Multiple Mobile Chargers-assisted Efficient Green Energy Wireless Charging for WRSNs

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***Abstract*—With the development of Internet of Things (IoT), wireless rechargeable sensor networks (WRSNs) have been widely applied in modern society. There has a greater demand for green and efficient remote wireless charging to power the wireless sensor nodes (SNs) in WRSNs. However, few has tackled the wireless charging efficiency problem that can achieve the low dead SNs percentage (DSP) in far-field wireless charging. Existing far-field wireless charging schemes cannot meet the energy supply requirement of large-scale SNs. Therefore, this work proposes the multiple mobile chargers (MCs)-assisted efficient green energy wireless charging for WRSNs. Firstly, according to the existing Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, the area not covered by the wireless charging base stations (BSs) is divided into multiple irregular-shape sub-regions. Then, we leverage multiple MCs to wirelessly charge the SNs located in these sub-regions. Finally, we propose the Minimal chArging grouPings (MAP) algorithm to minimize the number of the MCs' anchor points (APs) and efficiently charge the SNs. The simulation results validate that our proposed algorithm can effectively improve the wireless charging energy efficiency and reduce the DSP.**

I. Introduction

With the rapid development of Internet of Things (IoT), wireless rechargeable sensor networks (WRSNs) have been widely deployed in modern agriculture, smart factory and intelligent transportation [1], [2]. WRSNs highly bestrew convenience and efficiency into our daily lives. However, the battery capacity of a sensor node (SN) is usually limited; the SNs' limited energy is the main factor affecting the long-term normal function of WRSN.

In order to prolong the WRSN's lifetime, a number of methods have been proposed to alleviate the SNs' energy issue. The first method is periodical battery replacement [3]. However, for a large-scale WRSN, replacing batteries not only leads to vast operational cost but also wastes time. The second method is to conserve the energy of a SN by minimizing its energy consumption [4]. Plenty of network management strategies [5], data fusion protocols [6], and sleep-scheduling mechanisms [7] have been proposed to reach this aim. By the second method, although the lifetime of a SN can be prolonged to a certain extent, this does not fundamentally resolve the energy sustainability issue. The third method is to equip the wireless SNs with ambient energy harvesting capabilities [8], i.e., the SNs are able to collect surrounding solar, wind, or thermal energy to power themselves. However, this method is greatly affected by the local physical environment; the ambient energy is unstable and unpredictable.

At present, far-field wireless charging is an essential and promising technique to intentionally power the remote SNs [9], [10]. Far-field wireless charging leverages the electromagnetic waves to transmit wireless energy to the SNs [11]. Electromagnetic beams can be more efficient (concentrated) when the wireless energy emitter (wireless charging base station (BS) or mobile charger (MC)) is equipped with multiple antennas. This technique can also adjust the width of the energy beamlet according to the particular charging scenario so that the wireless energy transmission loss can be reduced and the charging distance can be extended. Therefore, it is beneficial for the large-scale WRSN.

In WRSN, in order to further decrease the energy loss and reduce the number of exhausted SNs (i.e., becoming dead SNs), many existing works have studied the wireless charging schemes. An MC was leveraged by Xie *et al.* [12] to more efficiently charge SNs by moving close to them. According to the preplanned moving path, the energy consumption of the MC is minimized. A minimal charging time strategy for WRSN was proposed by Fu *et al.* [13]; they designed a moving scheme for the MC to fully charge all the SNs in the network within a short time. Wang *et al.* [14] studied the optimal charging radius for wireless power transmission (WPT). The optimal charging radius is determined to maximize the received energy. Lin *et al.* [15] investigated the minimal charging delay scheme to improve the charging efficiency. The linear programming approach was adopted to solve the multiple chargers' minimal charging delay problem.

Most studies only adopt the omnidirectional wireless charging (i.e., they did not consider the directional charging beams), thus resulting in a low charging efficiency and a high dead SNs percentage (DSP). In addition, most of the existing MC charging schemes adopt periodic charging and they do not consider the dynamics of SNs' energy consumptions; some SNs may run out of energy soon by implementing their proposed schemes. In order to efficiently charge the SNs and maintain most of the SNs alive, we first adopt the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm [16] to classify the SNs. By equipping multiple antennas at the MCs, we then propose the Minimal chArging grouPings (MAP) algorithm to reduce the number of anchor points (APs), i.e., stops of the MCs to save the energy consumed in the

MCs' moving paths and reduce the total charging time in the network. In the MAP algorithm, more SNs can receive enough energy replenishment in time. It improves the WRSN's wireless charging energy efficiency and reduces the DSP.

