Calculate $p_{charge}$ according to Equ. (28);}
Case 2: /* Disjoint case */
Partition $S_i$ into $|S_i|/3$ groups;
Let $P_{i,j}$ denote the $j$-th group;
For ($j$=1, $j \le |S_i|/3$, $j$++) {
If $(s_a \cap l(\hat{s}_{a-1}, \hat{s}_{a+1}) \neq \emptyset)$
{ Calculate $E^{gain}$ according to Equ. (29);
If $(B_{sensor} - e_{\hat{s}_a, t_{sensor,a}^{rech}}^{rem} \le E^{gain})$
$P_i^{new} = (s_{i,1}, \ldots, \hat{s}_{a-1}, \hat{s}_{a+1}, \ldots, s_{i,q})$;
else
{ Calculates $E^{gain}$ according to Equ. (31);
If $(B_{sensor} - e_{\hat{s}_a, t_{sensor,a}^{rech}}^{rem} \le E^{gain})$
$P_i^{new} = (s_{i,1}, \ldots, \hat{s}_{a-1}, p_2, p_3, \hat{s}_{a+1}, \ldots, s_{i,q})$ ; } };
End for
/* *Super Mobile Charger Phase* */
/* Calculate the number of super mobile chargers */
Calculate $p$ according to Exp. (37);
Applying the *Dijkstra*'s algorithm to construct the shortest path $P^{super} = (s_1^{closest}, s_2^{closest}, \ldots, s_m^{closest})$;
/* *Global Path Reduction Phase* */
$L_i = (s_i^{closest}, s_{i+1}^{closest})$ for all $L_i \in L_{initial}^{super}$;
$L^{max} = \max_{L_i \in P^{super}} len(L_i)$;
For each $L_i \in L_{initial}^{super}$
{ Calculate $L^{max} \odot L_i$ according to Equ. (42);
$L^{best} = arg \min_{L_i \in P_{super}} (L^{max} \odot L_i)$ ;
If ( $L_{adjusted}^{super} < L_{initial}^{super}$)
Break edges $L^{max}$ and $L^{best}$;
Connect $S_{max}^{start}$ and $S_i^{start}$; Connect $S_{max}^{end}$ and $S_i^{end}$;}}
Applying the path partitioning operation to each subpath ;
Calculates $n^i$ according to Equ. (45);

## E. Complexity Analysis

The proposed PLPR mainly consists of the initialization phase, local path reduction phase, super MC phase, and the global path reduction phase. Recall that $m$ denotes the number of MCs. In the initialization phase, the complexities of steps 1, 2, and 3 are $O(m)$, $O(n \times n \log n)$, and $O((|S_i|-1) \times \log|S_i|)$, respectively. Therefore, the complexity of the initialization phase is $O(n \times\ n \log n)$.

The following presents the complexity analysis of local path reduction phase, which consists of steps 4–24. Step 4 performs the *for*-instruction with $m$ times. The complexity of step 4 is $O(m)$. The complexities of step 5 and step 6 are $O(k)$. In step 7, the charging ranges of $k$ sensors $s_1, s_2, \ldots, s_k$ are overlapped and the overlapped region is formed by $q$ intersection points. The computational complexity of step 7 is $O(q)$. Since step 7 is enclosed by step 4, its complexity is $O(mq)$. The complexity of step 8 is $O(m|S_i|)$ since it is enclosed by step 4. In step 9, the required energy for sensor $s_i$ is $e^{\text{requir}}_{s_i, t^{\text{rech}}_{\text{sensor},j}}$. However, step 9 is enclosed by steps 4 and 8. Hence, the complexity of the step 9 is $O(m^2|S_i|)$. The complexities of steps 10, 11, and 13 are $O(m^2|S_i|k)$, $O((m^2|S_i|)$, and $O(m^3|S_i|)$, respectively. Similarly, the complexities of steps 13, 15, 16, and 17 are $O(m|S_i|)$, $O(m|S_i|)$, $O(m|S_i|)$, and $O(m|S_i|\text{len}(l(p_1, p_2)))$, respectively. The complexities of steps 18 and 19 are $O(m|S_i|)$. The complexities of steps 21, 22, and 23 are $O(m|S_i|(\text{len}(l(p_2, p_3))/v))$, $O(m\ \ |S_i|)$, and $O(m\ \ |S_i|)$, respectively. Therefore, the complexity of local path reduction phase is $O(m^3|S_i|)$.

