Hindawi
International Journal of Distributed Sensor Networks
Volume 2023, Article ID 5092972, 12 pages
https://doi.org/10.1155/2023/5092972

Research Article

Collaborative Energy Optimization of Multiple Chargers Based on Node Collaborative Scheduling

Minghua Wang, Ying Zeng, Jiaqi Li, and Yan Wang

Hunan Province Key Laboratory for Ultra-Fast Micro/Nano Technology and Advanced Laser Manufacture, School of Electrical Engineering, University of South China, Hengyang 421001, China

Correspondence should be addressed to Yan Wang; wangyan5406@163.com

Received 31 December 2022; Revised 5 May 2023; Accepted 8 May 2023; Published 5 June 2023

Academic Editor: Valerio Freschi

Wireless rechargeable sensor network (WRSN) uses mobile chargers (MCs) to charge sensor nodes wirelessly to solve the energy problems faced by traditional wireless sensor network. In WRSN, mobile charging schemes with multiple MCs supplementing energy are quite common. How to properly plan the MC's moving path to reduce the charge energy loss and deploy nodes to improve network coverage rate has become a huge research challenge. In this paper, a collaborative energy optimization algorithm (CEOA) is proposed for multiple chargers based on k-mean++ and node collaborative scheduling. The CEOA combines internal energy optimization and external device power supply, effectively prolongs network lifetime, and improves network coverage rate. It uses the k-mean++ to cluster nodes in the network; then, the nodes in the network are scheduled to sleep based on the confident information coverage (CIC) model. Finally, the CEOA uses a main mobile charger to carry multiple auxiliary mobile chargers to charge all the nodes in the cluster. Simulation results show that the proposed algorithm increases the network lifetime by more than 8 times and the coverage rate by about 20%.

1. Introduction

Wireless sensor network(WSN) is composed of several sensor nodes and one or more data centers. The advantages of small sensor node size and low cost make WSN play an important role in natural and production fields, such as forest fire prevention, harsh environment monitoring, and large-area environmental monitoring [1–3]. At present, the sensor began miniaturization, integration, intelligence, biochemical, and other modular direction development. Low power consumption, low cost, standardization, and other industrial characteristics of the trend are increasingly obvious [4]. However, energy consumption is still a difficult problem in WSN. To solve the problem of energy consumption in WSN, researchers have put forward a variety of solutions. They are mainly the following three: energy saving [5], natural energy collection [6], and wireless charging [7]. Energy saving scheme mainly reduces network energy consumption by optimizing the routing structure. The main methods include energy balance tree, network clustering, and packet compression.

Although the energy saving scheme can effectively reduce the network energy consumption, the sensor nodes will eventually die due to energy exhaustion, resulting in network breakdown. So the researchers set out to solve this problem from the energy supply side and came up with different solutions.

In the early 21st century, due to the application of solar energy, wind energy, and other new energy technologies, energy collection technology has been widely used in WSN [8]. This technology is used to equip sensor nodes with corresponding energy collection modules and energy conversion modules so that natural energy can be converted into electricity to supply energy for WSN and extend the network lifetime. With the development of technology, energy collection technology is also equipped with mobile energy collection and conversion equipment to supply energy to sensor nodes in a small range [9]. However, energy conversion technology still needs to be equipped with a large number of professional equipment, which increases the network cost and takes up too much space. In addition, the variability of the natural environment also makes energy harvesting technology unstable and cannot guarantee continuous power supply, so researchers are trying to use wireless rechargeable devices to provide power to the network.

At present, wireless rechargeable sensor network (WRSN) is developing rapidly due to the flexibility, stability, and security of wireless rechargeable devices. Generally, wireless rechargeable devices can carry energy over long distances and move independently. Using electromagnetic induction technology or radio frequency technology, they can replenish energy to rechargeable wireless sensor nodes, thus extending network lifetime [10]. With the progress of technology, the realization of a permanent wireless sensor network will become a reality.

Researchers have designed a variety of WRSN. From the initial use of a single mobile device to provide energy to the network, Wei et al. and Mo et al. [11, 12] use multiple devices to jointly supply energy, and finally, Han et al. [13] use multiple devices to cooperate to jointly complete the energy supply task. As for the mobile path of charging devices, researchers have also proposed many schemes, but the shortest path for the cooperation of multiple charging devices remains to be optimized.

The WRSN nodes described above all work independently of each other. They all use the disk model and its derivative model to complete the sensing task [14]. The sensors work independently, which consume a lot of energy and has a poor sensing effect. The CIC model overcomes this defect by fully exploiting and utilizing the spatial characteristics of the monitored physical quantity and the collaboration ability between adjacent nodes to extend the sensing area of these nodes, thus reducing the number of active nodes and improving the coverage of the network.

Aiming at the internal energy saving optimization and external energy supply path optimization in WRSN, this paper proposes a multicharger collaborative energy supply scheme based on node collaborative scheduling. The main contributions of this paper are as follows:

(1) To better balance the number of nodes in each cluster and achieve a better clustering effect, the k-mean ++ clustering model is adopted to reduce the energy loss in the transmission process and reduce the waiting time of charging

(2) To optimize the internal energy saving of WSN, we propose a confident information coverage model. It can increase network coverage while reducing working nodes

(3) To reduce the loss of external power supply, we propose a collaborative charging scheme with multiple chargers. It can reduce the moving path of MC, save the charging time of the network, and improve the stability of the network

The content of this paper is arranged as follows. In Section 2, we introduce the current research on wireless rechargeable sensor networks and node sleep scheduling. The basic composition and selection of the basic coverage model in the network are described in Section 3. Section 4 describes the data transmission mechanism and movement path planning of the network in detail. In section 5, the simulation results are listed and compared with other algorithms in detail. Section 6 summarizes the whole paper and looks into the future research direction.

