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Research paper

On Optimizing Mobile Charger Scheduling in Wireless Sensor Networks

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Abstract

Wireless rechargeable sensor networks (WRSNs) find widespread applications in numerous fields. However, the limited battery capacity of sensor nodes (SNs) hinders their long-term development. To address this issue, a potential solution is to charge SNs using a mobile charger (MC) equipped with radio frequency-based directional wireless power transfer (WPT) technology. In this work, we focus on optimizing the stopping points (SPs), orientation charging angles, and the traveling path of the MC in an on-demand scenario. We first present a mixed integer linear programming (MILP) model with aim of minimizing the charging delay. We then utilize *k*-means algorithm and a discretization technique to select the appropriate SPs and charging orientations. After that, we employ a heuristic method to determine an optimized traveling path of the MC. Finally, we carry out extensive simulations and compare the results of the proposed method with two baseline methods and the optimal solution. In particular, the simulation results indicate that the proposed method reduces the traveled distance, charging delay, and energy consumption compared to the baseline methods by up to 80.28%, 54.71%, and 69.78%, respectively.

1. Introduction

In the past few years, the researchers have devoted significant efforts to the field of Internet of Things (IoT). One particular area of focus has been wireless rechargeable sensor networks (WRSNs), which play a crucial role in IoT applications such as healthcare and smart cities [1-3]. However, the implementation of these networks faces a major challenge in the form of limited battery power for the sensor nodes (SNs) due to their small size and limited battery capacity. To tackle this challenge, a promising solution lies in the implementation of wireless power transfer (WPT) technology [4-5]. This technology presents a fresh approach to overcome the constraints of previous solutions in this field. The fundamental concept revolves around equipping a robot with a powerful battery, called mobile charger (MC) that roams around the network and recharges the SNs wirelessly.

The majority of research has focused on the periodic request-response model, where the MC follows a designated path to charge the SNs. Periodic charging using an MC ensures continuous operation of the WRSNs [6-8]. However, this approach's predetermined charging schedule is unsuitable for the dynamic nature of WRSNs due to the uncertain energy consumption patterns of the SNs. Furthermore, the existing periodic charging schemes mostly rely on an omnidirectional charging model [9, 13]. In this approach, the MC equipped with omnidirectional WPT technology emits electromagnetic waves uniformly in all directions. As a result, to ensure efficient charging of the SNs, the MC needs to transmit energy at a higher power level, which can be costly due to the reduced WPT efficiency with increasing distance between the transmitter and the receiver.

In contrast to periodic charging, the on-demand scheme offers a more realistic approach by dynamically responding to the energy demands of the SNs in real-time. Additionally, directional wireless energy transmission employs an energy beam to capture energy radiated in specific directions [10]. This ensures that energy receivers can only receive energy within the coverage of the transmitter. By incorporating directional WPT technology in an MC, it becomes possible to achieve more precise energy transfer and greater efficiency. As a result, energy consumption is reduced by minimizing energy wastage [10-15].

This paper addresses the issue of on-demand charging in WRSNs by employing a directional MC. In particular, we develop an optimized on-demand strategy to schedule an MC for charging the energy-critical SNs while minimizing their charging delay. In the proposed strategy, the MC first accumulates the charging requests of the SNs and then prepares an optimized charging tour for the MCs. The MC then starts its journey from the base station (BS), traverses the candidate charging stopping points (SPs), and recharges the SNs at these SPs using appropriate charging angles. Upon completing the charging tour, the MC returns to the BS to recharge its own battery for the subsequent tour. In particular, we make the following major contributions:

- We formulate the on-demand charging using an MC equipped with directional charger as a mixed integer linear programming (MILP) problem to minimize the charging delay.
- We then utilize *k*-means clustering algorithm and a discretization technique to optimize the number of SPs with their locations and the charging angles at these SPs, respectively.
- Next, we present a heuristic to determine an optimized tour the MC through the selected SPs for minimizing the charging.
- Finally, we conduct simulations and compare the results of the proposed method with two baseline methods to show its efficacy.

The remaining sections of this paper are structured as what follows. Section 2 provides an overview of WRSNs. In Section 3, we present the proposed algorithm, along with the network model and problem formulation. The performance analysis is presented in Section 4. Lastly, the conclusions are provided in Section 5.

2. Related Works

WPT technology evolved considerably in the development of WRSNs in the recent years. In addition, various studies have been undertaken on the subject of traveling path scheduling of MC in WRSNs [15-16]. We classified this issue in greater detail in [18]. In this section, the topic of charging scheduling is examined in terms of two models, the periodic model and the on-demand model. Furthermore, these models can be divided into two sub-categories according to the charging model of MC based on WPT technology including omnidirectional and directional. Also, these schemes are established on the point-to-point or point-to-multi-point charging model. Periodic model, MC charges SNs in periodic approaches using a pre-determined route [11, 15-20]. It is assumed that all SNs are needed to be recharged, hence MC will charge all SNs in each cycle along the defined path.

On-demand model, the SNs that require the charging per round will be charged by the MC(s). The charging schedule adjusts in real time to the SNs' activity in each cycle. The network structure is dynamic, and the energy consumption rate of SNs is not constant. According to the on-demand technique, the MC can accept new charge requests at any moment and only charge these demands during each period. Thus, the construction and adjustment of MC's journey path will be an on-demand process. This method works well for networks with varying energy consumption rates in SNs, and it improves network efficiency and lifespan [21-22].