The next task is to analyze the complexity of the super MC phase, which consists of step 25 and 26. The complexities of step 25 are $O(1)$. Steps 26 is $O(m\ \ \times \log m)$. Therefore, the complexity of super MC phase is $O(m \times\ \ \log m)$.

The final task is to analyze the complexity of global path reduction phase, which consists of steps 27–36. The complexities of steps 27 and 28 are $O(m)$. Step 29 performs the *for*-instruction with $m$ loops. Its complexity is $O(m)$. Inside the loop, the complexities of steps 30 and 31 are $O(m)$. The complexities of steps 32–34 are $O(m)$. The complexities of steps 35 and 36 are $O(m)$ and $O(q)$, respectively. As a result, the complexity of global path reduction phase is $O(m)$. In summary, the overall complexity of the proposed PLPR is $O(m^3|S_i|)$.

# V. Performance Evaluation

This section investigates the performance improvement of the proposed PLPR algorithm against the existing algorithms RPC [9], 2-level knowledge centralized coordination (2KCC) [18], and MCCA [17], in terms of the average energy consumption, the total recharging time, charging efficiency, average traveling distance of MC, fairness indices, the standard deviation (SD) of recharging efficiency, and average waiting time. The RPC constructs a charging path for the MC in the monitoring region. Then the MC adopts the policy of "recharging while moving" and recharges all sensors at a constant speed.

The 2KCC divided the monitoring region into several equal-sized sub-regions according to the number of MCs. Each MC

TABLE II

Simulation Parameter Setting

| Parameters | Values |
|---|---|
| Node deployment | Random |
| Region size | 600*600 |
| The number of sensor nodes | 200-600 |
| The charging range | 3 m |
| Mobile charger speed ν | 5m/s |
| Sensor node transmission range | 20m |
| Energy consumption rate $e_{i,j}^{consume}$ of node | 0.02J |
| The efficiency factor ϑ of mobile charger | 5J/m |
| The energy consumption $e_i^{move}$ of movement for the mobile charger | 10J/m |
| The transmitted power of the mobile charger | 5 J/s |
| The initial energy of each sensor node | 200J |

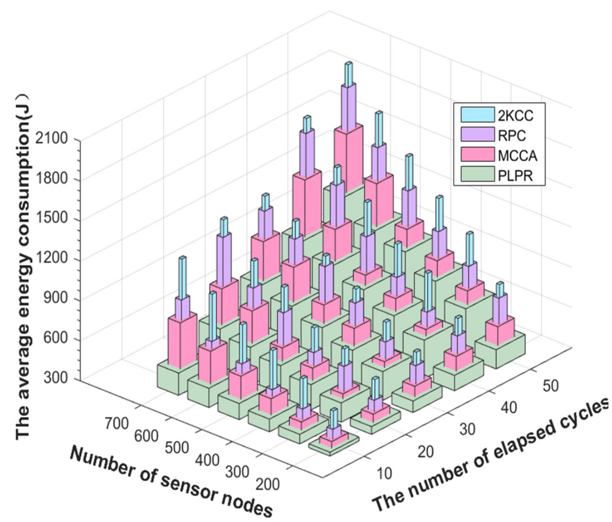



Fig. 8. Comparison of the four approaches in terms of the average energy consumption.

was responsible for charging nodes that belong to its sub-region. The MCs were further divided into several groups according to the number of super MCs. Each super MC was responsible for charging the MCs belonging to its group. The MCCA divided the network into several clusters and assigned them to multiple MCs, which cooperatively charged all sensors.