2. Related Works

Various wireless charging schemes have been proposed to extend the lifetime of WRSN. These charging methods include static charging and dynamic charging. Zhang et al. proposed fixed placement of chargers and rechargeable devices within the two-dimensional target area to maximize charging quality by considering charger placement and power distribution [15]. Arivudainambi and Balaji used the Daubechies wavelet algorithm to enhance sensor coverage to identify the optimal location of wireless chargers and, at the same time, transferred redundant chargers to the optimal location. Wireless chargers transmitted power to sensor nodes through the air, solving the problem of energy shortage [16]. Static charge can solve the problem of energy supply in a small area, it is difficult to overcome the energy loss in the long-distance charge, and fixed charging device will take up a lot of space. In some harsh environments, fixed charging device is difficult to maintain. Therefore, dynamic charging schemes are now widely used. The charging scheme also includes partial charging and full charging. Priyadarshani et al. proposed an on-demand multinode charging scheme based on a partial charging model, which combines the advantages of partial charging and multinode charging to optimize the charging travel of multiple charging vehicles (MCVs). Minimize the energy spent by MCVs during travel and maximize the network life cycle [17]. Liang et al. expressed the mobile charging scheduling problem as the problem of full and partial charging reward maximization, aiming to maximize the total return obtained by the charged sensor under the limitation of the energy capacity of the mobile charger [10]. Wang et al. proposed a partial charge scheduling scheme that allows partial charging of sensor nodes to minimize the overall stagnation time of nodes, thereby extending the lifetime of the network [18].

For the dynamic charging scheme, researchers also put forward different ideas. He et al. proposed an on-demand charging scheme that sends MC to charge nodes once nodes in the network send charging requests [19], and this lays a theoretical foundation for the on-demand charging scheme. To improve the lifetime of WSN, Wang et al. proposed a dynamic charging algorithm based on on-demand charging. It uses MC to collect node data and provide energy [20]. The above two schemes are both proposed for on-demand charging. In this case, once the node sends a charging request, the MC will go to the network to recharge the node. So, MCs move frequently, resulting in increased energy loss and resource waste. To solve this problem, Shu et al. proposed a periodic charging scheme. In this scheme, the base station charges the sensor nodes according to a certain period of time, and the optimal moving speed of MC is approximated by the spatiotemporal discretization method [21]. It reduces the movement loss of MC but also leads to increased node mortality of the network to a certain extent.

To reduce the mortality of nodes in the network, the researchers considered the use of multiple MCs for network power supply. But in this way, how to allocate MCs' charging tasks is a difficult problem. Han et al. proposed to divide the network into multiple clusters based on the k-means algorithm and then used two MCs to visit the nodes to be charged in each cluster through the shortest Hamiltonian period [22]. If any of the two MCs runs out of energy before reaching the base station (BS), the BS will automatically send standby MCs to continue to replenish energy. This situation can temporarily relieve the MC's charging pressure. However, for small-scale networks, the movement loss of two MCs is too large. For a large-scale network, there are too many nodes in the network, and two MCs are not enough to complete the charging task. At this time, Han et al. proposed a WRSN mobile charging algorithm based on a nonuniform cluster, which uses multihop wireless energy transmission technology to charge multiple nodes in the network at the same time, and the nodes also transmit data to MC through multihop [23]. Ma et al. also proposed to charge multiple sensors simultaneously considering the location information of sensor nodes when the mobile charging vehicle has limited energy. In this case, the moving distance of MC is greatly reduced, and the movement loss is also relatively reduced [24]. However, multihop charging is subject to various limitations and time delays, and some nodes may die under the condition of energy delay.

At present, most charging schemes use one-to-one charging. To prolong the lifetime of the network, Nguyen et al. proposed a weighted algorithm based on the importance of sensor nodes, which solved the PERDCLMD problem and had some effect on improving the stability of the network [25]. However, this method can only ensure the survival of some important functional nodes. To ensure the overall survival rate of nodes and solve the overall energy shortage problem of WSN, Zhang et al. proposed scheduling multiple MCs to optimize energy use efficiency and allow collaborative mobile charging among MCs to ensure that each sensor node would not be exhausted, which verified the advantages of the PW algorithm in energy use efficiency and charging coverage [26].

Qian et al. proposed an optimal charging scheduling algorithm that maximizes the charging energy of the equipment and minimizes the discharge energy of the MC by combining the methods of evolution and clustering, thus improving the execution speed of the algorithm [27]. Han et al. proposed a collaborative energy supply scheme using MWCV to carry SWCV, which effectively reduced the death rate of nodes and saved the charging cost. However, the above algorithms only consider the extension of network life from the aspect of external power supply, without considering the internal energy saving. Although the energy loss of data collected by mobile charging devices is reduced, the sensing loss of sensor nodes and communication loss between nodes are not considered. In addition, none of the algorithms mentioned above takes network coverage into account. Although they prolong the network life, they cannot guarantee the stability of the network. When some nodes die, network coverage is greatly reduced.

In this paper, we propose a collaborative energy optimization algorithm for multiple chargers based on k-mean++ and node collaborative scheduling (CEOA). It uses the cooperation of the main mobile charger (MMC) device and the auxiliary mobile charger (AMC) to design a mobile path with low mobile cost and short charging time, effectively prolong the network lifetime, improve the coverage rate, and save the cost of charging.

3. Network Model

In this section, we describe in detail the basic components and some assumptions of WRSN. Then, the basic coverage model and energy transfer model are introduced.

3.1. Network Model and Assumptions. In this article, the base station(BS) is located in the center of the WRSN. It acts as a charging center for the MCs, equips with multiple backup chargers, and collects data information from sensors. Therefore, it is responsible for allocating routes for mobile charging devices, which return to the BS to recharge after a charging round. N static sensor nodes are deployed in a two-dimensional region, which is divided into clusters. Each cluster contains an unequal number of sensor nodes, which will be described in detail in the clustering algorithm. The abscissa of node i is x_i, the ordinate is y_i, and the node is represented by $S(i)$. Each node has a battery of the same capacity, which is denoted by E. Each node goes to sleep when its capacity falls below the minimum and dies when its capacity falls below 0. Table 1 lists some of the symbols used in this article.

In a network environment, it is equipped with one MMC and several AMCs. Chargers all start from the BS. When MCs arrive at the charging docking point, MMC releases AMC to provide energy to each cluster. The MMC can charge the AMC. AMC can supply energy to the sensor node. In this paper, we assume that MMC has infinite energy, and the moving speed is expressed as V_M. The battery capacity of AMC is small, which is represented by E_{AMC}, and the moving speed is represented by V_A. The speed of the secondary charging device is significantly faster than that of the primary charging device, because the size of the primary charging device is significantly larger than that of the secondary charging device, and the speed of the primary charging device is much smaller under the same power supply.