II. System Model

Consider the green energy wireless charging framework with a charging area with multiple wireless charging BSs as shown in Fig. 1. A wireless charging BS first harvests green energy through their solar panels and wind turbines [17]–[19] and then transmits the harvested green energy in the form of three energy beams (i.e., a beam covers $120°$) to charge its covered SNs and MCs [20]. A wireless charging BS covers a circular zone with radius R_{bs}.

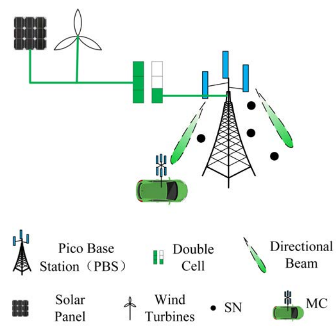

Fig. 1. Green energy wireless charging framework for WRSNs.

According to the DBSCAN algorithm, the area not covered by the wireless charging BSs is divided into three irregular-shape sub-regions. These irregular-shape sub-regions can be denoted by $\mathbb{Q}_\mu$, $\mu = 1, 2, 3$. The DBSCAN algorithm is a cluster-based algorithm, which considers the number and density of SNs in the WRSN. By adopting this algorithm, the SNs in a sub-region, which has a high SNs density, first form a cluster. In the meantime, after all the clusters (sub-regions) are formed, the numbers of SNs in all sub-regions are almost the same. An MC is responsible to charge the SNs in a sub-region. Each MC principally charges the hungry SNs (i.e., the SNs that request energy replenishment). At the same time, the non-hungry SNs (i.e., the SNs that do not request energy replenishment) located in the MC's energy beam can also receive wireless energy. Hence, the non-hungry SNs can also be charged by the way when the MC charges the hungry SNs (without inducing extra energy consumption to the MC). An MC is installed with multiple directional antennas to form six directional beams (i.e., a beam covers $60°$) to cover its surrounding $360°$ circular zone, and an MC's coverage radius is R_{mc}. The specific wireless charging framework with sub-regions division is shown in Fig. 2.

Assuming there are Ψ_μ SNs in the μth sub-region. We denote an AP selection matrix $\mathbf{\Omega}$ with three rows and $max\left(\Psi_\mu\right)$ columns. We adopt $\Omega\left(\mu, \psi\right)$ to represent the AP selection decision variable. $\Omega\left(\mu, \psi\right) = 1$ represents that the μth row and the ψth column in the $\mathbf{\Omega}$ is selected as AP. $\Omega\left(\mu, \psi\right) = 0$ represents that the μth row and the ψth column in the $\mathbf{\Omega}$ is

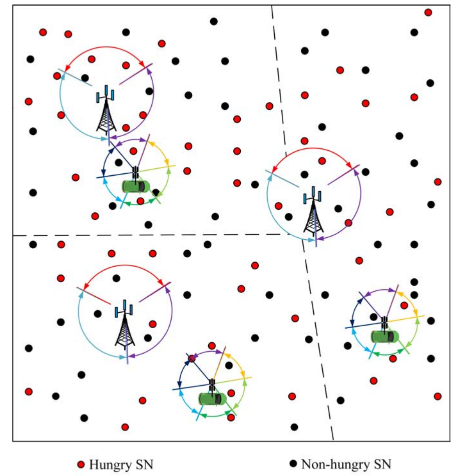

Fig. 2. Specific wireless charging framework with sub-regional division.

