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Energy efficiency optimization for multiple chargers in Wireless Rechargeable Sensor Networks

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ABSTRACT

To guarantee the continuous coverage of the rechargeable sensors, Wireless Rechargeable Sensor Networks (WRSNs) has emerged with the advantages of high charging efficiency and reliable charging timeliness. Charging planning is an important problem in theoretical research and practical applications, and it faces more difficulties and challenges for multiple mobile chargers. In this paper, we introduce a charging planning problem for multiple chargers, namely Charging Energy Efficiency Maximization problem for Multi-Chargers in WRSNs (CEEM-MC Problem), and prove its NP-hardness. The problem aims to maximize the charging energy efficiency of the charging process by assigning the charging amount and planning the charging path. To balance the charging consumption among multiple chargers, we propose two algorithms which are different on the charging path planning, Ring-Wandering Algorithm and Eight-Wandering Algorithm. To evaluate the performance on energy efficiency, we perform a series of simulations and the results verify the effectiveness of the proposed algorithms.

1. Introduction

High quality of service and continuous coverage are the most important requirements in the most applications of Wireless Sensor Networks (WSNs) [1], which brings the energy efficiency problems to the battery-powered sensors in virtual backbone construction [2,3] and routing protocols design [4]. Therefore Wireless Rechargeable Sensor Networks (WRSNs) have emerged with the advantages of high charging efficiency via static charging stations or mobile charging vehicles, which cannot only guarantee the timeliness of charging but also avoid the reduction of data reliability or low efficiency of energy transformation.

For cooperative coverage in WRSNs, the charging scheduling design should take the working pattern of the chargers and the energy consumption mode of the sensors into account. And the research on the charging scheduling can be divided into two cases, single-charger and multiple-charger as shown in Fig. 1. For the small-scale monitoring tasks in WRSNs, single-charger charging scheduling has the advantages of low cost and high planning efficiency. For the large-scale coverage

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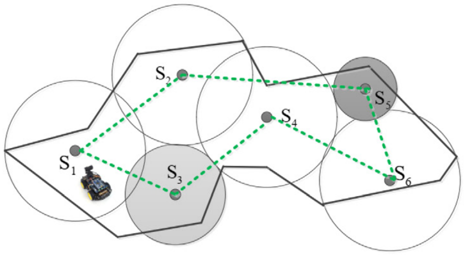
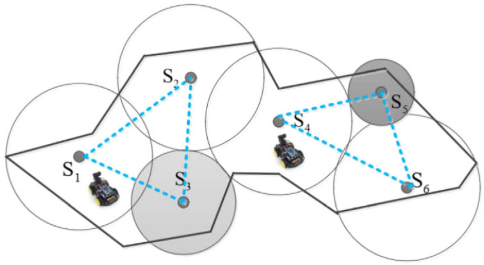


(a) The case of a single mobile charger



(b) The case of multiple mobile chargers

Fig. 1. An instance of Charging Planning.

missions in WRSNs, multiple-charger charging scheduling can avoid the fast charging consumption in single-charger case, and perform parallel charging to reduce the latency of charging and improve the scalability.

The working of the chargers in WRSNs depends on the moving mode and the charging pattern. For the moving mode, there are mainly two kinds, periodical charging and demand-driven charging. The former can avoid frequent checking the sensors' remaining energy or predicting the consuming trend of the sensors' energy. For the charging pattern, it can be classified into two types, single-charger-to-single-sensor charging and single-charger-to-multiple-sensor charging. It seems that the latter one can save more moving consumption than the former one. But the former one is beneficial for the dense-distributed or low-power-consumed WSNs. Thus we consider the chargers' working pattern of demand-driven and single-charger-to-single-sensor charging.

In this paper, we focus on designing the charging planning strategy with multiple chargers in the WRSN, which mainly depends on the charging pattern, charging order arrangement and charging amount assignment. This paper studies the charging planning problem of multiple mobile chargers from the perspectives of charging amount assignment and charging path planning, which is to maximize the charging efficiency of the charger for guaranteeing the continuously works of the WRSN. The contributions of this paper are shown as below.

(1) We propose multiple-charger charging planning problem for WRSNs, called Charging Energy Efficiency Maximization problem for Multi-Chargers in WRSNs (CEEM-MC Problem) based on the energy consumption model. The goal of the problem is to maximize the charging energy efficiency of the charging process. The mathematical model and NP-hardness proof of problem are both given.

(2) To solve CEEM-MC problem, we propose two algorithms, Ring-Wandering Algorithm and Eight-Wandering Algorithm, which are both composed of Charging Region Division, Charging Energy Assignment and Charging Path Planning. The differences between the two algorithms are region dividing and path planning. And we analyze the time complexities of the algorithms.

(3) The extensive simulations are performed to verify the effectiveness of the proposed algorithms for CEEM-MC problem.

The remainder of this paper is organized as follows. Section 2 introduces related works. In Section 3, we introduce the network model, energy consumption model and problem formulation. In Section 4, we propose two algorithms for solving the CEEM-MC Problem. Simulations are shown in Section 5. Section 6 concludes this paper.

2. Related works

In this section, we briefly review the literature related to the charging planning problems of WRSNs for sensors coverage. Based on the charging patterns of mobile chargers, the existing works on charging planning can be classified into two kinds: demand-driven charging strategies and periodic charging ones.

Demand-Driven Charging Strategies

For the demand-driven charging strategies, [5] proposed a path planning algorithm to choose the sensors in low-power status and satisfy their charging requirement based on a threshold value β on the remaining energy. The authors in [6] predicted the energy consumption of sensors and transformed the charging cost as a monotone submodular function, then introduced a $\frac{(1-\frac{1}{e})}{4}$-ratio algorithm for the problem. The authors in [7] proposed a spatial-and-temporal optimization algorithm for real-time charging for eliminating the exhausted sensors and adding the powered new ones. The studies in [8,9] aimed at designing the algorithm of path planning and charging assignment to maximize the network lifetime and minimize the charging consumption.

Periodic Charging Strategies

For periodic charging strategies, the authors in [10] designed a constant-ratio approximation algorithm for charging path planning problem under the powering limitation model. And the authors in [11] applied the region-separation and charging-discretion into the charing solution and proposed a $\frac{1-\xi}{4(1-1/e)}$-ratio algorithm. The authors in [12] considered the one-to-many charging model and designed a constant-ratio algorithm. Recently, the new charging technology has drawn attentions of researchers like the $\frac{(1-\xi)(1-e)}{e}$-ratio algorithm based on the energy transferring depending on the obstacles

Table 1
Notations and illustrations.

Node	Notations	Illustrations
Sensors	S	Set of rechargeable sensors
	s_i, $(x[s_i], y[s_i])$	Static sensor and its position
	n	Number of rechargeable sensors
	E_i^0	The maximum battery capacity of sensor s_i
	E_i^r	Remaining energy of sensor s_i in the coverage task
	E^{low}	Minimum energy level for the coverage task
Chargers	C	Set of mobile chargers
	c_j, $(x[c_j], y[c_j])$	Mobile charger and its starting station
	m	Number of mobile chargers
	E_{max}	The initial energy for all the chargers
	α, β	Parameters for energy consumption

in [13], the $(3+\xi)$-ratio algorithm for multiple-chargers in one-vehicle model in [14] and the periodic charging algorithm with the optimal movement speed in [15].