The assumptions in this paper are as follows: (1) BS is located in the center of the network. (2) BS can locate the coordinates of all nodes in the network. (3) The power of the MMC is enough to complete the task allocation of a charging cycle. (4) When the energy of the AMC is too low, it can actively return to the main charging device to replenish energy. (5) The charging time of AMC equipment is ignored.

Table 1: Notation lists.

Notation	Definition
N	The set of sensor nodes
Leng	The boundary size of WRSN
$S(i)$	The ith sensor node
$c(i)$	The ith cluster
(x_i, y_i)	The coordinate of the node $s(i)$
E_B	Battery capacity
E_{res}	The remaining energy of the node
E_{lc}	Energy consumption per bit of data sent
R_{ch}	Threshold for the MC to request a charging task
E_{AMC}	The total energy of AMC

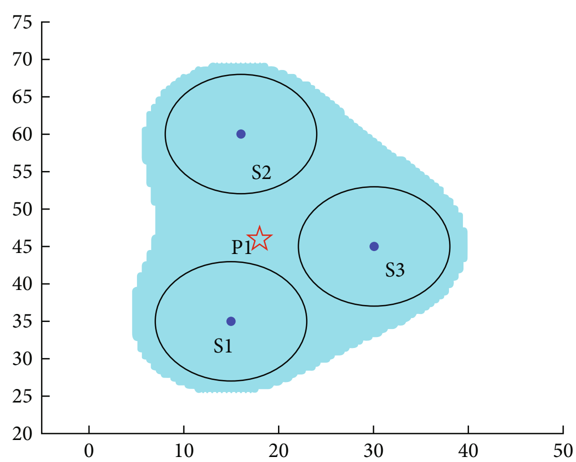


Figure 1: Confident information coverage model.

3.2. Confident Information Coverage Model. In this paper, the confident information coverage model is used as the basic coverage model for node deployment and scheduling. This model describes the sensor perception quality and capability from the perspective of information collaborative reconstruction. The core ideas and principles of the trusted information coverage model are described as follows. Please refer to the literature [28, 29] for a detailed process and analysis.

In physical space, there is a strong correlation between environmental variables, and they can be represented by correlation range. Different physical quantities have different spatial correlation ranges. This means that the physical quantity to be measured has spatial correlation only in the range of variation. As shown in Figure 1, P_1 represents the position of reconstructed points. S_1, S_2, and S_3 are three sensors. If the disk model is used, the information of P_1 point will not be sensed by sensors, while the confident information coverage model can cover positions similar to P_1 point, increase the coverage area of the network, and reduce the deployment cost. In practical application scenarios, environment variables have different actual measured values at different times. Therefore, root mean square error (RMSE) was adopted in this paper to measure and evaluate reconstruction and estimated quality [28], as shown below.

$$\phi(p) = \sqrt{1/T \sum_{t=1}^{T} \left(v^t(p) - \hat{v}^t(p)\right)^2}. \tag{1}$$

For a target point P_1, if $\phi(p)$ is less than RMSE, then the target point P_1 can be collaboratively covered by nodes. The greater the RMSE value, the greater the network coverage rate. The covering function is expressed as follows:

$$\text{Cov}_{xy}(p, m_i) = \begin{cases} 1, \text{ifrmse}(m_i, p) \le \text{RMSE} \\ 0, \text{ifrmse}(m_i, p)\text{RMSE} \end{cases}. \tag{2}$$

3.3. Energy Consumption Model. The energy loss caused by data transmission is positively correlated with the transmission distance, which is the main energy loss of sensor nodes [30, 31]. The calculation equation is shown below.

$$E_t(\text{kb}, d) = \begin{cases} \text{kb} \times E_{lc} + \text{kb} \times \varepsilon_{\text{fs}} \times d^2, d \le d_0 \\ \text{kb} \times E_{lc} + \text{kb} \times \varepsilon_{\text{amp}} \times d^4, d \ge d_0 \end{cases}, \tag{3}$$
$$E_r(\text{kb}, d) = \text{kb} \times E_{\text{lc}},$$

where E_t represents the loss during data transmission, and E_r represents the energy consumed when receiving data. kb represents the number of bits.

4. Proposed Algorithm

In this section, we will introduce the collaborative energy optimization algorithm for multiple chargers based on k-mean++ and node collaborative scheduling(CEOA). Firstly, the data collection mechanism based on node scheduling is introduced, and then the mobile charging path planning based on the artificial potential field method is introduced.

4.1. Data Collection Mechanism Based on Confident Information Coverage. In this section, we will introduce a network energy-saving scheme based on node sleep scheduling. Firstly, k-mean++ clustering algorithm is used to make the nodes of each cluster evenly distributed. In order to meet the requirements of regional coverage and maximize the period of charging interval, we need to effectively schedule the energy of sensor nodes so that the nodes with current coverage redundancy are in a sleep state, thus extending the network lifetime. Then, we need to select the appropriate cluster head for each cluster and select the energy-saving data transmission scheme. The network structure is shown in Figure 2. The specific algorithm flow is shown in Algorithm 1.

4.1.1. K-Mean++ Clustering and Node Collaborative Scheduling Scheme. The traditional k-mean clustering algorithm randomly selects the cluster center, which will produce the unsatisfactory result of multiple iterations of clustering. To solve this problem, the k-mean++ algorithm