A. Omnidirectional charging model antenna

In [23], the first-come-first-served (FCFS) method was used to process charge requests based on their arrival time. To get around the constraint [23], nearest-job-next with preemption algorithm in [24] was suggested. It was able to respond to service requests in both a spatial and temporal manner. Their goal was to increase the MC's charging throughput while also reducing the SN's charging latency. The problem of charging utility maximization was formulated in [25] and [26] by taking into account the entire traveled distance by an MC throughout each tour as well as the charging time window for each SN. The authors in [27] provided a strategy that outperformed [23] and [24].

Due to the charging time of each SN, the travel time between SNs, and the waiting time of each SN to be charged, this strategy attempted to reduce the charging delay time for SNs. It used a gravitational search algorithm (GSA) to figure out the best charging order. In [28], the researchers combined particle swarm optimization and genetic algorithm to optimize the charge duration of SNs. They considered factors such as residual energy, distance to the MC, neighborhood criticality, and charging significance to develop an effective charging strategy [29]. They used the entropy weight technique [30] to determine the importance of different factors and employed a ranking approach

[30] to determine the MC's path. Simulation results showed their method outperformed previous approaches [23] and [24] in terms of charging efficiency and SN survival rate. Recent papers [18-20] have explored MC scheduling strategies using reinforcement learning methods.

B. Directional charging model antenna

The earliest investigations on the issue of MC directional charge by an MC in WRSNs have been given by the authors in [10, 13]. Their goal in [10] is to maximize charging efficiency. They've developed a way for calculating SPs and beam direction at each one. Furthermore, each SN can be charged in several directions. In [13], we looked into minimizing the charging delay time at all SPs. Applying the directional charge model, they provided a linear model for the charging delay time problem. Due to the complexity of the problem space, they have used the angle discretization method to reduce the computational complexity in limiting the search interval to find suitable charging angles. In their model, the charging points are fixed. Each SP is visited by the MC, and the SNs surrounding the SP are charged at various angles. The charging delay time is determined by the number of times each SP's SNs must be charged.

The issue addressed in article [13] was further explored by the authors in [15], focusing on deploying MCs to reduce charging delays in large spaces. In [19], a one-directional charging model with multiple directional antennas was introduced, enabling simultaneous charging from multiple directions. This approach demonstrated superior energy efficiency and reduced charge delay compared to methods using directional antennas [10, 13]. In [32], an adaptive directional charging algorithm was proposed to minimize energy consumption. The algorithm determines optimal charging stations and beam directions based on SN density, employing individual or multiple clustering and charging operations.

3. Proposed Work

In this section, we will first explore the network architecture of the proposed method, and then the details of the problem model are examined.

3.1. Network architecture

We consider a system that involves n rechargeable SNs in 2D that is denoted as $S=\{s_1,s_2,s_3,...,s_n\}$ that some SNs need to be charged by an MC in successive periods. We also assume that there is $m(m\ge1)$ pre-defined SPs denoted as $O=\{o_1,o_2,o_3,...,o_m\}$. As shown in Figure 1, when some SNs s_i send charging request, the MC travel and stop in some the SPs o_j to charge some SNs which deployed in distance less or equal d_{max} and an orientation angle $\vec{a_1}$ from the MC. The number of orientation angles denoted as $A=\{\vec{a_1},\vec{a_2},\vec{a_3},...,\vec{a_z}\}$ and z is between 0 to 2π. The MC can change its position at any time, is located at one of the selected SPs, and charges several selected SNs simultaneously.

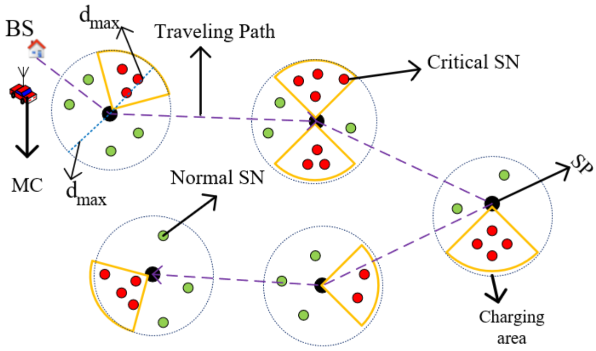


Figure 1. Architecture intended for the proposed method.

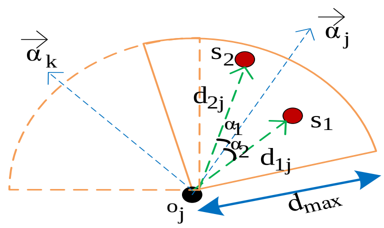


Figure 2. View of the directional charging model.

3.2. Directional charging model

We build our charging model based on empirical studies [13, 33]. The charging area of a directional charger can be modeled as a sector with radius d_{max}. d_{ij} is the Euclidean distance between the SN s_i and the MC. The SN can only receive energy when the orientation angle is within $-\frac{\pi}{2},+\frac{\pi}{2},\alpha\in\left[-\frac{\pi}{2},+\frac{\pi}{2}\right]$ and other parameters such as μ,β,c are constants that are determined by the experimental environment and the hardware parameters of MCs [34]. The energy transfer model can be expressed as:

$$P_r=\begin{cases}\mu\dfrac{\cos\alpha+c}{\left(d_{ij}+\beta\right)^2} & 0\le d_{ij}\le d_{max},-\dfrac{\pi}{2}\le\alpha\le+\dfrac{\pi}{2}\\ 0 & \text{otherwise}\end{cases} \tag{1}$$

$$\alpha=\cos^{-1}\left(\frac{\overrightarrow{o_js_i}}{\left|\overrightarrow{o_js_i}\right|}\right)$$

In Figure 2, d_{max} is the charging range (radius). SNs (i.e. s_1 and s_2) are covered by an effective directional area when the orientation angle of MC in SP o_j is $\vec{a}_j$. They will receive different energy amount under different angles (i.e. α_1 and α_2) and distance (i.e. d_{1j} and d_{2j}), respectively. Nevertheless, when MC rotates to $\vec{a}_k$, these two SNs (i.e. s_1 and s_2) cannot receive energy anymore.