In this paper, we consider the demand-driven charging planning for WRSNs and focus on the optimization goal of maximizing the energy efficiency of the chargers in the whole charging process, which has not been considered in the existing literature mentioned above. In [16], we proposed the charging scheduling problem with **single mobile charger**, Charging Scheduling problem with Maximized Energy Efficiency in WRSNs (CS-MEE Problem), and designed a heterogeneous-weighted-graph algorithm, CS-HWG Algorithm, which is composed of Charging Energy Assignment and Charging Path Planning. In this paper, we continue to study the charging scheduling problem with **multiple mobile chargers** and propose the charging planning algorithms for the chargers to realize maximizing charging energy efficiency.

3. System model and problem formulation

3.1. Network model

The WRSN considered in the paper is a network composed of n stationary rechargeable sensors deployed on a two-dimensional plane, which is denoted as a set $S = \{s_1, s_2, ..., s_n\}$. For each sensor s_i, its position and its maximum battery capacity are denoted as $(x[s_i], y[s_i])$ and E_i^0. It is assumed that the coverage scheduling for the sensors has been determined and doesn't change for a certain period of time T, which decides the remaining battery energy of sensor s_i, E_i^r. For the charging requirements for sensors, there are two kinds of status: **(1) Working Status.** $E^{low} < E_i^r \leq E_i^0$. The sensors in this status can maintain the coverage working and have low demand on charging; **(2) Charging Status.** $0 < E_i^r \leq E^{low}$. It is very necessary to charge the sensors in charging status and bring them back to working status. E^{low} is decided by the determined coverage scheduling and the sensor's battery limitation, which can be both reviewed as the predefined values in advance.

For the sensors in coverage task, there are m mobile chargers in charge of charging the sensor nodes according to their needs, which is denoted as set $C = \{c_1, c_2, ..., c_m\}$. For each charger c_j, it begins its charging task from its service station $(x[c_j], y[c_j])$ and ends the task back to the same station. For all the chargers, their initial energies are unified as E_{max}. We assume that E_{max} satisfies two cases: one case is that E_{max} can guarantee all the sensors' charging requirement for continuing the coverage task; the other one is that the charging amount of all the chargers in charging task cannot be less than $\theta \cdot E_{max}$, where θ is a parameter closed to 1.

In this paper, we consider the demand-driven charging mode. The sensors with lower remaining energy will be given high priorities for charging for the reason that they have high probabilities on causing exhaustion and monitoring failure. Thus the charging task firstly guarantees the impletion of the sensors in **Charging Status**, then meets the other sensors' charging requirements. We conclude the related notations in Table 1.

3.2. Energy consumption model

The cooperative coverage considered here has the determined coverage scheduling in advance, which adopts the periodic charging, e.g. charging at intervals of duration T according to the covering energy consumption. In the charging process, the mobile chargers preferentially charge the static sensor in Charging Status and the energy consumption of chargers includes two aspects:

(1) Energy Consumption of Charging. At the beginning of a determined coverage strategy, each sensor s_i has an initial energy E_i^0 which is the maximum battery capacity. In the charging task, s_i's energy has consumed partially and the remaining energy of s_i is E_i^r. Here we denote the charging energy of charger c_j for sensor s_i as $C(c_j, s_i)$ in the scheduling scheme. Furthermore, we consider the inevitable energy loss in the process of charging and the energy consumption of charging is α time of the required amount, i.e. $E_{j,i}^{charging} = \alpha \cdot C(c_j, s_i) \cdot g_{j,i}$, where $g_{j,i}$ is a binary variable to denote whether c_j is scheduled to charge sensor s_i, which is defined as follows:

$$g_{j,i} = \begin{cases} 1, & \text{if } c_j \text{ has been scheduled to charge sensor } s_i, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

(2) Energy Consumption of Moving. The charging model adopted in our paper is single-charger-to-single-sensor charging, i.e., the mobile charger is needed to reach the position of the sensor for the successful charging. In this model, the moving distance of the charger is the Euclidean distance from the current location of the charger to the position of the static sensor, which is denoted as $dist(c_j, s_i)$. If the energy consumption rate can be denoted as β, thus the energy consumption of moving is $E_{j,i}^{moving} = \beta \cdot dist(c_j, s_i) \cdot g_{j,i}$.

Based on the energy consumption of chargers on charging and moving, we define the energy efficiency of the charging process as shown in Definition 1.

Definition 1 ***(Charging Energy Efficiency)***. In a charging process for a determined coverage strategy, the charging energy efficiency is the proportion of the energy consumption on charging in the overall energy cost, which is denoted as $EneEff = \frac{\sum_{c_j \in C, s_i \in S} E_{j,i}^{charging}}{\sum_{c_j \in C, s_i \in S}(E_{j,i}^{charging} + E_{j,i}^{moving})}$.

3.3. Problem formulation

In this paper, we focus on the problem of maximizing the charging energy efficiency for WRSNs with multiply mobile chargers. To solve this problem, we need to design a charging scheduling strategy including charging path planning **PathSet** and charging energy assignment **EnergySet**. **PathSet** is the set of scheduled paths of the chargers $\{path_j | 1 \le j \le m\}$ (where $path_j$ is c_j's charging path composed of the positions of the charged sensors by c_j) and **EnergySet** is the charging energy assignment for each pair of charger-and-sensor $\{E_{j,i}^{charging} | 1 \le j \le m, 1 \le i \le n\}$. Based on the above preliminaries, we refer to the problem as the Charging Energy Efficiency Maximization problem for Multi-Chargers in WRSNs (CEEM-MC Problem) as shown in Definition 2.

Definition 2 ***(CEEM-MC Problem)***. Given a set $S = \{s_1, s_2, \cdots, s_n\}$ of n rechargeable sensors with their own battery capacity E_i^0 and the current remaining energy E_i^r, a set $C = \{c_1, c_2, ..., c_m\}$ of m mobile chargers with the uniform energy capacity E_{max}, the Charging Energy Efficiency Maximization problem for Multi-Chargers in WRSNs (CEEM-MC Problem) is to find **a charging scheduling strategy (PathSet, EnergySet)** such that

(1) for each sensor $s_i \in S$, the scheduled charging energy should bring s_i from Charging Status to Working Status or keep s_i in Working Status, but cannot beyond its battery capacity E_i^0;

(2) for each sensor, there is a charging priority according to its status: priority(**Working Status**)<priority(**Charging Status**). The specific value of each sensor's charging priority will be given in the scheduling;

(3) for each charger $c_j \in C$, the charging path begins and ends at c_j's service station $(x[c_j], y[c_j])$ and the overall charging energy cannot less than $\theta \cdot E_{max}$ or exceed its initial energy E_{max}, where θ is a parameter closed to 1. $\theta \cdot E_{max}$ is the lower bound of the overall charging energy, which can avoid the case that only one charger will be scheduled to work leading to a high energy efficiency but a low charging quality;

(4) the charging energy efficiency of the charging process in the duration T, $EneEff = \frac{\sum_{c_j \in C, s_i \in S} E_{j,i}^{charging}}{\sum_{c_j \in C, s_i \in S}(E_{j,i}^{charging} + E_{j,i}^{moving})}$, is maximized.