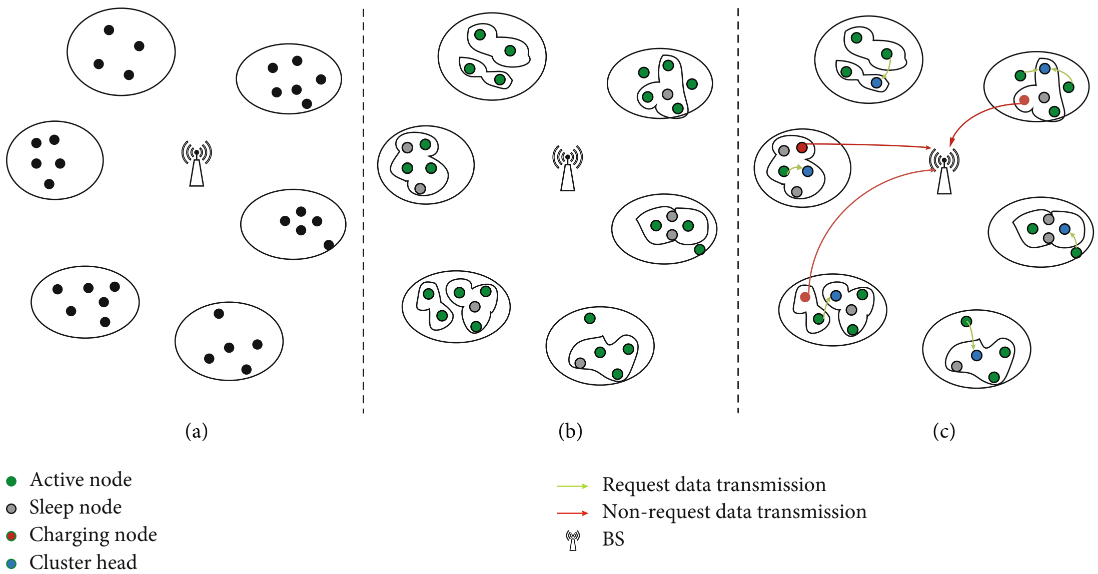


Figure 2: Network structure: (a) node cluster, (b) node coordination and scheduling, and (c) data transmission.

is adopted in this paper. In order to effectively reduce the internal energy consumption of the network and prolong the charging interval period, this paper proposes a node collaborative scheduling algorithm based on a greedy algorithm. After node clustering is completed, it is necessary to determine the coverage set that can cover the reconstructed points R_P. In each cluster, nodes in each grid are arranged in descending order according to the residual energy of nodes to form a node set chain. Then, the adaptability function of the CIC model is used to judge which nodes in the grid can carry out node collaborative sensing to form different coverage sets. When the node energy consumption reaches a certain value, the node will enter the hibernation state, and the current node will be removed from the working node set. If there is no sensor node in the grid or the sensor node cannot meet the condition of node collaborative sensing, it means that the current grid reconstruction point cannot be covered and is a covering hole. After the network coverage set is generated, the network coverage chain will be continuously updated according to the remaining energy of nodes. When the working node reaches the sleep threshold, the network coverage set will be updated automatically to ensure the maximum network coverage.

4.1.2. Cluster Head Selection in the Cluster. The cluster head is responsible for collecting data information in the cluster, so it consumes a lot of energy. The choice of cluster head should take into account both the remaining energy of nodes and the number of adjacent nodes. Therefore, this paper calculates the influence factor of each node based on the above two factors, and the calculation formula is as follows:

$$A_i = \rho \times \frac{n_i}{n_{tl}} + (1 - \rho) \times \frac{E_{\text{res}}}{E_B}, \tag{4}$$

where A_i is the cluster head competition value of the sensor node, ρ is the influence factor of cluster head competition, n_i is the number of sensor nodes within the communication radius of nodes, n_{tl} is the total number of nodes in the cluster, E_{res} represents the remaining energy, and E_B is the total capacity of the battery.

For each node in the cluster, the larger the cluster head competition value A is, the greater the probability of becoming a cluster head is.

4.1.3. Data Transmission Scheme. Long-distance transmission causes energy loss and difficult to guarantee the security of data. Data can be divided into the nonrequest data and the request data. Request data such as charging requests and equipment failures are transmitted directly to the BS. Other nonrequest data is transmitted back to the BS via the MC.

4.2. Mobile Charging Path Planning Based on Artificial Potential Field Method. The algorithm of mobile charging path planning consists of three parts, which are docking point selection, cluster charging sequence, and AMC path planning. The specific algorithm flow is displayed in Algorithm 2.

4.2.1. Docking Point Selection. In the working process of the network, the energy consumed by each node is different, so the position of each charging request node is also different. In order to minimize the travel distance of MC, a docking point needs to be selected in each cluster. In this paper, all nodes to be charged are first simulated as positively charged particles. It is assumed that there is a central particle in the network, and the position of the central point is a negatively charged particle. Gravity will be generated between the node and the central point. When the resultant force of all gravitation is zero, the

Input: k, N, Rc, Rp, $RMSE$, S;
Deployment.
k-mean++ clust.
for each Rp_i=1 to M **do**
  for each sensor $j \in Rp_i$ **do**
    $d_j = \sqrt{(S_j.x - rp_i.x)^2 + (S_j.y - rp_i.y)^2}$
    Sort S_j according d_j
  end for
end for
U $\longleftarrow$ S
C$\longleftarrow$ random initial coverage set
for each Rp_i=1 to M **do**
  while U $\neq \varnothing$ **do**
    for Rp_i = 1 to M **do**
      while $Rp_i \neq \varnothing$ **do**
        ϕ(i)= $Rp_i \bigcap C$
        for j=1:length(ϕ(i)) **do**
          if rmse(j)< RMSE **then**
            SP$\longleftarrow$ sensor j
            Rp$\longleftarrow$ Rp – Rp_i
          else
            j+1
            if rmse(j+1)< RMSE **then**
              SP$\longleftarrow$ sensor j,j+1
              Rp$\longleftarrow$ Rp-Rp_i
            else
              hole+1
            end if
          end if
        end for
      end while
    end for
    if S(i)$\in$ SP **then**
      S(i).state=work
    end if
  end while
end for
select the cluster head according to Eq. (4);
node sensing work
Output: S,SP.

Algorithm 1: Data collection mechanism.

actual position of the center is determined. At this point, the nearest charging node in each cluster is the center point, which is the docking point of the cluster. The formula for calculating the gravitational force is as follows:

$$\sum U_{\text{att}}(q_i) = \frac{1}{2}\zeta \text{dis}^2\left(\text{mq}_i, q_{\text{goal}}\right), \tag{5}$$

where ζ is the gravitational gain (approximately 1), mq_i is the node waiting to be charged in WRSN.