In the experiment, sensors are randomly deployed in a monitoring region with the size 600 × 600 m. The number of deployed sensors varies, ranging from 200 to 600. The initial energy of each sensor node is 200 J. The charging range is 3 m. The energy consumption rate $e_{i,j}^{\text{consume}}$ of node is 0.02 J. The MC speed $v$ is 5 m/s. The energy consumption $e_i^{\text{move}}$ of movement for the MC is 10 J/m. As shown in (11), the efficiency factor $\vartheta$ of MC is 5 J/m. All parameter values for the experiments are summarized in Table II. The MATLAB 2016a simulator is used as the simulation tool.

Fig. 8 compares the average energy consumption per ten cycles of the MC of RPC, 2KCC, MCCA, and PLPR. The average energy consumption of the MC includes the total required energy for recharging the sensors in its path and the

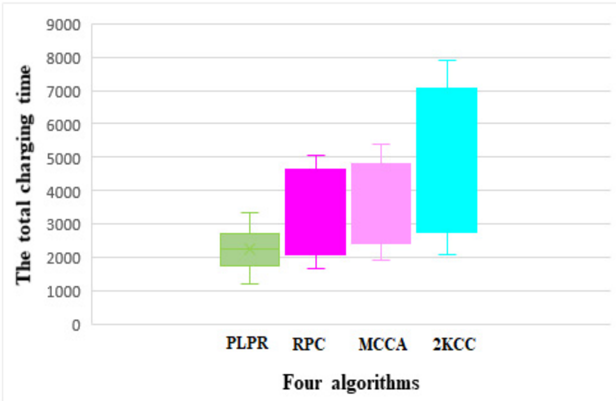



Fig. 9. Comparison of four approaches in terms of the total charging time.

required energy for movement over ten cycles. The number of sensor nodes varies from 200 to 700 and the number of elapsed cycles ranges from 10 to 50. As shown in Fig. 8, when the number of sensors and the number of elapsed cycles increased, the average energy consumption also increased. The PLPR can reduce the energy consumption of MCs and sensors. This occurs because the PLPR takes into account the path reduction for each MC and the residual energy of sensors. The RPC could further reduce the path length. However, it did not consider the increased number of sensors. This leads to the increase of the path length. The MC consumed more energy for movement, resulting in the problem of nodes deaths. The 2KCC divided the network region into several equal sized sub-regions, assigned each MC to each sub-region, and then charged those sensors along the constructed path. However, the 2KCC did not take into account the path optimization in each sub-region. As a result, the 2KCC included longer paths for each MC and increased the energy consumption of MCs. The MCCA divided the network region into several clusters and assigned them to multiple MCs, which cooperatively charged all sensors. However, the MCCA did not take into account the path optimization in each cluster. In comparison, the proposed PLPR outperforms the RPC, 2KCC, and MCCA schemes in terms of the average energy consumption.

Fig. 9 compares the total charging time of RPC, 2KCC, MCCA, and PLPR. The number of sensor nodes varies from 200 to 600 and the number of MCs is 17. The size of the region is $600 \times 600$. The total charging time consists of the individual charging time for each sensor node, the time taken for the MC to travel, and the charging time required for the MC itself. As shown in Fig. 9, the proposed PLPR approach outperforms the compared RPC, 2KCC, and MCCA in terms of the total charging time. This occurs because the proposed PLPR further removes the long edge. This takes the advantage of short path lengths. The RPC constructed one cycle which might contain long edges. The 2KCC divided the network region into several equal sized sub-regions, assigned each MC to each sub-region, and then charged those sensors along with the constructed path. However, the 2KCC did not take into account the path optimization in each sub-region. As a result, the 2KCC included longer path length, which increases the charging time of MCs. Similarly, the MCCA did not take into account the path optimization in each cluster, resulting in the long paths.