To elaborate the problem in detail, we also introduce the mathematical formulation of CEEM-MC Problem and give the NP-hardness proof of the problem in Theorem 1.

$$Maximize \quad \frac{\sum_{c_j \in C, s_i \in S} \left(\alpha \cdot C(c_j, s_i) \cdot g_{j,i}\right)}{\sum_{c_j \in C, s_i \in S} \left(\alpha \cdot C(c_j, s_i) \cdot g_{j,i} + \beta \cdot dist(c_j, s_i) \cdot g_{j,i}\right)} \tag{2}$$

s.t.

$$E_i^r + \sum_{c_j \in C} \left(\alpha \cdot C(c_j, s_i) \cdot g_{j,i}\right) \le E_i^0 \qquad i = 1, 2, \cdots, n \tag{3}$$

$$\sum_{1 \le j \le m} g_{j,i} \le 1 \qquad i = 1, 2, \cdots, n \tag{4}$$

$$\theta \cdot E_{max} \le \sum_{s_i \in S} \left(\alpha \cdot C(c_j, s_i) \cdot g_{j,i}\right) \le E_{max} \qquad j = 1, 2, \cdots, m \tag{5}$$

$$g_{j,i} \in \{0,1\} \qquad i = 0, 1, \cdots, n \quad j = 0, 1, \cdots, m \tag{6}$$

The optimization objective is to maximize the charging energy efficiency as shown in (2). Constraint (3) expresses that the remaining energy and the charged energy amount of each sensor cannot beyond the sensor's battery capacity. Constraint (4) states that each sensor should be charged by at most one charger according to the sensor's status. Constraint (5) is the charging energy consumption constraint which guarantees the charging requirement of the sensors in **Charging Status** and ensures that the charging energy amount of the charger will not exceed the initial energy of the charger. Constraint (6) defines the domain of the variable $g_{j,i}$. In the mathematical formulation, we can find that there are mainly two variables $C(c_j, s_i)$ and $g_{j,i}$ whose value ranges are non-integer and integer respectively. Thus the existing solutions for integer linear programming problems cannot be applied directly in our problem.

Theorem 1. *CEEM-MC Problem is NP-hard.*

Proof. To prove the NP-hardness of CEEM-MC Problem, we consider a special case of it: there is only one charger ($m = 1$, $C = \{c_1\}$) and all the sensors are in Charging Status. In this case, the charging energy for sensor s_i, $C(c_1, s_i)$, is the maximum amount $E_i^0 - E_i^r$ (shortly denoted by $C(s_i)$), which is decided by the expected E_i^r from the coverage scheduling. And charger c_1 will charge all the sensors, i.e., $g_{1,i} = 1$ for $1 \leq i \leq n$. Since there is only one charger, $\theta = 1$ represents that the only one charger is bound to charger the sensors and it is out of consideration for the case that there is no consumption for the only charger.

Thus the objective of the problem is driven to maximizing $\frac{\sum_{s_i \in S} (\alpha \cdot C(s_i))}{\sum_{s_i \in S} (\alpha \cdot C(s_i) + \beta \cdot dist(c_1, s_i))}$. Based on equivalent conversion, the objective can be rewritten into maximizing $\frac{1}{1 + \frac{\beta}{\alpha \cdot C(s_i)} \sum_{s_i \in S} dist(c_1, s_i)}$. Note that α, β and $C(s_i)$ are predefined or can be calculated. By denoting $\frac{\beta}{\alpha \cdot C(s_i)}$ as a constant *ctemp* the objective becomes from maximizing $\frac{1}{1 + ctemp \cdot \sum_{s_i \in S} dist(c_1, s_i)}$ to minimizing $\sum_{s_i \in S} dist(c_1, s_i)$. Thus the problem in this special case can be represented to the following formulation:

Given a set $S = \{s_1, s_2, \cdots, s_n\}$ of n rechargeable sensors with their charging requirement $C(s_i)$, one mobile charger c_1 with the sufficient energy capacity, the problem is to plan the charging path such that

(1) for each sensor $s_i \in S$, the scheduled charging energy should maintain s_i in Working Status, but cannot beyond its battery capacity E_i^0;

(2) for the charger c_1, the charging path begins and ends at the service station $(x[c_1], y[c_1])$ and the overall charging energy cannot exceed its initial energy E_{max};

(3) the length of charging path of c_1, $\sum_{s_i \in S} dist(c_1, s_i)$, is minimized.

It can be easily found that the above problem can be reduced to the Travelling Salesman Problem (TSP). To conclude, when the original problem is considered in the special case $m = 1$ and $g_{1,i} = 1$ for $1 \leq i \leq n$, CEEM-MC problem can be reduced to TSP, which has been proved NP-hard [17]. Since a special case of CEEM-MC problem is NP-hard, CEEM-MC problem is also NP-hard, which completes the proof. □

4. Algorithms for CEEM-MC Problem

When designing a charging scheduling strategy for WRSNs, several critical factors should be considered which directly determine the charging sequence and the charging amount allocation. The first one is the remaining energy of the rechargeable sensors, which guarantees the continuous coverage of the network. The second factor is the moving distance of the chargers, which influences the total energy consumption. The last important factor is the initial energy and the charging consumption of the chargers, which can insure to finish the charging task. In this section, we propose two algorithms to solve the CEEM-MC Problem, Ring-Wandering Algorithm and Eight-Wandering Algorithm, based on the CS-HWG Algorithm in [16] for our charging scheduling problem in the case of $m = 1$.

4.1. Ring-Wandering Algorithm for CEEM-MC Problem

For the large-scale WRSNs, it is necessary to arrange multiple chargers for satisfying the charging requirement of the sensors in coverage task. Since the sensors' energy residual values in the coverage task are different, it is considered to divide the charging range (e.g. the subset of sensor set S) of responsibility for each charger. Furthermore, considering the initial energy amount of each charger is the unity value E_{max}, controlling the energy consumption gap between each pair of chargers should be considered in charging scheduling. The energy consumption of the charger including the charging consumption and the moving part, and we focus on the moving consumption to control the gap under the assumption that each charger cost E_{max} or near E_{max} in the charging task. To this end, the first phase of the proposed algorithm is **Charging Region Division**. After clarifying each charger's responsibility, we adopt the CS-HWG Algorithm in [16], which is composed of two phases **Charging Energy Assignment** and **Charging Path Planning**, for designing the charging scheduling scheme of each charger.

Phase 1: Charging Region Division for Ring-track

Phase 1.1: Heterogeneous-weighted Graph Construction

To solve the CEEM-MC Problem, we firstly model the network with sensors and chargers into an auxiliary graph. In most related works on constructing the auxiliary graph, the auxiliary graph is either a node-weighted graph or an edge-weighted graph. But in our solution, we construct a particular auxiliary graph with node-weights (depending on the charging cost) and edge-weights (decided by the moving cost), i.e., construct a heterogeneous-weighted graph as shown in Lines 2-8 of Algorithm 1. The node set is composed of the positions of sensors and chargers, $V = S \bigcup C$. For the edge set, we consider the sensor deployment density: for spares graphs, we introduce a limitation value l_0 of the moving distance between twice of charging, which can avoid excess consumption of the chargers' energy for some single charging. Thus $E = \{(v_i, v_j)|\forall v_i, v_j \in V \text{ and } dist(v_i, v_j) \leq l_0\}$; for dense graphs, l_0 can be regarded as infinity.

The weight assignment is with the consideration of the charging cost and the moving cost: Considering the charging cost, it is decided by each sensor's maximum charging requirement. Thus the node weight is denoted as $weight(s_i) = \alpha \cdot (E_i^0 - E_i^r)$ for sensors and $weight(c_j) = 0$ for chargers. Thus the node weight set $VW = \{weight(v_i)|\forall v_i \in V\}$. Considering the moving cost, it is determined by the Euclidean distances between the pairs of nodes in the network, i.e., the edge weight is calculated by $weight(v_i, v_j) = \beta \cdot dist(v_i, v_j)$. And the edge weight set $EW = \{weight(v_i, v_j)|\forall (v_i, v_j) \in E\}$. Then we complete the construction of the heterogeneous-weighted graph $G = (V, E, VW, EW)$.