not selected as AP, where $\psi = 1, 2, \cdots, \max\left(\Psi_\mu\right)$. Assuming there are K_μ APs in the μth sub-region, represented by the charging sequence set $\boldsymbol{S_\mu} = \left\{s_{(\mu,1)}, s_{(\mu,2)}, \cdots, s_{(\mu,K_\mu)}\right\}$; $s_{(\mu,k)}$ indexes the kth AP in the μth sub-region. The charging sequences in the three sub-regions can be represented by the matrix $\boldsymbol{S} = \left\{\boldsymbol{S_1}, \boldsymbol{S_2}, \boldsymbol{S_3}\right\}$. When the MC charges the SNs at the kth AP, there are I_k hungry SNs and J_k non-hungry SNs covered by this MC. I_k hungry SNs can be represented by set $\boldsymbol{H_k}= \left\{h_{(k,1)}, h_{(k,2)}, \cdots, h_{(k,I_k)}\right\}$; $h_{(k,i)}$ represents the ith hungry SN within the MC's coverage zone when the MC charges the SNs at the kth AP. J_k non-hungry SNs can be represented by set $\boldsymbol{N_k}= \left\{n_{(k,1)}, n_{(k,2)}, \cdots, n_{(k,J_k)}\right\}$; $n_{(k,j)}$ represents the jth non-hungry SN within the MC's coverage zone when the MC charges the SNs at the kth AP.

In this system model, assuming all SNs' batteries are furnished with the same capacity ε. If the amount of residual energy of a SN is less than the alarm energy threshold γ, this SN is called the hunger SN. It sends energy request message, $A_{h_{(k,i)}} = \left\{\left(x_{h_{(k,i)}}, y_{h_{(k,i)}}\right), \alpha_{h_{(k,i)}}, d_{\left(h_{(k,i)},mc\right)}\right\}$, to its associated BS (i.e., the BS provides the SN with the best power gain, according to Strongest Signal First [21]). Then, this BS will assign the MC (responsible for this sub-region) to charge this hungry SN. Here, $\left(x_{h_{(k,i)}}, y_{h_{(k,i)}}\right)$ and $\alpha_{h_{(k,i)}}$ respectively represent the position and residual energy of the ith hungry SN within this MC's coverage zone when the MC charges the SNs at the kth AP. When $\alpha_{h_{(k,i)}} \leq 0$, it means that the ith hungry SN is dead. $d_{\left(h_{(k,i)},mc\right)}$ is the distance between the ith hungry SN and the MC.

A. Charging Priority Model

When the MC charges the SNs at the kth AP, the ith hungry SN's energy consumption rate within the MC's coverage zone is $c_{h_{(k,i)}}$. The ith hungry SN's residual lifetime is $\beta_{h_{(k,i)}}$, which can be obtained as

$$\beta_{h_{(k,i)}} = \frac{\alpha_{h_{(k,i)}}}{c_{h_{(k,i)}}}. \tag{1}$$

In order to determine a SN's charging priority in the μth sub-region, we first define the ith hungry SN's residual lifetime priority function as

$$\chi^{\mu}_{h_{(k,i)}} = \frac{\sum_{k=1}^{K_\mu}\sum_{i=1}^{I_k}\beta_{h_{(k,i)}}}{\beta_{h_{(k,i)}}}. \tag{2}$$

Here, $\sum_{k=1}^{K_\mu}\sum_{i=1}^{I_k}\beta_{h_{(k,i)}}$ represents the summation of the residual lifetimes of all covered hungry SNs in the μth sub-region. Then, we define the ith hungry SN's distance priority function as

$$\partial^{\mu}_{h_{(k,i)}} = \frac{\sum_{k=1}^{K_\mu}\sum_{i=1}^{I_k} d_{\left(h_{(k,i)},mc\right)}}{d_{\left(h_{(k,i)},mc\right)}}. \tag{3}$$

Here, $\sum_{k=1}^{K_\mu}\sum_{i=1}^{I_k} d_{\left(h_{(k,i)},mc\right)}$ represents the summation of distances between all covered hungry SNs and the MC in the μth sub-region. According to Eq. (2) and Eq. (3), the ith hungry SN's charging priority function is defined as

$$O^{\mu}_{h_{(k,i)}} = \chi^{\mu}_{h_{(k,i)}} + \partial^{\mu}_{h_{(k,i)}}. \tag{4}$$

A hungry SN with a larger value of the priority function $O^{\mu}_{h_{(k,i)}}$ has a higher the charging priority. The zone's charging sequence is determined by the highest charging priority of the hungry SNs within the zone.