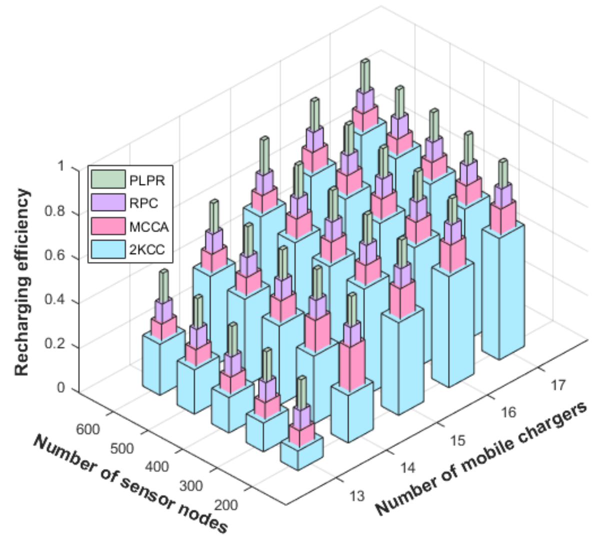



Fig. 10. Comparison of four algorithms in terms of the recharging efficiency.

Fig. 10 compares the recharging efficiency of the four algorithms by varying the number of sensor nodes ranging from 200 to 600 and the number of MCs from 13 to 17. Fig. 10 depicts the recharging efficiency of an MC when its speed settings are 5 m/s. The recharging efficiency is measured by the total energy received by the sensor nodes divided by the energy consumed by MCs. As shown in Fig. 10, the four compared algorithms have a similar trend that the recharging efficiency increases with the number of sensors. When the number of sensors increases, the density of this monitoring region increased, reducing the length of the path from one sensor to another. Another trend is that the recharging efficiency also increases with the number of MCs. The primary reason is that the proposed PLPR adopts a cluster partitioning method, which divides the blocks connected by the long paths. This approach allows for the elimination of long paths, reducing the total energy consumption of the MC. Additionally, the super MC enables the MC to recharge more efficiently. The MCs can receive power from the super MC without the need for extra movement.

Fig. 11 evaluates the average traveling distance of the MC by applying the proposed PLPR algorithm. The number of clusters varied ranging from 14 to 20 while the number of sensor nodes varied ranging from 350 to 600. As shown in Fig. 11, the traveling distance of MCs generally increases with the number of sensor nodes. This is because a larger cluster which is composed of more sensors will result in a larger total distance for MC to recharge all sensors in that cluster.

Fig. 12 further compares the four approaches in terms of fairness indices which are used to measure the balance degree of energy consumption of each sensor node. The fairness index is defined by the following equation:

$$\xi_{\text{fairness}} = \frac{\left(\sum_{i=1}^{n} E_{S_i}^{\text{round}}\right)^2}{n \times \sum_{i=1}^{n} {E_{S_i}^{\text{round}}}^2} \tag{46}$$

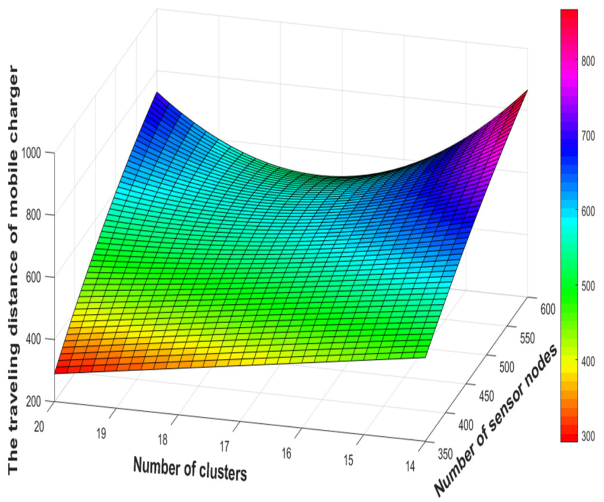



Fig. 11. Traveling distance of MC for the proposed PLPR algorithm.