Phase 1.2: Charging Clustering for Ring-track

Before the charging amount assignment and the charging path planning, the charging region division should be realized first as shown in Lines 9-17 of Algorithm 1. The region division is mainly decided by the Euclidean distances between each pair of the nodes in G, thus we focus on the edge-weighted graph $G = (V, E, EW)$ to divide regions. Here we adopt the K-Means Algorithm based on Minimum Spanning Tree to partition set V into m subsets, which will be charged by the m chargers respectively. The detailed process is as follows:

(i) We construct the Minimum Spanning Tree (MST) T for the edge-weighted graph $G = (V, E, EW)$ via the Kruskal Algorithm [18].

(ii) We sort the edges on T in the increasing sort on the edge weight $\{(v_1, v_2), (v_2, v_3), \ldots, (v_{|V|-1}, v_{|V|})\}$ and eliminate the first $m-1$ edges in the sort, i.e., delete $\{(v_1, v_2), (v_2, v_3), \ldots, (v_{m-1}, v_m)\}$. Then the MST T is divided into m disconnected subgraph $\{T_1, T_2, \ldots, T_m\}$.

(iii) For each connected subgraph T_j $(1 \leq j \leq m)$, the average edge weight will be calculated for finding the initial clustering center and finally we perform the K-Means Algorithm [19] from the m initial clustering centers and obtain m divided clusters T'_j $(1 \leq j \leq m)$.

Phase 2: Charging Energy Assignment

Phase 2.1: Charging Prioritization

Since the sensors with the higher charging requirements have larger priorities, we give a baseline value according to the divergence indicator among the sensors' battery capacities, i.e., $DI = \lceil \max_{1 \leq i,j \leq n} \frac{E_i^0}{E_j^0} \rceil$. We assign the priorities for the two kinds of sensors' status respectively: (1) For the sensors in Charging Status, its priority $pri(s_i) = DI^2$. These sensors' charging requirement is greatest and the maximum charging energy $(E_i^0 - E_i^{cur})$ could be satisfied; (2) For the sensors in Working Status, the charging priority is assigned as $pri(s_i) = \frac{1}{DI}$. This priority assignment measure can widen the gap between the pairs of the priorities belonged to different requirements.

Phase 2.2: Charging Node Filtering

Based on the heterogeneous-weighted graph $G = (V, E, VW, EW)$ and m clusters T'_j $(1 \leq j \leq m)$ obtained by Phase 1, we perform charging energy assignment for each charger c_j on the heterogeneous-weighted subgraph T'_j. The main idea is filtering the nodes with necessary charging requirements, e.g. sensors in Charging Status, and assigning them the charging energy.

Considering high charging efficiency and limitation of each charger's initial energy E_{max}, we filter the sensors with necessary charging requirements, e.g. the ones in Charging Status. Since E_{max} is limited which may only satisfy part of sensors' charging requirements, we firstly reserve the consumption on charging movement E_{moving}^{res} from E_{max}, which is calculated in Steps 25-26. And the calculation is based on the length of the Minimum Hamilton Cycle which can guarantee to pass across all the sensors in Charging Status. Then the remaining energy $E_{max} - E_{moving}^{res}$ can be assigned for charging sensors.

Based on the reserved E_{max}, we assign the charging amount according to the sensors' charging priorities, filter the sensors with necessary charging requirements and eliminate the ones with unnecessary requirements. The assignment is realized in two loops as shown in Lines 28-31: firstly the charging requirement of the sensors in Charging Status can be satisfied and the assigned charging amount is $E_{j,i}^{charging} = \frac{pri(s_i)}{DI^2} \cdot (E_i^0 - E_i^{cur})$. If the charger has the remaining energy, the sensors in Working Status can be charged. The filtering is based on the assigned charging energy $E_{j,i}^{charging}$ as shown in Lines 32-33: if $E_{j,i}^{charging} = 0$, s_i will be out of the consideration later and eliminated from $V[T'_j]$ and $E[T'_j]$. Then we obtain the filtered node set $V'[T'_j]$, node set $E'[T'_j]$ and the charging energy assignment $EnergySet = \{E_{j,i}^{charging}|1 \leq j \leq m, 1 \leq i \leq n\}$.

Phase 3: Charging Path Planning for Ring-track

In the constructed heterogeneous-weighted graph $G = (V, E, VW, EW)$, the weights' distribution on both nodes and edges is not beneficial to global optimization. Thus the two kinds of energy cost should be measured by uniform standard, and we adopt the edge weight as the integrated measurement. Here we introduce an equivalent transformation method of blending node weights into edge weights, as shown in Lines 37-41 of Algorithm 1: for each node in the filtered set $V'[T'_k]$, we revalue the node weight according to the charging priority and the uniform magnitude of node weights and edge weights, i.e., $weight'(s_i) = \frac{1}{pri(s_i)} \cdot \beta \cdot avrdist \cdot \frac{weight(s_i)}{E_i^0}$, where $avrdist_k = \frac{\sum_{1 \le i,j \le n} dist(v_i, v_j)}{|E'[T'_k]|}$ is the average distance among all the pairs of sensors. Note that $avrdist_k$ is a normalization factor for modifying the node weight into the similar magnitude with those of the edge weight. And $\frac{1}{pri(s_i)}$ indicates that the node with higher charging priority has smaller node weight, which is consistent with that the node pair with low moving cost has smaller edge weight. Since the sensor's charging can be finished by the charger's only one pass, we equally divide the node weight into two parts, e.g. $\frac{1}{2} weight'(s_i)$. And then we distribute the divided node weight to the weight of the node's associated edges, i.e., $weight'(v_i, v_j) = weight(s_i, s_j) + \frac{1}{2} weight'(s_i) + \frac{1}{2} weight'(s_j)$, which updates the edge weight set. Then we will perform charging planning based on the transformed edge-weighted graph $T'_j = (V'[T'_j], E'[T'_j], EW'[T'_j])$.

Based on the auxiliary graph T'_j, we perform the algorithm for TSP Problem and the charging path $path_j$ of the charger c_j can be obtained. The detailed description is shown in Algorithm 1.

Algorithm 1 Ring-Wandering Algorithm for CEEM-MC Problem.