4.2.2. Cluster Charging Sequence. The number of nodes in each cluster may not be the same, so the charging sequence of the cluster should be adjusted accordingly. We set charging demand R_p for each cluster according to the remaining energy of the cluster and the geographical location between clusters to determine the charging sequence of the cluster. The higher the charging demand R_p value is, the higher the charging sequence is. The calculation process is as follows:

Input: k, R_{ch},S;
for i= 1:N **do**
  if S(i).E < E_{th} **then**
    R_{ch}+1
    S(i).state=R
    c=S(i).clust
    ch(c)$\longleftarrow$ i
  end if
end for
while R_{ch} > Threshold **do**
  for i= 1:length(ch) **do**
    $\sum U_{att} = \sqrt{((q_i.x - q_{goal}.x)^2 + (q_i.y - q_{goal}.y)^2)}$
    $\sum U_{att} = 0 \longrightarrow q_{goal}$
  end for
  for i= 1:k **do**
    for j= 1:length(clust(i)) **do**
      if S(j).state=R **then**
        $d_m(j) = \sqrt{((S_j.x - q_{goal}.x)^2 + (S_j.y - q_{goal}.y)^2)}$
      end if
    end for
    docking(i)= min[n, d_m(n)]
  end for
  caculate Rp for each cluster according to Eq. (8);
  obtain the shortest path of AMC according to Eq. (9);
  perform charging tasks;
end while
Output: dis,t,death_nodes.

Algorithm 2: Mobile charging path planning.

$$R_{\text{pe}}(g) = \frac{\sum_{i=1}^{n_g} E_{\text{res}}}{n_g \times E_B}, \tag{6}$$

$$R_{\text{pd}}(g) = \frac{\text{dis}(g-1, g)}{\sum_{p=g}^{N} \text{dis}(g-1, p)}, \tag{7}$$

$$R_p(g) = \mu \times R_{\text{pe}}(g) + (1-\mu) \times R_{\text{pd}}(g), \tag{8}$$

where the election factor of energy priority and distance priority is represented by μ, E_{res} is the total energy remaining in each cluster, N is the total number of clusters in WRSN, ng represents the number of sensor nodes in the gth cluster, $\text{dis}(g-1, g)$ indicates the distance between the previous cluster and this cluster, R_p is a cluster consisting of the charging coefficient values of all clusters, R_{pe} represents the energy coefficient of the gth cluster, and R_{pd} represents the distance coefficient of the gth cluster.

4.2.3. AMC Path Planning. When the number of charging requests is n, the MMC carries three AMCs, and the charging problem becomes an integer programming problem. The starting point and end point of each cluster are the docking points obtained in the previous section, and the moving

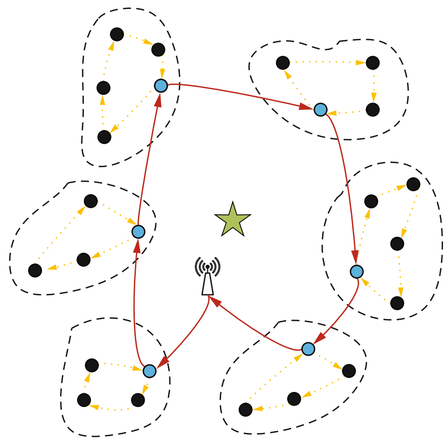


Figure 3: Mobile charging path planning based on artificial potential field method.

Table 2: Simulation parameters.

Parameters	Value
Network size	100 m × 100 m
RMSE	0.5
Total sensor nodes	100
Node initial energy	2 J
Energy sensing efficiency	45×10^{-9} J/b
Charging speed	0.005 J/s
MMC travel speed	2 m/s
AMC travel speed	5 m/s
MMC traveling energy consumption	5 J/m
AMC traveling energy consumption	1 J/m

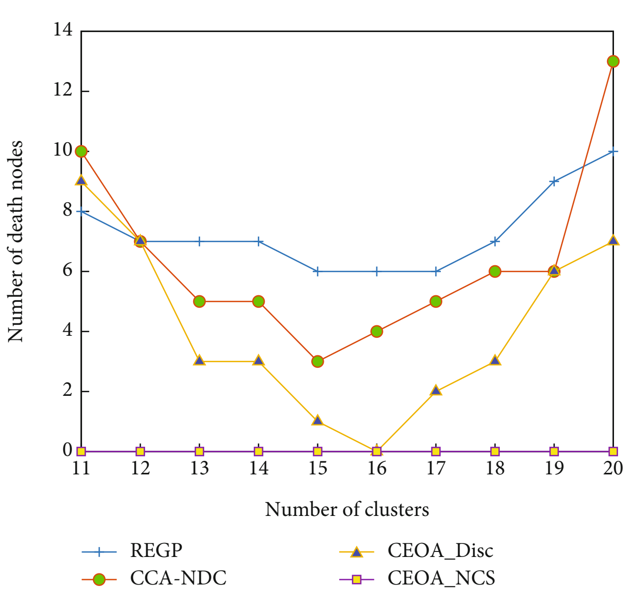


Figure 4: Number of dead nodes after the first round of charging.

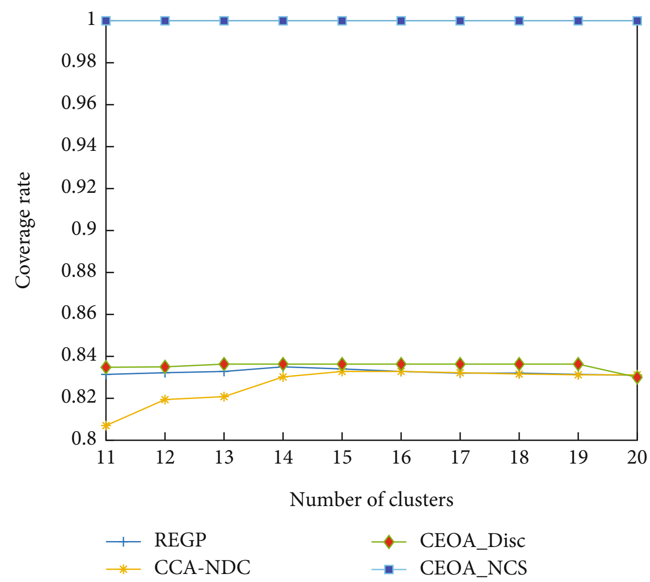


Figure 5: Comparison of initial coverage under different algorithms.