B. Charging Model

When electromagnetic wave propagates in space, the power attenuates with the increase of transmission distance. According to Friis transmission equation [22], the ith hungry SN's received power can be expressed as

$$P_{r_{h_{(k,i)}}} = P_{t_{mc}} \frac{G_t G_{r_{h_{(k,i)}}}\eta}{L_p}\left(\frac{\lambda}{4\pi d_{\left(h_{(k,i)},mc\right)}}\right)^2. \tag{5}$$

Here, $P_{t_{mc}}$ represents the wireless charging power of the MC. G_t represents the transmission antenna gain. $G_{r_{h_{(k,i)}}}$ represents the reception antenna gain of the ith hungry SN. η is the diode rectification efficiency. L_p is polarization loss of the reception antenna (supposing all SNs in this network are identical, and so η and L_p are the same for all the SNs). λ is the wavelength of the electromagnetic wave for wireless charging. $d_{\left(h_{(k,i)},mc\right)}$ represents the distance between the ith hungry SN and the MC. When the distance between the SN and the MC exceeds the maximal charging radius R_{mc} of MC, the received power of the SN can be neglected.

C. Charging Time Model

In each round of charging scheduling, MC mainly charges the hungry SNs. At the same time, the non-hungry SNs covered by the MC's energy beam can also receive wireless energy. Therefore, the MC's charging time is determined by the charging demand time of the hungry SNs. The ith hungry SN's charging time is defined as

$$t_{h_{(k,i)}} = \frac{\varepsilon - \alpha_{h_{(k,i)}}}{P_{r_{h_{(k,i)}}}}. \tag{6}$$

Here, $\varepsilon - \alpha_{h_{(k,i)}}$ represents the ith hungry SN's demand energy. The MC only needs to fully charge all the hungry SNs in the coverage zone. Therefore, the charging time of the MC at the kth AP is defined as

$$t\left(s_{(\mu,k)}\right) = \max_{h_{(k,i)}\in \boldsymbol{H_k}} \left(t_{h_{(k,i)}}\right). \tag{7}$$

The charging time of the MC at all APs in the μth sub-region is denoted by set $\boldsymbol{T_\mu}$. The charging time periods in the three sub-regions can be represented by the matrix $\boldsymbol{T} = \{\boldsymbol{T_1}, \boldsymbol{T_2}, \boldsymbol{T_3}\}$.

D. SNs' Received Energy Model

After the MC charges the SNs covered by the kth AP, the batteries of all hungry SNs within this MC's coverage zone are fully charged. Therefore, the energy obtained by the ith hungry SN is defined as

$$E_{h_{(k,i)}} = \varepsilon - \alpha_{h_{(k,i)}}. \tag{8}$$

The amount of energy received by a non-hungry SN is related to the charging time of the MC in this charging zone. Therefore, the maximal energy received by the jth non-hungry SN from the MC is

$$E'_{n_{(k,j)}} = P_{r_{n_{(k,j)}}} t\left(s_{(\mu,k)}\right), \tag{9}$$

where $P_{r_{n_{(k,j)}}}$ represents the jth non-hungry SN's received power. As a SN's battery capacity is limited, the total energy obtained by the jth non-hungry SN is defined as

$$E_{n_{(k,j)}} = \min\left(E'_{n_{(k,j)}}, \left(\varepsilon - \alpha_{n_{(k,j)}}\right)\right). \tag{10}$$

Here, $\varepsilon - \alpha_{n_{(k,j)}}$ represents the jth non-hungry SN's demand energy.

After the MC charges the SN covered by the kth AP, the energy received by all SNs within this coverage zone can be defined as

$$E\left(s_{(\mu,k)}\right) = \sum_{i=1}^{I_k} E_{h_{(k,i)}} + \sum_{j=1}^{J_k} E_{n_{(k,j)}}. \tag{11}$$

Here, $\sum_{i=1}^{I_k} E_{h_{(k,i)}}$ is the total amount of energy received by all hungry SNs after the MC charges the SNs covered by the kth AP. $\sum_{j=1}^{J_k} E_{n_{(k,j)}}$ is the total amount of energy received by all non-hungry SNs after the MC charges the SNs covered by the kth AP. Therefore, the total energy received by all SNs in the μth sub-region is defined as

$$E_{r_\mu} = \sum_{k=1}^{K_\mu} \left(E\left(s_{(\mu,k)}\right)\right). \tag{12}$$