Input: $S = \{s_1, s_2, \cdots, s_n\}$, $\{E_i^0 | 1 \le i \le n\}$, $\{E_i^r | 1 \le i \le n\}$, $\{C(s_i) | 1 \le i \le n\}$, a set $C = \{c_1, c_2, ..., c_m\}$ and E_{max}

Output: $(PathSet, EnergySet)$, where $PathSet = \{path_j | 1 \le j \le m\}$ and $EnergySet = \{E_{j,i}^{charging} | 1 \le j \le m, 1 \le i \le n\}$

1: //**Phase 1: Charging Region Division for Ring-track**
2: //**Phase 1.1: Heterogeneous-weighted Graph Construction**
3: Set V, E, VW, $EW \leftarrow \emptyset$
4: $V \leftarrow S \bigcup C$, $E = \{(v_i, v_j) | \forall v_i, v_j \in V$ and $dist(v_i, v_j) \le l_0)\}$
5: **for** $\forall v_i \in V$ **do**
6: $\quad weight(v_i) = \alpha \cdot (E_i^0 - E_i^r)$, $VW = VW \bigcup \{weight(v_i)\}$
7: **for** $\forall (v_i, v_j) \in E$ **do**
8: $\quad weight(v_i, v_j) = \beta \cdot dist(v_i, v_j)$, $EW = EW \bigcup \{weight(v_i, v_j)\}$
9: //**Phase 1.2: Charging Clustering for Ring-track**
10: Perform Kruskal Algorithm on $G = (V, E, EW)$ and obtain a minimum spanning tree T
11: Sort the edges on T in increasing weight $\{(v_1, v_2), (v_2, v_3), ..., (v_{|V|-1}, v_{|V|})\}$
12: **for** $1 \le i \le m - 1$ **do**
13: $\quad T \leftarrow T \setminus (v_i, v_{i+1})$
14: Denote the disconnected subgraph of T as $\{T_1, T_2, ..., T_m\}$
15: **for** $\forall T_j \in T$ **do**
16: $\quad$ Calculate the center $cluster_j$ based on the average edge weight in T_j
17: Perform K-Means Algorithm on $(T, cluster_1, cluster_2, ..., cluster_m)$ and obtain $\{T'_1, T'_2, ..., T'_m\}$
18: //**Phase 2: Charging Energy Assignment**
19: //**Phase 2.1: Charging Prioritization**
20: Set the divergence indicator $DI = \lceil \max_{1 \le i,j \le n} \frac{E_i^0}{E_j^0} \rceil$.
21: **for** $\forall s_i \in S$ **do**
22: $\quad pri(s_i) = DI^2$ for s_i in Charging Status; $pri(s_i) = \frac{1}{DI}$ for s_i in Working Status
23: //**Phase 2.2: Charging Node Filtering**
24: **for** $1 \le j \le m$ **do**
25: $\quad$ Perform TSP Algorithm on $T'_j[\{s_i | \forall s_i$ in Charging Status$\}]$ and obtain a Hamilton Cycle with edge weight E_{moving}^{res}
26: $\quad E_{max} = E_{max} - E_{moving}^{res}$
27: $\quad$ Set $V'[T'_j] = V[T'_j]$, $E'[T'_j] = E[T'_j]$, $EW'[T'_j] \leftarrow \emptyset$, $E_{j,i}^{charging} = 0$
28: $\quad$ **while** $E_{max} > 0$ **do**
29: $\quad\quad$ For each s_i with $pri(s_i) \ge 1$, $E_{j,i}^{charging} = \frac{pri(s_i)}{DI^2} \cdot (E_i^0 - E_i^r)$, $E_{max} = E_{max} - E_{j,i}^{charging}$
30: $\quad$ **while** $E_{max} > 0$ **do**
31: $\quad\quad$ For each s_i with $pri(s_i) < 1$, $E_{j,i}^{charging} = \frac{pri(s_i)}{DI^2} \cdot (E_i^0 - E_i^r)$, $E_{max} = E_{max} - E_{j,i}^{charging}$
32: $\quad\quad$ **for** $\forall s_i \in V[T'_j]$ **do**
33: $\quad\quad\quad$ If $E_{j,i}^{charging} = 0$, $V'[T'_j] = V'[T'_j] \setminus \{s_i\}$, $E'[T'_j] = E'[T'_j] \setminus \{(s_i, s_j) | \forall s_j \in V\}$
34: $\quad EnergySet = \{E_{j,i}^{charging} | 1 \le j \le m, 1 \le i \le n\}$

35: //**Phase 3: Charging Path Planning for Ring-track**
36: **for** $1 \le j \le m$ **do**
37: **for** $\forall s_i \in V'[T'_j]$ **do**
38: $weight'(s_i) = \beta \cdot avrdist \cdot \frac{1}{pri(s_i)} \cdot \frac{weight(s_i)}{\alpha \cdot E_i^0}$, where $avrdist = \frac{\sum_{1 \le i,j \le n} dist(s_i,s_j)}{|E'|}$
39: **for** $\forall (s_i, s_j) \in E'[T'_j]$ **do**
40: $weight'(s_i, s_j) = weight(s_i, s_j) + \frac{1}{2} weight'(s_i) + \frac{1}{2} weight'(s_j)$
41: $EW'[T'_j] = \{weight'(s_i, s_j) | \forall (s_i, s_j) \in E'[T'_j]\}$
42: Perform TSP Algorithm on $T'_j = (V'[T'_j], E'[T'_j], EW'[T'_j])$ and obtain the charging $path_j$
43: $PathSet = \{path_j | 1 \le j \le m\}$

4.2. Eight-Wandering Algorithm for CEEM-MC Problem

We propose the second algorithm for solving CEEM-MC Problem, Eight-Wandering Algorithm. This algorithm is also composed of three phases, but Phase 1 (Charing Region Division) and Phase 3 (Charging Path Planning) are different from those in Ring-Wandering Algorithm, whose details are given in the following parts.

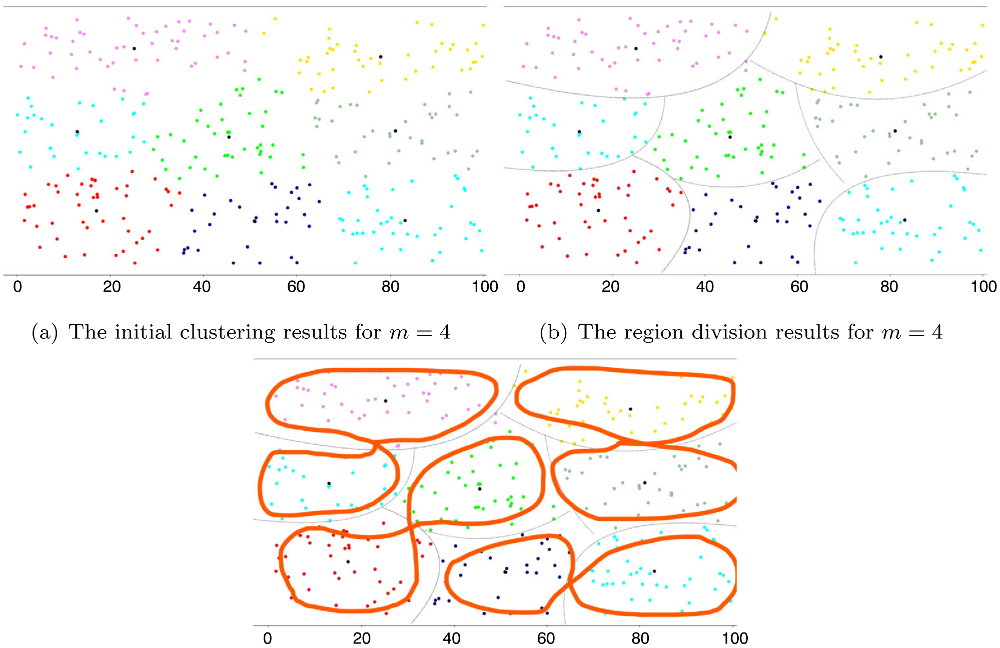
Phase 1: Charging Region Division for 8-track

In this phase, we also adopt the K-Means Algorithm based on Minimum Spanning Tree to partition the sensor set. Different from the Charging Region Division for ring-track, the sensor set is divided into $2m$ subsets which will be assigned to the m chargers respectively. Partitioning into not m but $2m$ subsets is for avoiding wide variance in the chargers' energy consumption due to the different iteration effect of the K-Means Algorithm. The detailed process is as follows:

(i) We construct the Minimum Spanning Tree (MST) T for the transformed edge-weighted graph $G' = (V', E', EW')$ via the Kruskal Algorithm.