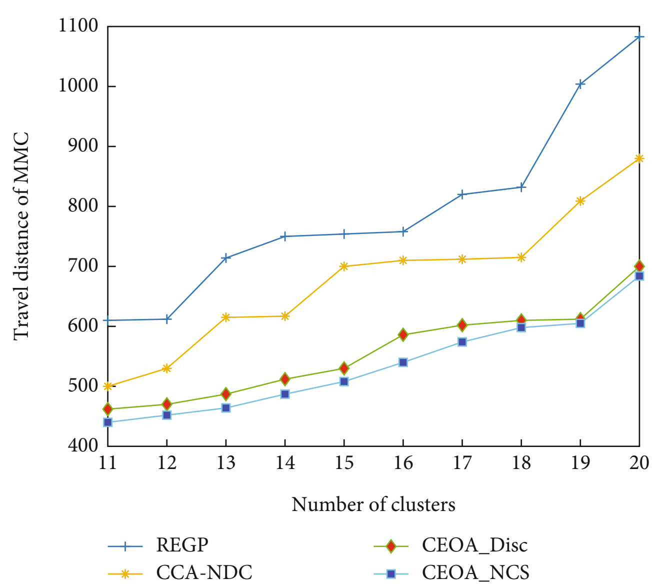


Figure 6: Travel distance of MMC.

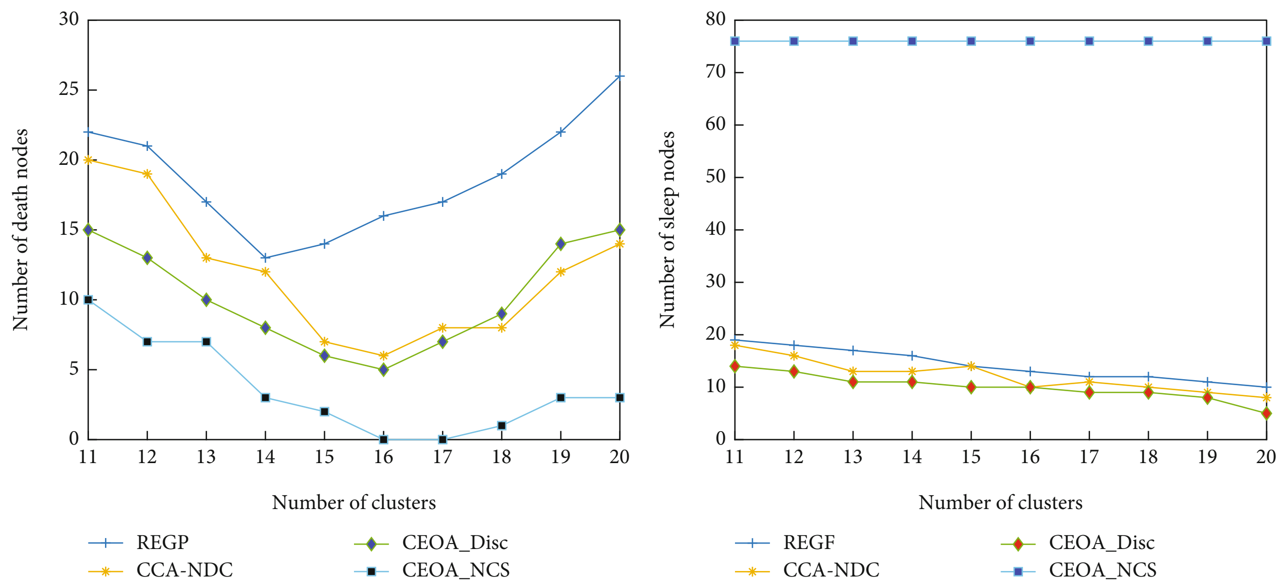
distance of each cluster can be modeled as follows:

$$\min \sum l_{ij} x_{ij}, \tag{9}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} x_{ij} = \sum_{j=1}^{n} x_{ji}, \tag{10}$$

$$\sum_{j=1}^{n} x_{ij} \leq 1, \ \sum_{j=1}^{n} x_{ji} \leq 1, \tag{11}$$

$$\sum_{j=1}^{n} x_{aj} = 1, \ \sum_{j=1}^{n} x_{ja} = 0, \tag{12}$$



(a) (b)

Figure 7: Comparison between different algorithms: (a) dead nodes; (b) sleep nodes.

$$\sum_{j=1}^{n} x_{\mathrm{dj}} = 0, \ \sum_{j=1}^{n} x_{\mathrm{jd}} = 1, \tag{13}$$

$$x_{\mathrm{ij}} \in \{0, 1\}, \tag{14}$$

where l_{ij} is the distance from node i to node j, x_{ij} indicates whether the node needs to be charged. x_{aj} and x_{dj} represent departure and return from the docking point.

To ensure that AMC can carry out the next round of charging tasks, the objective function has constraints.

$$\sum_{i=1}^{p} E_{i\_\mathrm{ne}} + \sum_{i=1}^{p-1} j_{i,i+1} \times e_{\mathrm{st}} > E_{\mathrm{sc}} - \mathrm{dis}_{p,\mathrm{BC}} \times e_{\mathrm{ac}}, \tag{15}$$

where E_{i_ne} is the total energy required by the first p nodes, e_{ac} is the energy consumption rate of AMC as it moves.

This formula means that the total energy to be charged plus the energy consumed by each cluster during the charging process must be greater than the total energy possessed by AMC minus the energy consumed during the moving process, so as to ensure the normal charging of the cluster.

In the charging process, if the constraints listed above can be met, the charging task can be successfully completed. If not, the AMC will temporarily stop charging. When the AMC is fully charged, it will resume its previous charging task. The path planning for MMC and AMC is shown in Figure 3.

4.3. Complexity Analysis. In the time complexity analysis, the time complexity of the CEOA_Disc algorithm and CEOA_NCS algorithm is analyzed and compared theoretically. According to the CEOA_Disc algorithm, assuming that the time used to complete the working state determination algorithm of a node is T_x, the number of nodes to be charged is N_1, the time required for a path movement planning is T_m, and the charging time is T; then, the running time of this algorithm is $N_1 T_m T$. The running time of the CEOA_Disc algorithm is $T_x + N_1 T_m T$; for the CEOA_NCS algorithm, it is assumed that the running time required for node collaborative scheduling based on the greedy algorithm is T_c, the number of nodes to be charged is N_2, the time required for a path movement planning is N_2, and the charging time is T. Given that $T_m > T_e$, $N_1 > N_2$ according to the algorithm, the time of this algorithm is $N_2 T_e T$. The running time of the CEOA_NCS algorithm is $T_c + N_2 T_e T$.