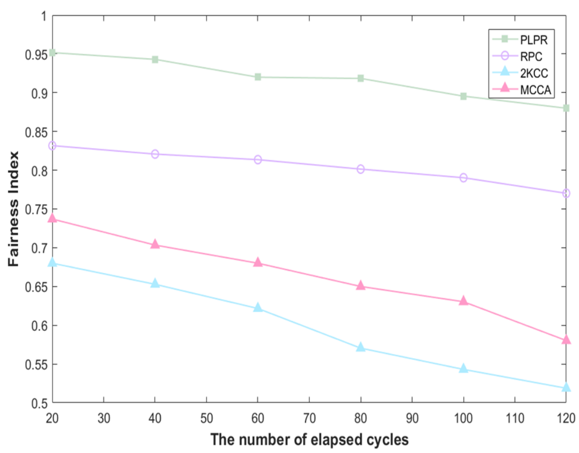



Fig. 12. Comparison of the four compared algorithms in terms of the fairness index.

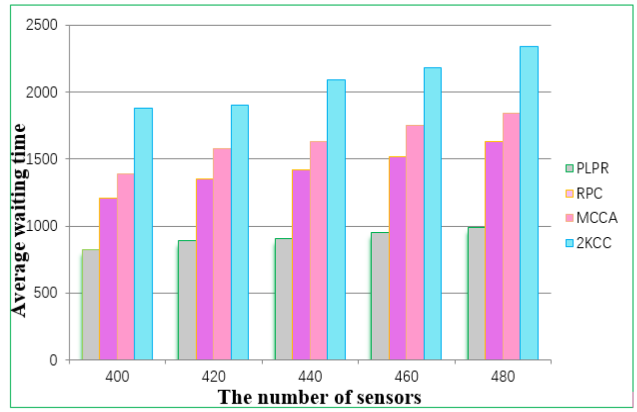



Fig. 13. Comparison of the four algorithms in terms of the average waiting time.

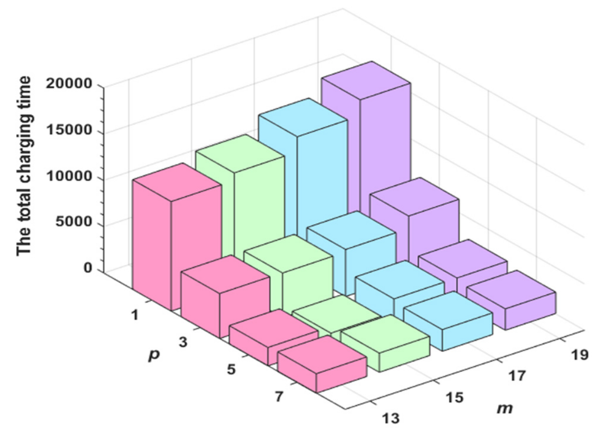



Fig. 14. Comparison of the total charging time by varying the values of $m$ and $p$.

where $E_{s_i}^{\text{round}}$ denotes the energy consumption of sensor node $s_i$ for each round. The $\xi_{\text{fairness}}$ value close to 1 indicates that the energy consumptions of all nodes are balanced. In this experiment, the number of elapsed cycles varies ranging from 20 to 120. In general, four approaches have a common trend that the fairness index value is decreased with the number of elapsed cycles. In comparison, 2KCC and MCCA yield smaller $\xi_{\text{fairness}}$ values because they do not optimize the path length in each cluster. The RPC had a better performance than 2KCC and MCCA because it reduces the path length within the cluster. The proposed PLPR allows for the elimination of long edges and hence reduces the sensor's charge waiting time. Consequently, the proposed PLPR mechanism has the largest $\xi_{\text{fairness}}$ value, as shown in Fig. 12.

Fig. 13 compares the average waiting time of RPC, 2KCC, MCCA, and PLPR. The number of sensor nodes varies from 400 to 480. The average waiting time is measured by the sum of the waiting times of all sensors in the cluster divided by the number of sensors in the cluster. As shown in Fig. 13, the proposed PLPR approach outperforms the compared RPC, 2KCC, and MCCA in terms of the average waiting time. This occurs because the proposed PLPR removes the long edge and hence reduces the waiting time. The RPC constructed one cycle without partitioning the path into several clusters, which might contain long edges in the constructed path. The 2KCC and MCCA did not take into account the path reduction in each sub-region. As a result, their paths included long edge, which increased the charging time of MCs.