(ii) We sort the edges on T in increasing edge weight $\{(s_1, s_2), (s_2, s_3), \ldots, (s_{|V'|-2}, s_{|V'|-1})\}$ and eliminate the first $2m-1$ edges in the sort, i.e., delete $\{(s_1, s_2), (s_2, s_3), \ldots, (s_{2m-1}, s_{2m})\}$. Then the MST T is divided into $2m$ disconnected subgraph $\{T_1, T_2, \ldots, T_{2m}\}$ in Lines 5-8 of Algorithm 2.

(iii) For each connected subgraph T_k $(1 \le k \le 2m)$, the average edge weight will be calculated for finding the initial clustering center and finally we perform the K-Means Algorithm from the $2m$ initial clustering centers and obtain $2m$ divided clusters T'_k $(1 \le k \le 2m)$ in Lines 9-11 of Algorithm 2. As shown in the subgraph (a) in Fig. 2, there are 8 clusters generated by K-Means Algorithm for the case of $m = 4$.



(a) The initial clustering results for $m = 4$ (b) The region division results for $m = 4$

(c) The path planning results for $m = 4$

Fig. 2. The instance on Charging Clustering and Charging Path Planning of Eight-Wandering Algorithm.

(iv) Based on the $2m$ subgraph T'_k, the region division is double realized, e.g. the region is divided into 8 subregions based on the 8 clusters in the subgraph (b) in Fig. 2. For the convenience of the later phases, we divide the $2m$ new cluster centers into m pairs based on their shortest distances: we firstly order each pair of cluster centers in ascending order of their distances; then for each round, we select the shortest unconsidered pair under the constraint that one cluster center cannot belong to more than one pair, which is repeated until all the clusters are paired. Then we number each pair of clusters as $cluster_k, cluster_{k'}$ $(1 \le k \le m)$.

(v) We match $\{T'_1, T'_2, ..., T'_{2m}\}$ into m pairs according to their cluster centers' new numbers obtained in (iv), and combine each pair $T'_k \bigcup T'_{k'}$ into one T'_k for Phase 2.

Phase 2: Charging Energy Assignment

For charing energy assignment, the main idea is the same as that in Ring-Wandering Algorithm, which generates the assignment result $EnergySet = \{E^{charging}_{j,i} | 1 \le j \le m, 1 \le i \le n\}$.

Phase 3: Charging Path Planning for 8-track

For each subgraph T'_j $(1 \le j \le 2m)$, we transformed the heterogeneous-weighted graph into an equivalent edge-weighted graph according to the same idea as that in Algorithm 1 (Lines 17-21 in Algorithm 2). Then we perform TSP Algorithm on each edge-weighted graph $T'_j = (V'[T'_j], E'[T'_j], EW'[T'_j])$ and obtain the path $path'_j$ as shown in Line 22 in Algorithm 2.

Based on the obtained $2m$ paths, we generate m eight-wandering routes which is shaped like the number 8 as follows: for each pair $T'_k \bigcup T'_{k'}$ obtained in Phase 1, their paths $path'_k$ and $path'_{k'}$ can be regarded as two cycles since they are Hamilton Cycles. Then we find a knot to tie such two cycles, i.e., we select the nearest two nodes v and v' which are respectively on $path'_k$ and $path'_{k'}$ and link the two nodes as an edge (v, v'). Finally, two cycles $path'_k$, $path'_{k'}$ and the knot (v, v') compose the eight-wandering route. As shown in the subgraph (c) in Fig. 2, there are 4 eight-wandering paths generated for 4 chargers. The detailed description of Eight-Wandering Algorithm for CEEM-MC Problem is shown in Algorithm 2.

Algorithm 2 Eight-Wandering Algorithm for CEEM-MC Problem.

Input: $S = \{s_1, s_2, \cdots, s_n\}$, $\{E^0_i | 1 \le i \le n\}$, $\{E^r_i | 1 \le i \le n\}$, $\{C(s_i) | 1 \le i \le n\}$, a set $C = \{c_1, c_2, ..., c_m\}$ and E_{max}

Output: $(PathSet, EnergySet)$, where $PathSet = \{path_j | 1 \le j \le m\}$ and $EnergySet = \{E^{charging}_{j,i} | 1 \le j \le m, 1 \le i \le n\}$

1: //**Phase 1: Charging Region Division for Ring-track**
2: //**Phase 1.1: Heterogeneous-weighted Graph Construction** (the same as Algorithms 1)
3: //**Phase 1.2: Charging Clustering for 8-track**
4: Perform Kruskal Algorithm on $G = (V, E, EW)$ and obtain a minimum spanning tree T
5: Sort the edges on T in increasing weight $\{(v_1, v_2), (v_2, v_3), ..., (v_{|V|-1}, v_{|V|})\}$
6: **for** $1 \le i \le 2m - 1$ **do**
7: $\quad T \leftarrow T \setminus (v_i, v_{i+1})$
8: Denote the disconnected subgraph of T as $\{T_1, T_2, ..., T_{2m}\}$
9: **for** $\forall T_j \in T$ **do**
10: $\quad$ Calculate the center $cluster_j$ based on the average edge weight in T_j
11: Perform K-Means Algorithm on $(T, cluster_1, cluster_2, ..., cluster_{2m})$ and obtain $\{T'_1, T'_2, ..., T'_{2m}\}$ and their new cluster centers $\{cluster'_1, cluster'_2, ..., cluster'_{2m}\}$
12: Divide the $2m$ new cluster centers into m pairs based on their shortest distances and number each pair as k, k' $(1 \le k \le m)$
13: Reorder $\{T'_1, T'_2, ..., T'_{2m}\}$ according to the their cluster centers' new numbers and combine each pair $T'_k \bigcup T'_{k'}$ into one T'_k in Phase 2.
14: //**Phase 2: Charging Energy Assignment** (the same as Algorithms 1)
15: //**Phase 3: Charging Path Planning for 8-track**
16: **for** $1 \le j \le 2m$ **do**
17: $\quad$ **for** $\forall s_i \in V'[T'_j]$ **do**
18: $\quad\quad weight'(s_i) = \beta \cdot avrdist \cdot \frac{1}{pri(s_i)} \cdot \frac{weight(s_i)}{\alpha \cdot E^0_i}$, where $avrdist = \frac{\sum_{1 \le i,j \le n} dist(s_i, s_j)}{|E'|}$
19: $\quad$ **for** $\forall (s_i, s_j) \in E'[T'_j]$ **do**
20: $\quad\quad weight'(s_i, s_j) = weight(s_i, s_j) + \frac{1}{2} weight'(s_i) + \frac{1}{2} weight'(s_j)$
21: $\quad EW'[T'_j] = \{weight'(s_i, s_j) | \forall (s_i, s_j) \in E'[T'_j]\}$
22: $\quad$ Perform TSP Algorithm on $T'_j = (V'[T'_j], E'[T'_j], EW'[T'_j])$ and obtain the charging $path'_j$
23: **for** $1 \le k \le m$ **do**
24: $\quad$ Find the closest two nodes respectively on $path'_k$ and $path'_{k'}$, v and v'
25: $\quad path_k \leftarrow path'_k \bigcup path'_{k'} \bigcup \{(v, v')\}$
26: $PathSet = \{path_k | 1 \le k \le m\}$

4.3. Theoretical analysis

Before analyzing the time complexity of the two algorithms for CEEM-MC Problem, we reviewed the time performance of the referenced algorithms, Kruskal Algorithm, K-Means Algorithm and TSP Algorithm. Firstly, in the time complexity computation of Kruskal Algorithm, the dominant part is the edge sorting whose time complexity is $O(|E|\log|E|)$, where E is the number of edges in the graph [18]. Secondly, running a fixed number t of iterations of K-Means Algorithm takes only $O(t \cdot k \cdot n \cdot d)$, for n (d-dimensional) points, where k is the number of cluster) [19]. Thirdly, TSP Algorithm is applied in Phase 1.2 and Phase 2, which has a larger time complexity of $O(n^3)$, where n is the number of nodes in the graph [20].