E. MC's Energy Consumption Model

The total energy carried by an MC is E_{mc}. The energy consumed by the MC to move one meter is e_m. The MC's moving distance for fully charging all the hungry SNs in the μth sub-region is represented as

$$L_{m_\mu} = d_{bs,s_{(\mu,1)}} + \sum_{k=2}^{K_\mu - 1} d_{s_{(\mu,k)},s_{(\mu,k+1)}} + d_{s_{(\mu,K_\mu)},bs}. \quad (13)$$

Here, $d_{bs,s_{(\mu,1)}}$ represents the distance between the first AP in the μth sub-region and its associated BS. $d_{s_{(\mu,k)},s_{(\mu,k+1)}}$ represents the distance between the kth AP and $(k+1)$th AP. $d_{s_{(\mu,k_\mu)},bs}$ represents the distance between the last AP and its associated BS. Therefore, the energy consumed by the MC movement in the μth sub-region is defined as

$$E_{m_\mu} = e_m L_{m_\mu}. \quad (14)$$

The MC's charging energy consumption in the μth sub-region is

$$E_{c_\mu} = P_{t_{mc}} \sum_{k=1}^{K_\mu} t\left(s_{(\mu,k)}\right). \quad (15)$$

Here, $t\left(s_{(\mu,k)}\right)$ is the MC's charging time when MC stops at the kth AP in the μth sub-region.

III. Problem Formulation

Based on the above system model, we formulate the MCs' maximal wireless charging energy efficiency problem as

$$\max_{\{\boldsymbol{\Omega},\boldsymbol{S},\boldsymbol{T}\}} \sum_{\mu=1}^{3} \frac{E_{r_\mu}}{E_{m_\mu} + E_{c_\mu}} \quad (16)$$

$$\text{s.t.} \quad E_{m_\mu} + E_{c_\mu} \le E_{mc}, \quad (17)$$

$$d_{\left(h_{(k,i)},mc\right)} \le R_{mc},\ h_{(k,i)} \in \boldsymbol{H_k}, \quad (18)$$

$$d_{\left(n_{(k,j)},mc\right)} \le R_{mc},\ n_{(k,j)} \in \boldsymbol{N_k}. \quad (19)$$

Here, E_{r_μ} represents the total amount of energy received by the SNs in the μth sub-region. $E_{m_\mu} + E_{c_\mu}$ represents the total amount of energy consumption of the MC in the μth sub-region. Eq. (17) indicates that the total amount of energy consumed by the MC should be less than or equal to the total energy carried by the MC. Eq. (18) and Eq. (19) indicate that the distance between the SN and the MC is less than or equal to the maximal charging radius of the MC.

Our optimization problem is to maximize the wireless charging energy efficiency, which is decided by $\boldsymbol{\Omega}$, $\boldsymbol{S}$ and $\boldsymbol{T}$. This is an AP selection problem (i.e., the MC can cover all hungry SNs). The well-known Discrete Unit Disk Coverage (DUDC) problem [23] is to cover all target points with the fewest circles, which is an NP-hard problem. In our formulated problem, the APs and hungry SNs can be regarded as the circle centers and target points in the DUDU problem, respectively. The essences of our problem and those of the DUDC problem are the same. Hence, our formulated problem can be reduced to the DUDC problem. Therefore, our wireless charging energy efficiency maximization problem is also NP-hard.

IV. MAP Algorithm

According to the above analysis, as our wireless charging energy efficiency maximization problem is an NP-hard problem, the optimal solution cannot be obtained in polynomial time. Therefore, we propose the MAP algorithm to efficiently solve this problem. The pseudo code of this MAP algorithm is shown below.