Table 1. Symbols definition.

S	Number of SNs, defined as $S=\{s_1,s_2,s_3,...,s_n\}$
O	Number of SPs for MC, defined as $O=\{o_1,o_2,o_3,...,o_m\}$
A	Number of orientation angles for MC in each SP as $A=\{\vec{a}_1,\vec{a}_2,\vec{a}_3,...,\vec{a}_z\}$
o_j	Coordinate of the j-th SP
s_i	Coordinate of the i-th SN
x_{it}	SN i-th is charged in the t-th period
d_{ij}	The distance between the i-th SN and the j-th SP
$d_{jj'}$	Distance between the j-th SP and the j′-th SP
d_{max}	Maximum effective charging distance of the MC
y_{jt}^k	j-th SP in the t-th period is chosen with the k-th orientation angle equal to one.
γ	Very large number.
P_{ij}^k	Charging power for the i-th SN at the j-th SP with the k-th orientation angle.
$\beta1$	Number of charged SNs in each period
α	Orientation angle between a MC in a SP and a SN.
P_r	Charging power
v	Moving speed of MC
re_i	Residual energy of SN s_i
CT_{jt}	Charging time in the j-th SP in the t-th period
WT_{jt}	Waiting time in the j-th SP in the t-th period
TT_{jt}	Traveling time in the j-th SP in the t-th period

3.3. Problem formulation

In this section, the MC charging scheduling problem with the directional charging model is formulated as a mixed integer linear programming problem. The proposed model is presented below.

$$\min T_{Delay} \tag{2}$$

$$\sum_{t=1}^{T} x_{it} = 1 \quad \forall\, i \tag{3}$$

$$\sum_{j=1}^{m}\sum_{k=1}^{z} y_{jt}^k \le 1 \quad \forall\, t \tag{4}$$

$$\sum_{i=1}^{n} x_{it} \le \beta1 \sum_{j=1}^{m}\sum_{k=1}^{z} y_{jt}^k \quad \forall\, t \tag{5}$$

$$x_{it} * d_{ij} \le d_{max} + \gamma\left(1-\sum_{k=1}^{z} y_{jt}^k\right) \quad \forall\, i,j,t \tag{6}$$

$$x_{it} * \alpha_{ij}^k \le 90 - \gamma\left(1-\sum_{k=1}^{z} y_{jt}^k\right) \quad \forall\, i,j,t \tag{7}$$

$$x_{it} * \alpha_{ij}^k \ge -90 + \gamma\left(1-\sum_{k=1}^{z} y_{jt}^k\right) \quad \forall\, i,j,t \tag{8}$$

$$r_{jj'} \ge \sum_{k=1}^{z} y_{jt+1}^k + \sum_{k=1}^{z} y_{j't}^k - 1 \quad \forall\, j', j, t \tag{9}$$

$$\sum_{j=1}^{m}\sum_{k=1}^{z} y_{jt+1}^k \le \sum_{j=1}^{m}\sum_{k=1}^{z} y_{jt}^k \quad \forall\, t \tag{10}$$

$$x_{it},\ y_{jt}^k \in \{0,1\},\ r_{jj'} \ge 0 \tag{11}$$

$$TT_{jt} = \sum_{j=1}^{m} \frac{d_{jj'}}{v} * r_{jj'} \quad \forall\, t \tag{12}$$

$$CT_{jt} = MAX\left(\sum_{i=1}^{n} x_{it} * \left(\frac{re_i}{P_{ij}^k}\right) - \gamma * \left(1-y_{jt}^k\right)\right) \quad \forall\, t,j,k \qquad CT_{jt} \ge 0 \tag{13}$$

$$WT_{jt} = CT_{jt-1} + TT_{jt-1} \tag{14}$$

$$T_{Dealy} = \frac{\sum_{j=1}^{m} TT_{jt} + CT_{jt} + WT_{jt}}{w} + \sum_{j=1}^{m} TT_{j(t-1)} \quad \forall\, t \tag{15}$$

Condition (2): Minimize the total charging delay time as T_{Delay}.

Condition (3): We have assumed that all requesting SNs that must be charged by the MC at different period.

Condition (4): Since we have only one MC that can be in only one SP in each period, so in the t-th period only one of the values y_{jt}^k can take the value 1. T is the maximum number of times periods, $T=\{1,2,3,...,t\}$.

Condition (5): The MC has the ability to charge a maximum of $\beta1(\beta1 \ge 3)$ SNs in each period. The range $\sum_{j=1}^{m}\sum_{k=1}^{z} y_{jt}^k$ on the right states that if one of the SNs is charging during the t-th period, the MC must be active.

Condition (6), (7), and (8): To receive the energy emitted by the MC, the SN must be placed at a certain distance and orientation angle from it. We denote the maximum radial distance from the MC by d_{max}. α_{ij}^k shows the orientation charging angle in the i-th SN at the j-th SP by the k-th orientation angle based on charging model (Eq. (1)). d_{ij} is equal to the distance between the i-th SN and the j-th SP (the place of MC). This constraint states that x_{it} can take the value 1 if d_{ij} is less than d_{max} and α_{ij}^k consider between -90 to 90 degrees. if the MC is not in the j-th SP, the relationship will be redundant due to the very large γ.

Condition (9), (10): These conditions guarantees that if the MC is inactive in one charging period, it cannot be active in the next period. The variable $r_{jj'}$ according to its coefficient in the above constraints will have a value of only one if the MC is in the $j-$th SP in the (t +1)-th period and the $j'-$th SP in the t-th period. The variable $r_{jj'}$ is considered as positive variable.