In conclusion, the CEOA_Disc algorithm can effectively reduce the moving distance of MWCV, and the CEOA_NCS algorithm can calculate the shortest moving path of MWCV, both of which save the charging time and cost. At the same time, these two algorithms are better than other algorithms in related performance indexes.

5. Performance Evaluation

5.1. Simulation Environment. In this paper, we use MATLAB 2021a to test the performance of the proposed algorithm. Table 2 lists the parameters used in this simulation experiment. 100 sensor nodes are randomly deployed in a 100 m × 100 m network. The communication distance between nodes is 15 m. RMSE value of CIC model is 0.5. The running speed of the MMC is 2 m/s, and the running consumption is 5 J/m. The speed of the AMC is 5 m/s, and the running consumption is 1 J/m. They all charge at 0.05 J/s. The initial power of the auxiliary mobile charging device is 1000 J. The comparison algorithm of simulation results is the CCA-NDC [13] and the REGP [20] algorithm.

5.2. Performance Analysis. k-mean++ clustering is an exclusive clustering method based on distance, and the number of clusters needs to be set initially. In previous studies, we have confirmed that when there are 16 clusters, the number of

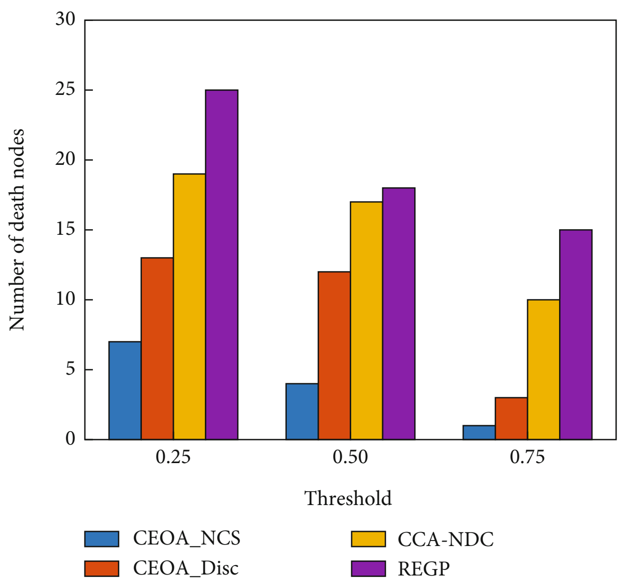


Figure 8: Comparison of dead nodes at different charging thresholds.

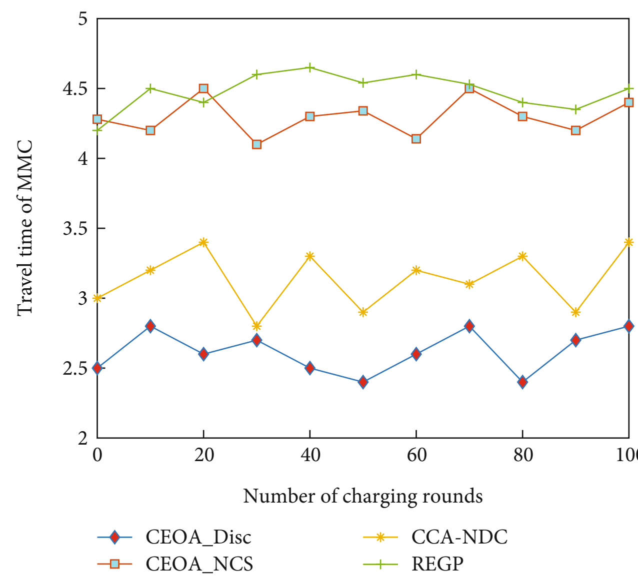


Figure 9: Time consumed per round of charging.

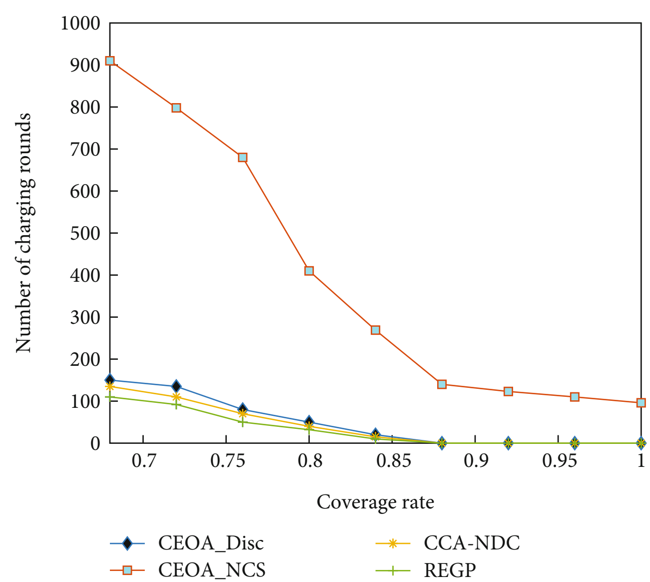


Figure 10: Comparison of charging rounds under different coverage rates.

dead nodes is the least. In this section, we still select clusters 11 to 20 for result analysis. When the number of clusters is too small, the mobile range is too large, and the AMC cannot be charged at one time. When there are too many clusters, the nodes in the cluster with a lower charging priority die due to the long waiting time. Figure 4 shows the node death result of node redundancy scheduling using the disk model during the first round of charging. REGP adopts k-mean clustering and randomly selects the initial clustering center, while CCA-NDC adopts mean shift clustering. The nodes in the network of these two algorithms are not evenly distributed, the waiting time of the main mobile charging device is too long, and the number of dead nodes increases. CEOA_Disc indicates that when the disk model is applied, the nodes in the network are scheduled for sleep. It can be seen from the figure that in the network with node scheduling, the charging pressure will be relatively reduced, and the dead nodes will be reduced due to the sleeping of some nodes. Because CEOA_NCS adopts the CIC model as the basic coverage model, the node mortality rate in the first round of charging is 0, no matter how many clusters there are.