Algorithm 1 MAP Algorithm

Input: $\boldsymbol{\Gamma_\mu}$,$\boldsymbol{N\_\Gamma_\mu}$, where $(\mu = 1, 2, 3)$
Output: $\boldsymbol{\Omega}$,$\boldsymbol{S}$,$\boldsymbol{T}$

$R_{mc} \leftarrow \frac{\lambda}{4\pi}\sqrt{\frac{P_{r_{\min}} L_p}{P_{t_c} G_t G_r \eta}}$;
for $\mu = 1$ to 3 **do**
    $\boldsymbol{\Theta_\mu} \leftarrow \boldsymbol{\Gamma_\mu} \cup \boldsymbol{N\_\Gamma_\mu}$;
    while $\boldsymbol{\Gamma_\mu} \neq \emptyset$ **do**
        for υ=1 to $|\boldsymbol{\Theta_\mu}|$ **do**
            Record the υth SN's coordinates (x_υ, y_υ) in the set $\boldsymbol{\Theta_\mu}$;
            Make the coverage zone of MC in each SN $0 \leftarrow (x - x_\upsilon)^2 + (y - y_\upsilon)^2 - R_{mc}^2$;
            $\vartheta_\nu \leftarrow$ the number of hungry SNs covered by the MC at each SN;
            $\boldsymbol{\Lambda} \leftarrow \boldsymbol{\Lambda} \cup \{\vartheta_\nu\}$;
        end for
        $\varkappa \leftarrow$ The index of the largest element in $\boldsymbol{\Lambda}$;
        $\boldsymbol{\Lambda} \leftarrow \emptyset$;
        $\mathcal{L} \leftarrow$ the $\varkappa$'s corresponding index in $\boldsymbol{\Theta_\mu}$;
        $\boldsymbol{S_\mu} \leftarrow \boldsymbol{S_\mu} \cup \{\mathcal{L}\}$;
        All SNs covered by MC at the $\mathcal{L}$th AP are denoted by set $\Im_{\boldsymbol{\mathcal{L}}}$;
        $\boldsymbol{\Theta_\mu} \leftarrow \boldsymbol{\Theta_\mu} \backslash \Im_{\boldsymbol{\mathcal{L}}}$;
        All hungry SNs covered by MC at the $\mathcal{L}$th AP are denoted by set $\Re_{\boldsymbol{\mathcal{L}}}$;
        $\boldsymbol{\Gamma_\mu} \leftarrow \boldsymbol{\Gamma_\mu} \backslash \Re_{\boldsymbol{\mathcal{L}}}$;
        $\psi \leftarrow$ the $\mathcal{L}$'s corresponding index in $\boldsymbol{\Theta_\mu}$;
        $\Omega(\mu, \psi) \leftarrow 1$;
        $\varrho_{\mathcal{L}} \leftarrow$ the highest charging priority of the hungry SNs in $\Re_{\boldsymbol{\mathcal{L}}}$;
        $\boldsymbol{\Pi_\mu} \leftarrow \boldsymbol{\Pi_\mu} \cup \{\varrho_{\mathcal{L}}\}$;
        $\tau_{\mathcal{L}} \leftarrow$ the maximal charging time of the hungry SNs in $\Re_{\boldsymbol{\mathcal{L}}}$;
        $\boldsymbol{T_\mu} \leftarrow \boldsymbol{T_\mu} \cup \{\tau_{\mathcal{L}}\}$;
    end while
    $[\boldsymbol{\Pi_\mu}\ index] \leftarrow sort(\boldsymbol{\Pi_\mu})$;
    $\boldsymbol{S_\mu} \leftarrow index(\boldsymbol{S_\mu})$;
    $\boldsymbol{T_\mu} \leftarrow index(\boldsymbol{T_\mu})$;
    $\boldsymbol{S} \leftarrow \boldsymbol{S} \cup \{\boldsymbol{S_\mu}\}$;
    $\boldsymbol{T} \leftarrow \boldsymbol{T} \cup \{\boldsymbol{T_\mu}\}$;
end for

According to the DBSCAN algorithm, the area not covered by the wireless charging BSs is divided into three sub-regions. In the three sub-regions, the hungry SNs and non-hungry SNs are denoted by set $\boldsymbol{\Gamma_\mu}$ and $\boldsymbol{N\_\Gamma_\mu}$, respectively. All SNs in the three sub-regions are denoted by set $\boldsymbol{\Theta_\mu}$ (here,