Condition (11): Since the MC is placed in one of the SPs in each period. We define the binary variable y_{jt}^k as corresponding to the MC at the j-th SP. If the MC is in the j-th SP during the t-period with $k-$th orientation angle it will take the value of one, otherwise the value of zero.

$$y_{jt}^k = \begin{cases} 1 & \text{if a MC in the t-th period is deployed in the j-th SP with k-th orientation angle} \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

Also, we consider the binary variable corresponding to the charge or non-charge of the i-th SN in the $t-$th period that defined by x_{it}.

$$x_{it} = \begin{cases} 1 & \text{if a SN } s_i \text{ in the t-th period is deployed in the j-th SP with k-th orientation angle} \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

Condition (12): It is considered as the time taken by the MC to move from the current location $o_{j'}$ in the $j'-$th SP in the (t+1)-th period to the location of an SP o_j in the j-th SP at the t-th period as traveling time.

Condition (13): It is equal to the maximum charge time required for charge one requesting SN among the other requesting SNs in the cluster as charging time. Denote by re_i residual energy of SN s_i in the t-th period. It is the time taken by the MC for charging SNs s_i in a SP as $\frac{re_i}{P_{ij}^k}$. P_{ij}^k $\left(P_{ij}^k = P_r\right)$ refers to the harvested power of i-the SN and the orientation angle α_{ij}^k based on Eq.(1).

Condition (14): It is the time taken by the MC to respond all the charging requests before the SP o_j, in the charging schedule as waiting time.

Condition (15): T_{Delay} is considered as the response charging delay time of the request, which is equal to the sum of charging time, waiting time and traveling time plus the time MC travel from the BS to the first SP on the number of charged SNs.

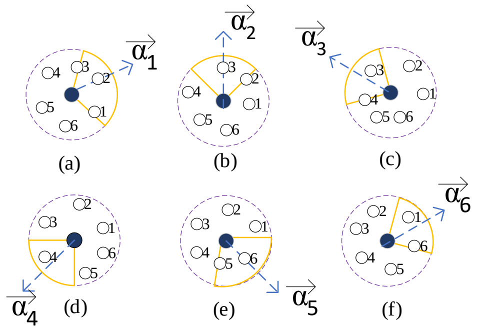


Figure 3. An example of extracting the candidate orientation charging angles at the SPs.

3.4. Proposed Method

We have formulated the minimum charging delay problem as a mixed integer linear programming problem. This is an NP-hard problem, since the use of linear programming solver requires heavy calculations to find the optimal possible orientation charging angles and charging SPs among a wide range of them. We propose a heuristic algorithm that divides the problem into two sub-steps (Algorithms 1 and 2).

Algorithm 1. Finding SP and charging orientation angle.

SS ← {} ➡ Set of selected SNs in each SP
SSP ← {} ➡ Set of selected SPs
SA ← {} ➡ Set of the orientation charging angles
TSO ← {} ➡ Result set for selected SPs, orientation charging angles, and associated SNs

While SN ≠ 0 **do**
  For *j* ← 1 to length (SP) **do**
    Find the best SP for the requests based on section (3.4).
    Find the appropriate orientation charging angle in based on section (3-4).
    Add to SS={ s_i }, SSP={ o_j }, SA={ $\overrightarrow{\alpha_k}$ }.
  End for
  Add to TSO = {SSP,SA,SS}
End while
Output: TSO

Algorithm 2. Finding optimal path.

Input: TSO
Output: Find the optimal charging path for MC by minimum charging delay.
For *j* ← 1 to SSP **do**
  CALL GAS $\left(CT_j, TT_j, WT_j\right)$ based on the calculated charging delay as the objective goal section (3.3).
End for

A. First stage

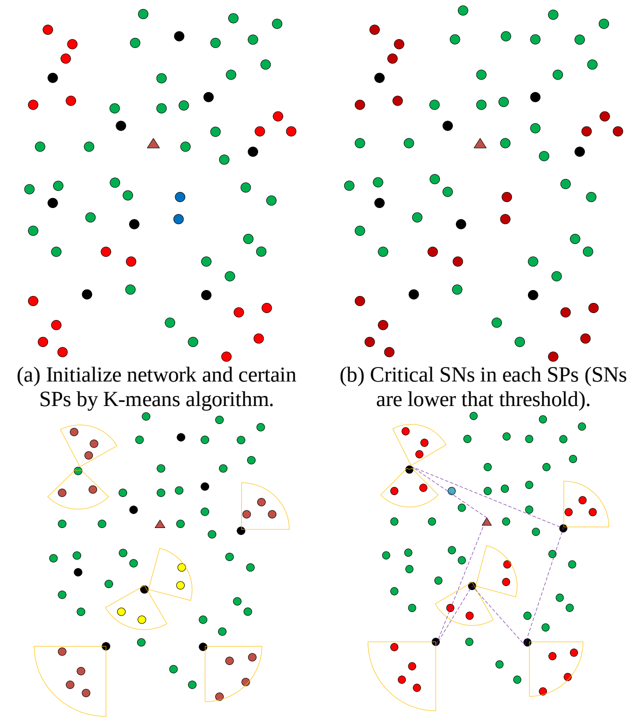
In this section, our objective is to minimize the number of candidate SPs. Due to the extensive search space, we have employed the k-means algorithm as a clustering method to narrow down the possibilities and identify suitable SPs. Subsequently, we aim to determine the optimal charging angle at the candidate SPs for charging the requested SNs, thereby improving the energy efficiency of the MC. Considering that the search space for finding the appropriate charging angle is continuous, the MC within a candidate SP has the flexibility to select any orientation angle ranging from 0 to 2π. To reduce the search space, we have adopted a similar approach as described in [35] for extracting the suitable orientation charging angle. Figure 3 illustrates our method for identifying effective orientation charging angle candidates for a given SP. The main idea of extracting the orientation charging angle is to rotate counterclockwise in the charging area so that at least one SN strikes the right border of the charging area. For example, in Figure 3, suppose we first have (in step (a)) SN s_1 at the right border of the charge area in SP o_j. At this point, the charge area o_j covers the SNs s_1, s_2 and s_3, and the orientation angle ($\overrightarrow{\alpha_1}$) is specified as the candidate orientation angle o_j. In the second step (in step (b)), in which we rotate the charge area around o_j so that the right border of the charge area hits the SN s_2 in the orientation angle ($\overrightarrow{\alpha_2}$). At this point, the charging area o_j covers SNs s_2 and s_3. But we do not consider($\overrightarrow{\alpha_2}$), as an orientation angle candidate because SNs s_2 and s_3 can be covered by placing o_j in the orientation angle ($\overrightarrow{\alpha_1}$) Similarly, we can determine that the two the. orientation angles ($\overrightarrow{\alpha_5}$) and ($\overrightarrow{\alpha_3}$) in steps (c) and (e) are candidates, respectively. Finally, in Figure 3, three the orientation angles($\overrightarrow{\alpha_1}$),($\overrightarrow{\alpha_3}$) and ($\overrightarrow{\alpha_5}$) are a set of candidates orientation charging angles at SP o_j, denoted by SA_j and a set of SNs covered by SS_j.