Theorem 2. *The time complexity of Ring-Wandering Algorithm is $O(n^3)$, where n is the number of sensors.*

Proof. According to the description of Algorithm 1, there are three parts as shown in Algorithm 1, Phase 1, Phase 2 and Phase 3. We analyze the time complexities for these parts as follows:

For the Phase 1, Phase 1.1 (Heterogeneous-weighted Graph Construction) performs for all the nodes and edges, whose time consumptions are directly related to the number of nodes and that of edges. Thus the time complexity is $O((n+m)^2)$. Here we consider the number of sensors is much larger than that of chargers, i.e., $m \ll n$, according to the most practical applications. Thus the time complexity of Phase 1.1 is $O(n^2)$.

Phase 1.2 first performs Kruskal Algorithm whose time complexity is $O(n^2 \cdot \log n)$ here. Then the clustering for the m subgraph T_j costs $O(m \cdot n)$ based on K-Means Algorithm, where the number of iterations t is much less than the number of sensors n, which can be regarded as a constant and the dimension number $d = 2$. Thus the time complexity of Phase 1.2 is $O(n^2 \cdot \log n)$.

For Phase 2, the charging priority assignment has the time complexity of $O(n)$ in Phase 2.1. And the node filtering in Phase 2.2 has the time complexity of $O(m \cdot n)$, which is less than $O(n^2)$. Thus the time complexity of Phase 2 is $O(n^2)$.

For Phase 3, the edge-weighted graph transformation also performs for all the nodes and edges like Phase 1.1. Thus its time complexity is $O(n^2)$. Furthermore, TSP Algorithm has a larger time complexity of $O(n^3)$ [20]. Thus the time complexity of Phase 3 is $O(n^3)$.

Therefore the time complexity of Algorithm 1 is $O(n^3)$, which completes the proof. □

Since the two algorithms for CEEM-MC Problem are similar on the main operating phases, the same conclusion on time complexity can be drawn for Eight-Wandering Algorithm as follows.

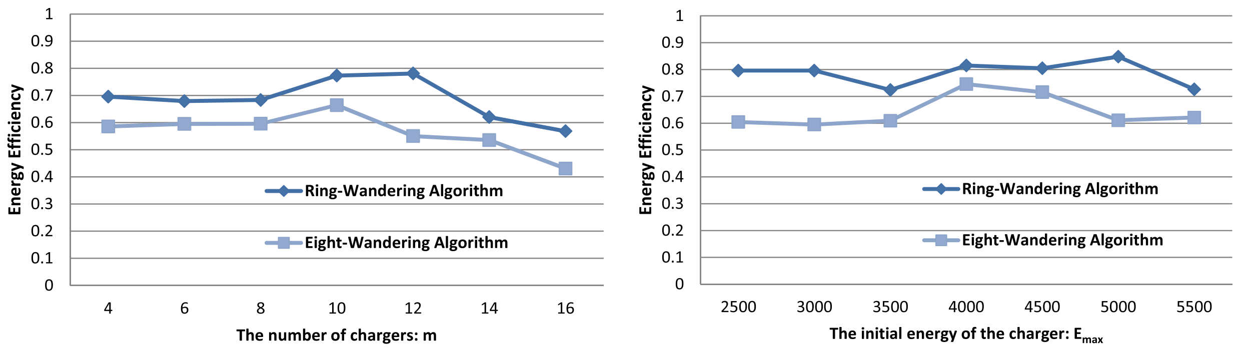
Theorem 3. *The time complexity of Eight-Wandering Algorithm is $O(n^3)$, where n is the number of sensors.*

5. Simulation results

We perform the simulation experiments in a two-dimension square planar with the side length of M. On the plane, there are n sensors randomly deployed with the uniform maximum battery capacity E^0, and m mobile chargers with their initial energy E_{max}. For each sensor s_i, s_i's remaining battery energy denoted as E_i^r is valued in the range of $[0, \omega_1 \cdot E^0]$. The indictor for the sensors' status, E^{low}, is assigned as $\omega_2 \cdot E^0$. Here we set $\omega_1 = \frac{4}{5}$ and $\omega_2 = \frac{3}{10}$ according to the sensors' covering energy consumption model and the battery capacity. The moving distance limitation between any pair sensors l_0 is set as 50.

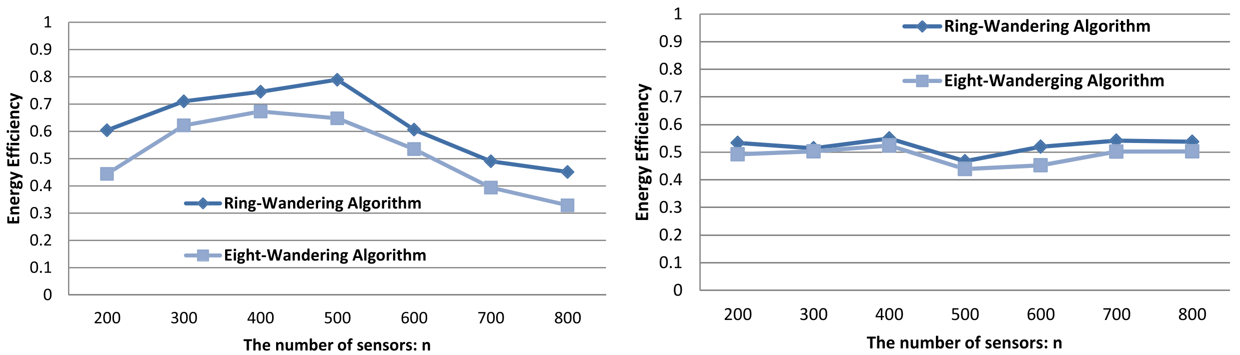
For the optimization goal of CEEM-MC Problem, we evaluate the proposed algorithms, **Ring-Wandering Algorithm** and **Eight-Wandering Algorithm**, in terms of the energy efficiency, which is denoted as **Energy Efficiency**. We evaluate their performance based on the changes of five parameters, the number of chargers m, the initial energy of the charger E_{max}, the number of sensors n, and the maximum energy capacity of sensors E^0 and the side length of the region M. These parameters are considered as the potential factors on performance of charing scheduling. And we consider the following five groups of parameter settings and we repeat the experiment 100 times and adopt the average values for each setting: (1) m varies from 4 to 16 by the step of 2 with fixed n, M, E^0 and E_{max}; (2) E_{max} varies from 2500 to 5500 by the step of 500 with fixed n, M, E^0 and m; (3) n varies from 200 to 800 by the step of 100 with fixed $m = 8, 12$, M, E^0 and E_{max}; (4) E^0 varies from 40 to 100 by the step of 20 with fixed $m = 8, 12$, M, n and E_{max}; (5) M varies from 40 to 160 by the step of 20 with fixed $n = 400, 600$, $m = 8, 12$, E^0 and E_{max}.