$\boldsymbol{\Theta}_{\mu} = \boldsymbol{\Gamma}_{\mu} \cup \boldsymbol{N}\_\boldsymbol{\Gamma}_{\mu}$), where $\mu = 1, 2, 3$. According to the Friis transmission equation, the maximal charging radius R_{mc} of the MC can be obtained. Lines 5 to 10 count the number of hungry SNs covered by the MC (when the MC reaches each SN). ϑ_{ν} is a temporary variable used to store the number of hungry SNs covered by the MC. Lines 11 to 14 represent that if the MC stops at an SN that can cover the most hungry SNs, this location is denoted by the $\mathcal{L}$th AP; then, we add the $\mathcal{L}$th AP to set $\boldsymbol{S}_{\mu}$. All SNs and all hungry SNs covered by MC at the $\mathcal{L}$th AP are denoted by sets $\Im_{\mathcal{L}}$ and $\Re_{\mathcal{L}}$, respectively. Then, we remove sets $\Im_{\mathcal{L}}$ and $\Re_{\mathcal{L}}$ from sets $\boldsymbol{\Theta}_{\mu}$ and $\boldsymbol{\Gamma}_{\mu}$, respectively. The $\mathcal{L}$'s corresponding index in $\boldsymbol{\Theta}_{\mu}$ is marked as ψ, and $\Omega(\mu, \psi)$ is set to 1. $\varrho_{\mathcal{L}}$ and $\tau_{\mathcal{L}}$ are two temporary variables used to store the highest charging priority and the MC's charging time (when MC stops at the $\mathcal{L}$th AP), respectively. Lines 27 and 28 obtain the target charging sequence $\boldsymbol{S}_{\mu}$ and the target charging time $\boldsymbol{T}_{\mu}$ in the μth sub-region, respectively. The three sub-regions will do the same operation; the AP selection matrix $\boldsymbol{\Omega}$, charging sequence matrix $\boldsymbol{S}$ and charging time matrix $\boldsymbol{T}$ all can be acquired.

V. Simulations

Simulations are set up as follows. We randomly distribute a number of wireless SNs, ranging between 100 and 1000, in the 2D square area of $100m \times 100m$. The battery capacities of all SNs are $50J$, and their initial energies are randomly distributed in the interval of $[0, 50J]$. The wireless charging electromagnetic wave's wavelength is $1GHz$, and the antenna polarization losses of all SNs are 0.5. The transmission gains of all MCs are $10dBi$. The charging powers and moving speeds of all MCs are $5w$ and $2m/s$, respectively.

In simulations, we evaluate the performance of our proposed algorithm by comparing it to those of the Traveling Salesman Problem (TSP) algorithm [24] and the On-Demand chaRging (ODR) algorithm [25]. The ODR algorithm only considers the residual lifetimes of the hungry SNs, and sorts the SNs according to their residual lifetimes (from low to high). Then, the MC charges the hungry SNs based on this order.

Fig. 3 shows the total charging groups formed by the three algorithms, with different SNs' deployment scenarios. In the scenarios, the numbers of SNs are increased from 100 to 1000. In each scenario, the distribution of SNs is the same for the three algorithms. It can be seen that when the number of SNs in the network is small, the numbers of charging groups formed by the three algorithms are almost the same. With the increase of deployed SNs, the numbers of groups formed by the TSP algorithm and ODR algorithm increase greatly. However, the number of groups formed by the MAP algorithm relatively increases slowly because the TSP algorithm and the ODR algorithm only perform charging grouping once, while the MAP algorithm groups the SNs in multiple iterations to find the "optimal" APs and save the MC's moving energy consumption.

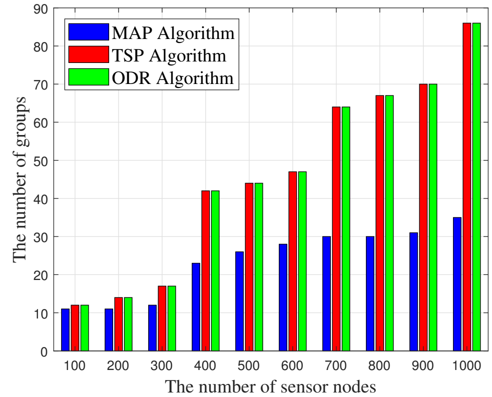

Fig. 3. The number of groups with different numbers of SNs.