$$
\begin{aligned}
&SA_j=\{\overrightarrow{\alpha_1},\overrightarrow{\alpha_3},\overrightarrow{\alpha_5}\}.\\
&SS_j=\{(s_1,s_2,s_3),(s_3,s_4),(s_5,s_6)\}\\
&TSO=\{(\overrightarrow{\alpha_1},(s_1,s_2,s_3)),(\overrightarrow{\alpha_3},(s_3,s_4)),(\overrightarrow{\alpha_5},(s_5,s_6))\}
\end{aligned} \tag{18}
$$

B. Second stage

According to the model defined in the section (3-3) for calculating the charging delay time, our goal is to find the optimal schedule for the movement of the MC between the SPs so that it responds to the charge requests with the least possible charging delay. It is worth noting that the number of selected SPs in a large-scale WRSN is very high. Therefore, finding the optimal charging order of SPs with a comprehensive search method becomes impractical. This is an NP-hard issue.

Hence, we utilize the heuristic search algorithm GAS, as proposed in [27], to determine the charging path of the MC based on the designated SPs.



(a) Initialize network and certain SPs by K-means algorithm.

(b) Critical SNs in each SPs (SNs are lower that threshold).

(c) Certain the orientation charging angles in each SP according section (3-4).

(d) Finding the optimal path based on GAS algorithm in section (3-4).

Figure 4. An example of the performance of the proposed method for responding to charging demands.

The GAS algorithm is able to find an almost optimal solution to an optimization problem in a reasonable amount of time and memory [36].

4. Simulation Results

In this section, we implement and compare the proposed method with two baseline methods and the optimal solution using Python. In particular, we consider three scenarios of WRSNs.

The first scenario consists of 20 to 100 SNs that are randomly deployed in an area of [500 x 500], while the second scenario includes 100 to 400 SNs located in an area of [500 x 500] m^2. Similarly, the third scenario comprises of 200 to 1000 SNs deployed in an area of [1000 x 1000] m^2. We assume that the BS is located at (0,0). Increasing the network area and the number of SNs lead to an increase in the number of charging demands and subsequently the traveling distance of the MC.
Besides, we assume that the energy capacity of each SN is $E_s = 600$ J and its energy consumption rate ρ_i is between 0.02 J and 1 J. The speed of the MC v is equal to 5 m/s. The wireless power transfer rate and the moving cost of the MC are 6

J/s and 20 J/m, respectively. The key simulation parameters are summarized in Table 2.

Table 2. Simulation parameters.

Parameters	Values
MC battery capacity	10000 kJ
Battery capacity of SN	600 J
Energy consumption rate	0.02 J to 1 J
Threshold	200 J
Speed of MC	5 m/s
Charging distance (or range)	100 cm

We intend to compare the proposed method with a one-directional charging-based method, an omni-directional charging-based method, and the optimal solution under various network scenarios. Thus, we [11], which uses directional charging. In this method, the SPs, orientation charging angles, and the traveling path of the MC are randomly selected. Next, we simulate an omni-directional charging method [27] called GAS-OMNI. The aim of the GAS-OMNI method is to minimize the charging delay of the SNs, which aligns with the objective of the proposed algorithm. In particular, the GAS-OMNI method employs the GSA algorithm to determine the charging order of the SNs. Finally, we also solve the presented MILP model using the Pulp Python library to obtain the optimal solution.

We compare the simulation results of the proposed method with Random method, GAS-OMNI method, and optimal solution using the traveled distance, charging delay, and energy consumption as the performance metrics.