We firstly analyze the algorithm performance influenced by the parameters about the chargers, m and E_{max}. For the number of chargers m, both of two algorithms show the stable status before the peak values appear at $m = 12$ for Ring-Wandering Algorithm and $m = 10$ for Eight-Wandering one, which is shown in subgraph (a) in Fig. 3. When m is larger than the peak value, the energy efficiency has a downtrend. It is because that the more chargers and the sensors with a fixed number may present a 'supply exceeds demand' condition, i.e., the additional chargers cost more moving energy to charging the sensors which can be charged by fewer chargers, which reduces the energy efficiency. For the initial energy of the chargers E_{max}, its influence on the charging scheduling algorithms is relatively mild, and the performance changes of two algorithms are in the range of $[0.60, 0.85]$, which can be seen in subgraph (b) in Fig. 3. The charging consumption of chargers is more decided by the charging requirement of sensors than the initial energy on chargers.

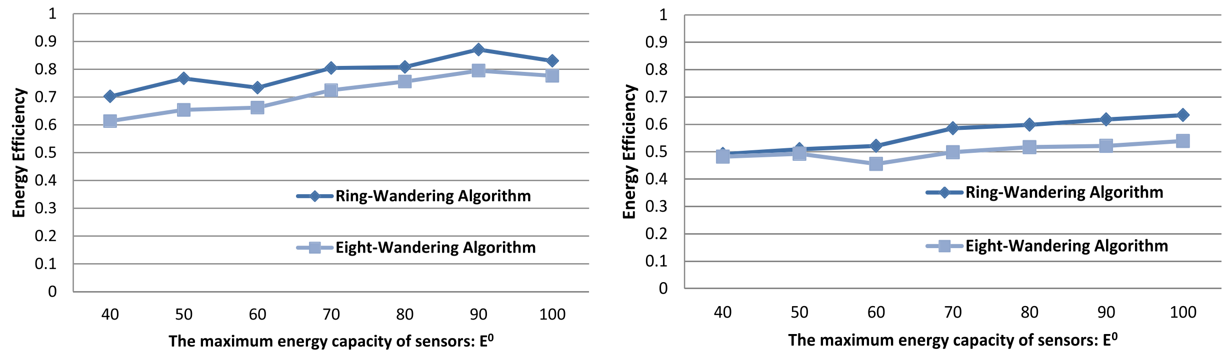


(a) $n = 400, M = 100, E^0 = 50, E_{max} = 2000$ (b) $n = 400, M = 100, E^0 = 50, m = 8$

Fig. 3. Energy Efficiency by Comparing two algorithms on charger parameters.



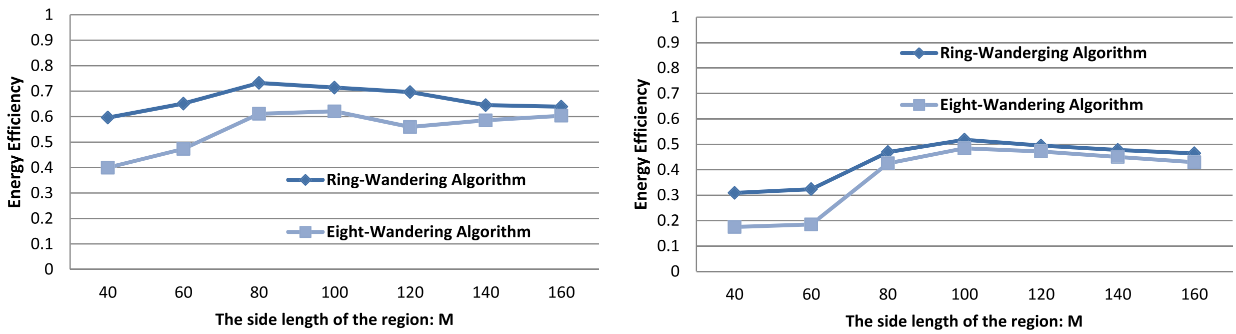
(a) $m = 8, M = 100, E^0 = 50, E_{max} = 2000$ (b) $m = 12, M = 100, E^0 = 50, E_{max} = 2000$



(c) $m = 8, M = 100, n = 400, E_{max} = 2000$ (d) $m = 12, M = 100, n = 400, E_{max} = 2000$

Fig. 4. Energy Efficiency by Comparing two algorithms on sensor parameters.

Secondly, we analyze the algorithm performance affected by the parameters about the sensors, n and E^0, as shown in Fig. 4. On the one hand, with the increasing of the network scale, the algorithm performance presents a rising trend until $n > 500$ for Ring-Wandering Algorithm and $n > 400$ for Eight-Wandering one in subgraph (a) of Fig. 4. That is because that the limited number of chargers cannot satisfy the charging requirement of the increasing number of sensors, which present a status like 'supply falls short of demand'. Thus the energy efficiencies of two algorithms are both decreased. When the number of chargers becomes more sufficient, the gap between two algorithms gets narrower in subgraph (b) of Fig. 4. On the other hand, the battery capacity of sensors E^0 has less influence on the performance than n in subgraphs (c) and (d) of Fig. 4. With the growth of E^0, the increasing charging requirement has been met and the moving energy cost stays fixed, thus the energy efficiency can be increased.



(a) $n = 400, m = 8, E^0 = 50, E_{max} = 2000$ (b) $n = 600, m = 12, E^0 = 50, E_{max} = 2000$

Fig. 5. Energy Efficiency by Comparing two algorithms on region parameter.

We thirdly analyze the algorithm performance impacted by the parameter about the deployment region, M. As shown in Fig. 5, despite Eight-Wandering Algorithm still shows more advantages, both of the two algorithms' performance presents an upward trend and trends to be stable and near to each other when $M > 140$ in subgraph (a) and $M > 100$ in subgraph (b) in Fig. 5. The reason is that the network's deployment density becomes sparse with the enlarging of the deployment region, which results in less difference on the lengths of the wandering paths. Thus the difference path planning schemes will generate the similar energy efficiencies.

Finally, we can draw the conclusion that depending on the advantage of balancing each charger's moving energy consumption, Eight-Wandering Algorithm outperforms Ring-Wandering Algorithm in most cases. Among the influencing factors for the two charging scheduling algorithms, the number of chargers m and the network scale n have more influence than the initial energy of the chargers E_{max}, the energy capacity of the sensors E^0 and the region scale M in terms of the energy efficiency of the whole charging process.

6. Conclusion

With the consideration of maximizing the energy efficiency, we investigate a charging planning problem for multiple chargers in WRSNs. Based on the NP-hardness proof of the problem, we propose two algorithms, Ring-Wandering Algorithm and Eight-Wandering Algorithm on heterogeneous-weighted graph construction and edge-weighted graph transformation to increase the charging contribution. The algorithms adopt the idea of K-Means Algorithm to divide the charged region of each charger, and perform the TSP Algorithm to minimize the moving consumption. To evaluate the proposed algorithms, we compare their performance in terms of energy efficiency. The simulation results show the advantages of Eight-Wandering Algorithm and the influences of the critical parameters. To extend this research, we will improve the charging scheduling strategy for different optimization goals and extend the strategies to the three-dimensional practical applications.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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