Fig. 4 illustrates the comparison of wireless charging efficiencies achieved by the three algorithms in different SNs deployment scenarios. The wireless charging efficiencies achieved by the three algorithms enhance with the increase of SNs because the density of SNs becomes higher in each MC's charging coverage. As the wireless charging encounters attenuation in space, the wireless charging efficiency is relatively low. However, our proposed algorithm enables the MC to travel shorter, cover more SNs with less APs and the wireless charging energy efficiency is about 2 times higher than those achieved by the other two algorithms.

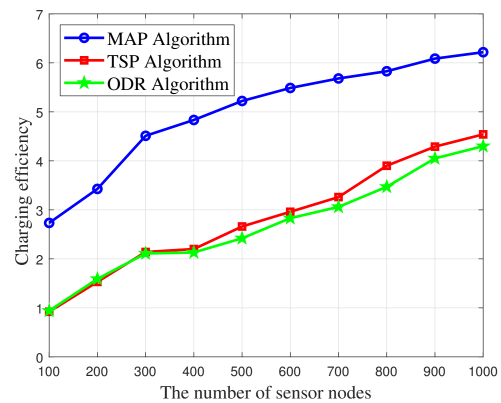

Fig. 4. The wireless charging efficiency with different numbers of SNs.

Fig. 5 shows the comparison of the numbers of dead SNs in the network by adopting different algorithms. It can be observed that our proposed algorithm leads to fewer dead SNs than the other two algorithms do. With the increase of the number of SNs in the network, the numbers of dead SNs in the network by adopting TSP algorithm and the ODR algorithm grow faster because the SNs' residual lifetimes and the distances between the hungry SNs and the MC are considered by the MAP algorithm, and so the SNs can be powered in time.

Fig. 6 shows the comparison of the total received wireless energy by the SNs by different algorithms. It can be seen that the amounts of total received wireless energy (by these algorithms) improve with the increase of the number of SNs. When the number of SNs in the network increases, our proposed algorithm enables the SNs to receive more energy from

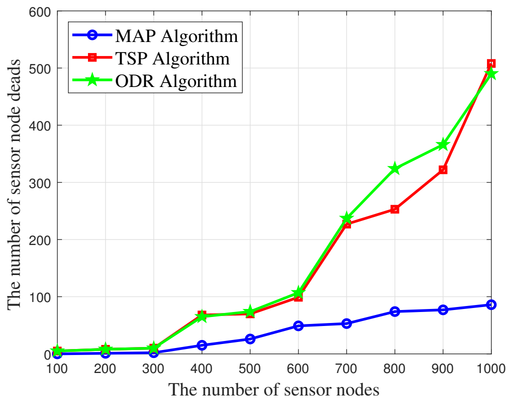

Fig. 5. The number of dead SNs with different numbers of SNs.

the MCs than the other two algorithm do because our proposed algorithm enables more SNs to simultaneously receive wireless energy.

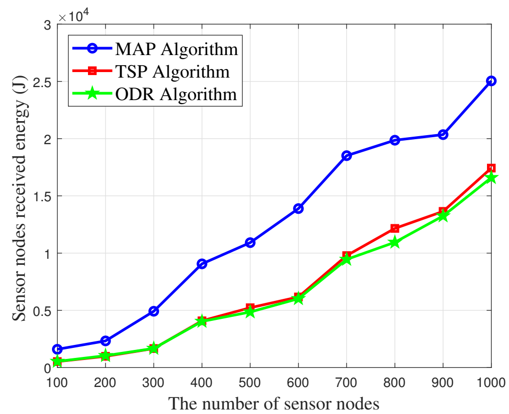

Fig. 6. The total received energy with different numbers of SNs.

VI. Conclusion

In this work, we aim to efficiently power the SNs in the whole charging area and maintain most of the SNs alive, by leveraging multiple MCs to wirelessly charge the SNs located in different sub-regions. In order to increase the MCs' wireless charging energy efficiency, we have further proposed the MAP algorithm to efficiently solve the formulated problem. This algorithm can well power all the hungry SNs in the WRSNs. The simulation results demonstrate that our proposed MAP algorithm can effectively improve the wireless charging energy efficiency and reduce the DSP.

VII. Acknowledgement

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