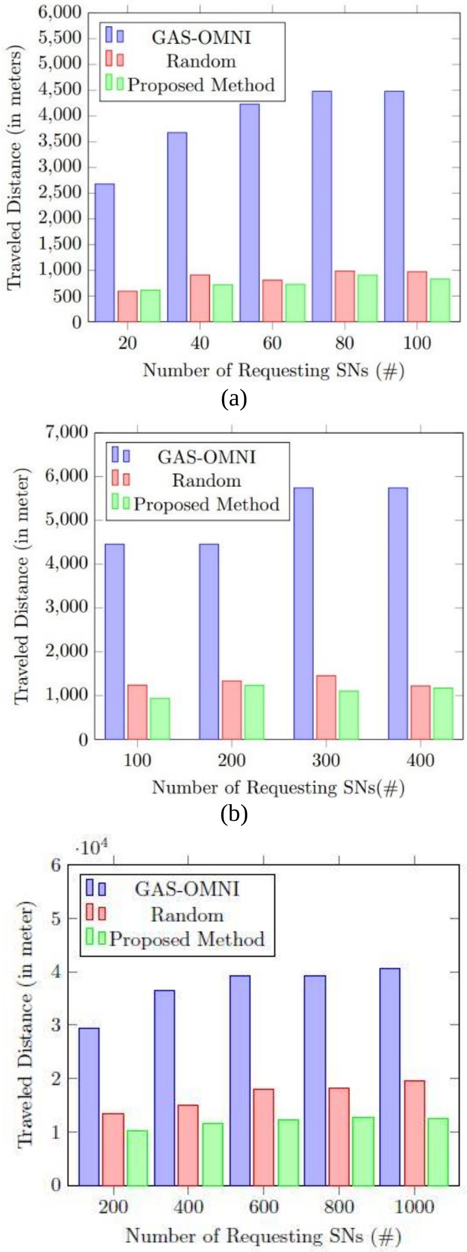
Traveled distance: It refers to the total traveled distance by the MC to fulfill the energy demands of the SNs.

Charging delay: It is defined as the average time required to fulfill the charging requests of the SNs. It is important to note that a lower value of the charging delay indicates that more SNs are successfully charged.

Energy consumption: Energy consumed by the MC during the charging process is defined as the sum of the energy used for charging the SNs and the energy required for traveling to the SNs. It is worth noting that the total energy consumption can be minimized by reducing the travel distance and selecting appropriate charging angles.

4.1. Comparison of traveled distance

In Figure 5(a), we display the average traveled distance by the MC in the proposed, Random, and GAS-OMNI methods for Scenario #1. Herein, we observe that the traveled distance of all the methods increases with the number of requesting SNs. This is because the MC has to cover a longer distance when there are more requesting SNs. On average, the proposed method shows a reduction in traveled distance by 10.07% and 80.28% than Random and GAS-OMNI methods, respectively.



(a)

(b)

(c)

Figure 5. Comparison of the traveled distance of the proposed method with the Random and GAS-OMNI methods for WRSN (a) Scenario#1, (b) Scenario #2, and (c) Scenario #3.

In Figure 5(b), we observe that the proposed method has about 15.05% lower traveled distance than Random method and 77.94% lower traveled distance than GAS-OMNI method, for Scenario #2. Similarly, in Figure 5(c), we can see that the proposed method has 29.16% and 67.92% lower traveled distance compared to the Random and GAS-OMNI methods, respectively in Scenario #3. The reduced traveled distance in the proposed method is attributed to the opportunities for further improvement in the Random and GAS-OMNI methods. In particular, the Random method randomly selects SPs and the traveling path of the MC along with the orientation charging angles at the selected SPs.

Likewise, the GAS-OMNI method considers the locations of the requesting SNs as the SPs for the MC and simply finds MC’s traveling path through these SPs. In contrast, the proposed method first finds the optimized SPs and charging angles at each SP and then determines the MC's traveling path with the shortest distance through the optimized SPs. As a result, this approach is able to reduce the traveled distance of the MC compared to the Random and GAS-OMNI methods. In precise, the proposed method proves its efficacy by selecting optimal SPs, obtaining the proper charging angles, and accurately forming an optimized traveling path of the MC.

4.2. Comparison of charging delay

Now, in Figure 6(a), we show the results of the proposed, Random, and GAS-OMNI methods in terms of charging delay for Scenario #1. On average, the proposed method has 21.44% less charging delay compared to the Random method and 51.71% less charging delay compared to the GAS-OMNI method. In Figure 6(b), we next show the charging delay of all the methods for Scenario #2. On average, the proposed method has about 9.38% less charging delay compared to the Random method, and about 29.63% less charging delay compared to the GAS-OMNI method. After that, we display the results for the Scenario #3 in Figure 6(c). We see that the proposed method has about 28.20% and 75.66% lower charging delay than the Random and GAS-OMNI methods, respectively.

The rationale behind the lower charging delay is that the proposed method is able to adjust the locations where the MC stops, the orientation charging angles at which it charges the SNs, and the route it takes to charge them in the real-time. It does this by using a combination of the k-means algorithm, a rotation strategy, and the GSA technique. This allows the MC to reach and recharge more SNs before running out of energy. On the other hand, the Random and GAS-OMNI methods are not as effective in reviving the energy-critical SNs because they do not properly optimize the SPs, orientation charging angles, and the traveling path of the MC.