Fig. 14 illustrates the variation of total charging time as the number of MCs (denoted by $m$) and super MCs (denoted by $p$) is adjusted. Here, $m$ ranges from 13 to 19, while $p$ ranges from 1 to 7. As evident from the figure, the total charging time gradually decreases as the number of both MCs and super MCs increases. However, a notable minimum in charging time is observed when $m = 15$ and $p = 5$, indicating that this specific combination of mobile and super MCs is most efficient in reducing the overall charging duration. This efficiency can be attributed to the optimal timing and distribution of these chargers, which enable them to effectively recharge the sensors and other MCs.

Fig. 15 further compares the four algorithms in terms of SD, which measures the degree of balance in recharging efficiency. The SD is defined by the following equation:

$$\mathrm{SD} = \sqrt{\frac{\sum_{1}^{m} (\omega_i - \varpi)^2}{m}} \tag{47}$$

where $\omega_i$ denotes the recharging efficiency of MC $M_i$ and $\varpi$ denotes the average recharging efficiency of all MCs. A smaller SD value indicates a more stable recharging

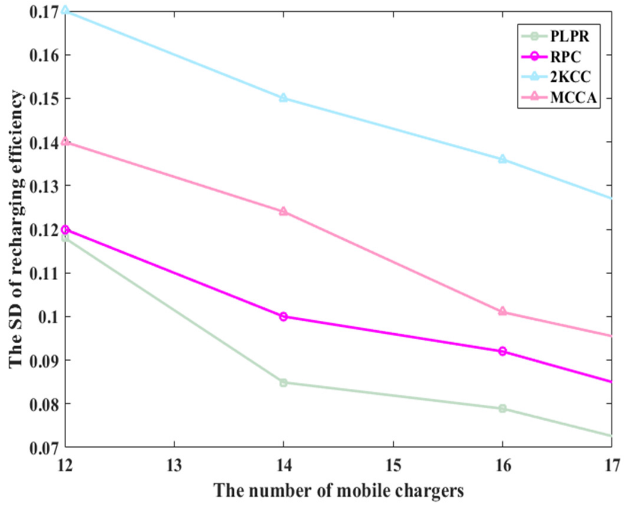



Fig. 15. Comparison of the four algorithms in terms of the SD of recharging efficiency.

efficiency across all MCs. In this experiment, the number of MCs varies from 12 to 17 and the number of sensor nodes is 600. The proposed PLPR approach outperforms the compared RPC, 2KCC, and MCCA algorithms in terms of the SD of recharging efficiency. This is because the PLPR approach utilizes path shortening method, eliminating the length of charging paths and reducing the overall energy consumption of the MC. Additionally, the super MC is positioned strategically to provide timely recharging to the MC, thereby reducing the energy consumption during movement.

## VI. Conclusion

This article investigates the issue of cooperative charging using multiple MCs and super MCs in WSNs. The article proposes a cooperative charging algorithm, called PLPR, aiming to minimize the numbers of the MCs and super MCs while achieving the purpose of sustainable survival for all sensors. The proposed PLPR primarily consists of four phases. In the initialization phase, the PLPR partitions the sensors into multiple clusters and constructs an initial path for each MC in each cluster. In the local path reduction phase, the PLPR further reduces the path length and helps improve the recharging efficiency of the MC. In the super MC phase, the PLPR determines the number of super MCs and constructs an initial path for them. In the global path reduction phase, the PLPR reduces the path length and dispatches the super MCs to different paths for recharging the MCs, improving the charging efficiency of the MCs. Performance evaluations show that the proposed PLPR outperforms existing schemes in terms of the average energy consumption, total recharging time, charging efficiency, traveling distance of MCs, fairness indices, SD of recharging efficiency, and average waiting time. Future work will further consider optimizing charging strategies in dynamic environments, including path planning and charging scheduling algorithms that adapt to changes in sensor node positions.

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