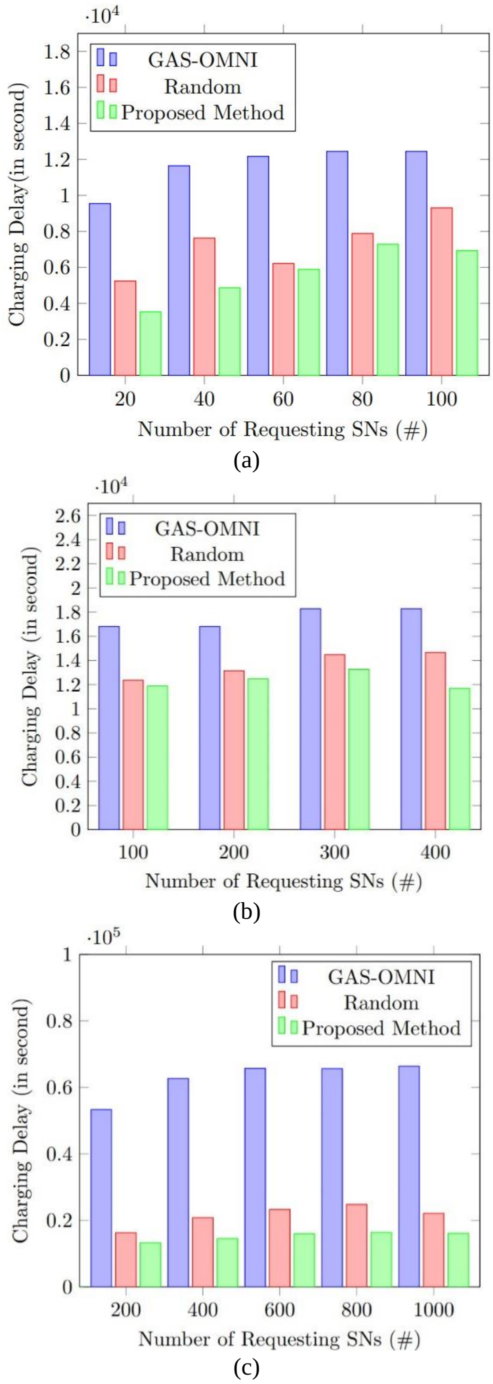
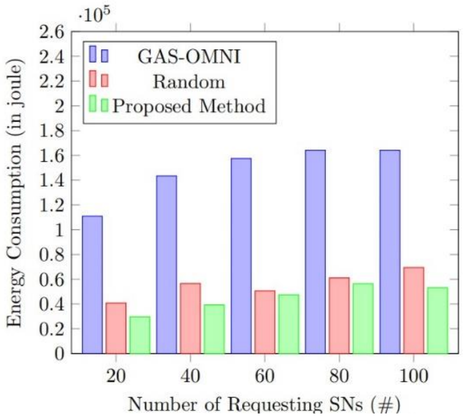


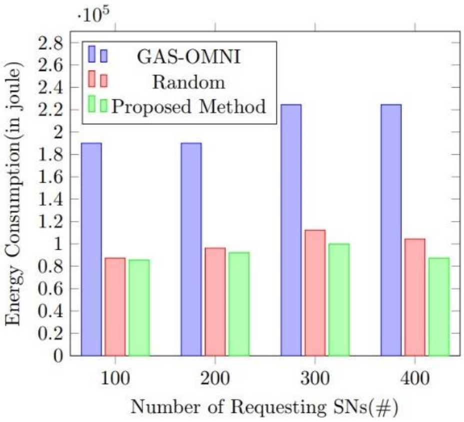
Figure 6. Comparison of the charging delay of the proposed method with the Random and GAS-OMNI methods for WRSN (a) Scenario#1, (b) Scenario #2, and (c) Scenario #3.

4.3. Comparison of energy consumption

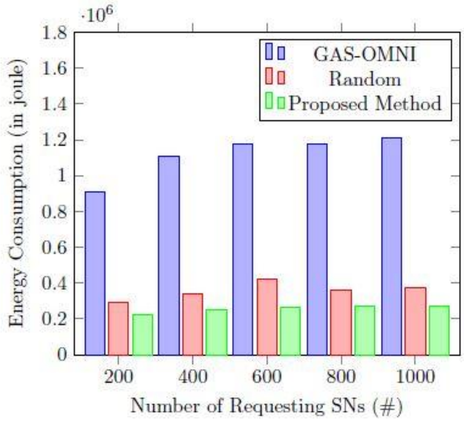
We show the energy consumption results of the proposed, Random, and GAS-OMNI methods in Figure 7.



(a)



(b)



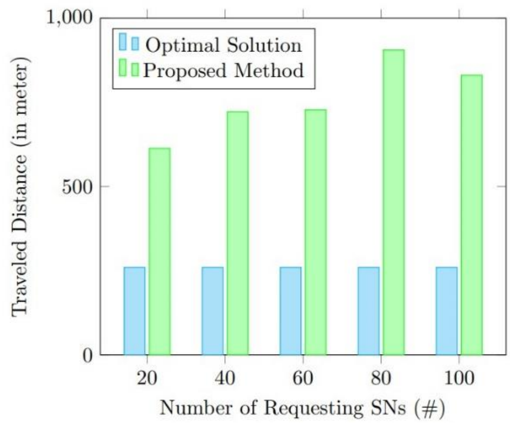
(c)

Figure 7. Comparison of the energy consumption of the proposed method with the Random and GAS-OMNI methods for WRSN (a) Scenario#1, (b) Scenario #2, and (c) Scenario #3.

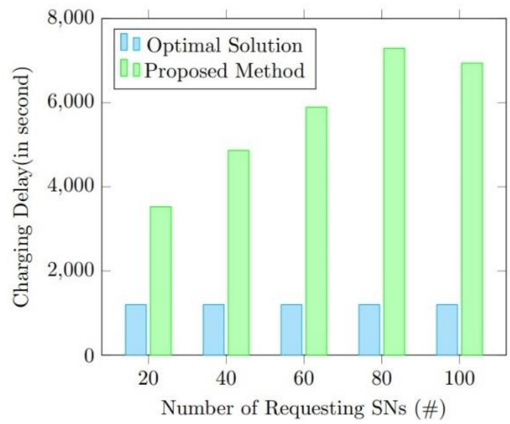
From these graphs, it is evident that the three algorithms exhibit a similar trend, i.e. energy consumption increases with the increase in the number of requesting SNs. In particular, Figure 7(a) displays the energy consumption of the three methods for Scenario #1. On average, we note that the proposed method has 19.07% and 69.78% less energy consumption as compared to the Random and GAS-OMNI method, respectively. In Figure 7(b), we reveal the energy consumed by different methods for Scenario #2. In this case, the proposed method consumes about 8.35% less energy than the Random method and 55.76% less energy than the GAS-OMNI method. Finally, we show the energy consumption of three methods for Scenario #3 in Figure 7(c), Again, the proposed method consumes about 27.67% and 76.8% less energy consumption than that of the Random and GAS-OMNI methods, respectively.

The favorable results achieved by the proposed method are due to the following reasons. Firstly, the proposed method uses a directional charging model that limits the energy transfer to optimized orientation charging angles at the SPs. In contrast, while the Random method also uses a directional charging model, it falls short in optimizing the selection of SPs and orientation charging angles due to the random selection. selection of SPs and orientation charging angles due to the random selection.

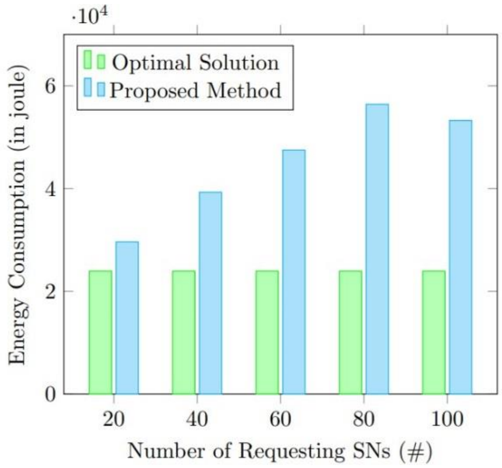
Similarly, the GAS-OMNI method uses an omni-directional charging model that transmits energy in all directions without any restriction, leading to significant energy wastage of the MC. Secondly, the proposed method ensures that the MC travels the minimum distance compared to the other two methods, as discussed in Section 4.1, resulting in a further reduction in the energy consumption of the MC.



(a)



(b)



(c)

Figure 8. Comparison of the proposed method with the optimal solution for Scenario#1 in terms of (a) traveled distance, (b) charging delay, and (c) energy consumption.

4.4. Comparison with the optimal solution

In this section, we contrast the results of the proposed method with the optimal solution for Scenario #1 to highlight the potential of improving the charging scheduling of the SNs in future works. In Figure 8, we display the comparison in terms of traveled distance, charging delay, and energy consumption. On average, we notice that the optimal solution is 65.18%, 77.50%, and 44.11% lower than the proposed method for traveled distance, charging delay, and energy consumption, respectively.

Overall, the simulation results indicate that the proposed method reduces performance metrics as compared to Random and GAS-OMNI methods. However, there is still ample scope for further optimizing its performance. We intend to do so in our future research. It is also worth mentioning that we were unable to solve the MILP for Scenario #2 and Scenario #3 due to computational constraints.

5. Conclusion

In this paper, we presented a directional mobile charging strategy for an MC equipped with a directional wireless charger within an on-demand scenario in WRSNs. Initially, we formulated the said problem as a MILP model with an objective of minimizing the charging delay. Subsequently, we solved the MILP model using a combination of the k-means algorithm, a discretization method, and a heuristic algorithm. After that, we simulated and compared the performance of the proposed method with two baseline methods, namely Random and GAS-OMNI. The simulation results demonstrated that the proposed method is able to significantly reduce the traveled distance, charging delay, and energy consumption than the compared methods. Specifically, our results indicate reductions of up to 80.28%, 54.71%, and 69.78%, respectively.

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بهینه‌سازی زمان‌بندی شارژر متحرک در شبکه‌های حسگر بی‌سیم

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چکیده:

شبکه‌های حسگر قابل شارژ مجدد بی سیم در بسیاری از حوزه‌ها استفاده‌های گسترده‌ای دارند. با این حال، ظرفیت محدود باتری گره‌های حسگر مانع از توسعه طولانی مدت آنها می‌شود. بر ای رفع این مشکل، یک راه حل بالقوه، شارژ گره‌های حسگر با استفاده از یک شارژر متحرک مجهز به فناوری انتقال انرژی بی‌سیم جهت‌دار مبتنی بر فرکانس رادیویی است. در این مقاله، ما بر روی بهینه سازی نقاط توقف، زاویه‌های شارژ جهت‌دار و مسیر حرکت شارژر متحرک در یک شبکه مبتنی بر درخواست تمرکز می‌کنیم. ما ابتدا یک مدل برنامه‌ریزی خطی عدد صحیح مختلط را با هدف به حداقل رساندن تاخیر شارژ ارائه می‌کنیم. سپس از الگوریتم خوشه بندی k-میانگین و تکنیک گسسته‌سازی بر ای انتخاب نقاط توقف مناسب و جهت‌گیری‌های شارژ استفاده می‌کنیم. پس از آن، ما از یک روش اکتشافی برای تعیین مسیر سفر بهینه شارژر متحرک استفاده می‌کنیم. در نهایت، شبیه سازی‌های گسترده ای انجام داده و نتایج روش پیشنهادی را با دو روش پایه و راه حل بهینه مقایسه می‌کنیم. به طور خاص، نتایج شبیه‌سازی نشان می‌دهد که روش پیشنهادی مسافت طی شده، تاخیر شارژ و مصرف انرژی را نسبت به روش‌های پایه به ترتیب تا ۸۰,۲۸ ، ۵۴,۷۱ و ۶۹,۷۸ درصد کاهش می‌دهد.

کلمات کلیدی: شبکه‌های حسگر قابل شارژ بی‌سیم، فناوری انتقال انرژی بی‌سیم، آنتن جهت دار، زمان‌بندی شارژ.