Figure 5 shows the initial coverage of different algorithms under the disk model and CIC model. When using the disk model, based on redundancy cover within a cluster to judgment, CEOA_Disc provides more uniform distribution of each cluster node in the network. The number of sleep nodes within the cluster nodes was similar, different clusters were similar, and the number of coverage was nearly without a sleep schedule. As a result, the coverage is relatively reduced, and the cluster with fewer nodes has fewer dormant nodes, but the coverage rate is smaller. Therefore, the overall coverage varies greatly when the number of clusters is different, and the coverage rate is smaller than that of CEOA_Disc. Under the CIC model, the overall coverage has been greatly improved. At the initial deployment of CEOA_NCS, the coverage has reached 1 in all cases.

The previous research results show that CEOA has great advantages over the other two algorithms. The docking point of each cluster is not only considered from a single cluster but also calculated according to all nodes to be charged in the network. The location of the docking point is the same as the location of the charging node. In this case, it cannot only reduce MMC mobile distance, but it can also reduce AMC mobile distance, as can be seen in Figure 6. With the increase of number of clusters, MMC's moving distance also increases, but CEOA's moving distance is the shortest.

The number of dead nodes is directly related to the stability of the network. After 100 rounds of charging, some

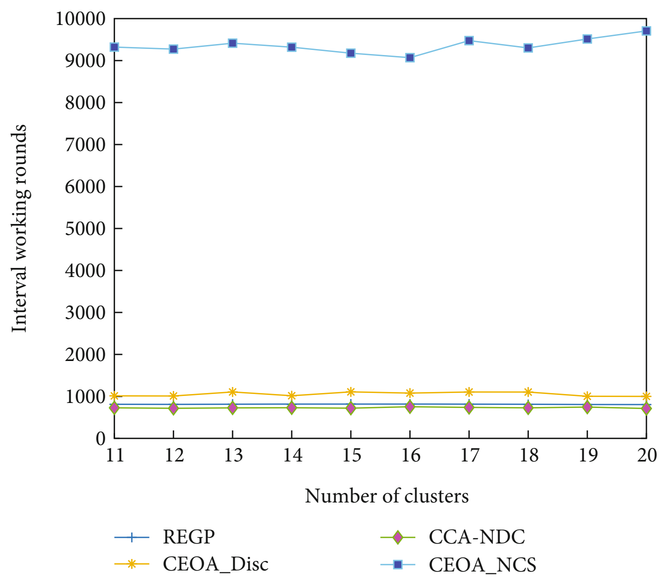


Figure 11: Comparison of working rounds of different algorithms.

nodes in the network die because they wait too long for one round of charging. Figure 7 shows the number of dead nodes and sleep nodes after 100 rounds of charging. It can be seen in Figure 7(a) that the number of dead nodes in the network is low when the CIC model is adopted. After 100 rounds, the number of dead nodes in CEOA_NCS is still 0 in 16 clusters. This is because the working nodes in the network are greatly reduced by adopting the CIC model. As can be seen in Figure 7(b), the number of sleep nodes using the CIC model is about 4 times that of the disk model. As the number of working nodes decreases, the sense energy and communication energy of nodes decrease, so the total energy consumption of the network decreases, and the number of dead nodes decreases.

Figure 8 shows the number of dead nodes at different charging thresholds after several rounds of charging. As can be seen in Figure 8, the number of dead nodes is significantly lower than that of the other two algorithms, because CEOA_Disc adopts k-mean++ for node clustering. Nodes in the network are more evenly distributed, and the number of nodes to be charged in each cluster does not differ much when the charging request is reached. This can effectively reduce the number of dead nodes. The number of dead nodes in CEOA_Disc is about half of that in REGP. However, we can also see from the figure that the performance of CEOA_NCS is better than other algorithms. It has the lowest number of dead nodes under any charge threshold request, far lower than other algorithms. The number of working cycles is more than 10 times that of other algorithms. This is because there are fewer working nodes in the confident information coverage model, and node sleep rotation is more likely.

As for network charging time, Figure 9 shows that the time spent per charge fluctuates up and down, especially for the disk model. This is due to the different nodes in each round of charging. After the charging request reaches the threshold in the network, the remaining energy of some nodes may be near the critical value. So in the next round of charging, the number of charging requests will increase. It can also be seen from the figure that the charging time of the CIC model is about 1.5 times longer than that of the disk model. This is because the network has a higher energy utilization rate, longer network work cycles, and longer charging time after nodes are coordinated with scheduling. However, CEOA_NCS's charging time is still lower than REGP's.

In the initial deployment, CEOA_NCS achieves a coverage rate of 1. After the network works for a period of time, the network coverage rate decreases due to the death of the node. Since there are fewer working nodes in the network and longer working rounds in the CIC model, the overall network lifetime will increase. It can be seen in Figure 10 that CEOA_Disc has lower node mortality and a longer network lifetime than the other two algorithms. Under the same coverage stopping condition, the CIC model has more charging cycles, which are more than 10 times that of the disk model.

After the mobile charging device is charged for the first time, it returns to the BS to replenish energy and bring the collected data back to the BS. At this time, the network will still run normally. Figure 11 shows that under the disk model, the working time of all nodes and the node scheduling state is much lower than that of the CIC model, which is about 10% of that. In the first round after charging, most nodes in the disk model network consume too much energy. At the end of charging, there will be a flood of charging requests again. There are few working nodes in the CIC model; in the first round, if all nodes have remaining energy even after charging, the charging interval period can be shortened.

6. Conclusion

This paper proposes a collaborative energy optimization algorithm for multiple mobile charging devices based on k-mean++ and node collaborative sensing. The nodes in the network are initially clustered to balance the number of nodes in each cluster and reduce the energy consumption on cluster heads. The global virtual force positioning algorithm is used to determine the docking points of mobile charging devices in each cluster, which reduces the moving distance of mobile charging devices and saved charging costs. A sleep scheduling algorithm based on the CIC model is proposed to prolong the lifetime of the network. It can extend network charging interval time and reduce the distance of mobile charging devices. The simulation results verify the advantages of CEOA in prolonging network lifetime, improving network stability, and saving charging cost. In future studies, we consider adopting more types of mobile charging devices to adapt to more complex environments.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China under Grant 61971215 and in part by the Scientific Research Fund of Hunan Provincial Education Department under Grant 21A0276.

References

[1] J. Guo and H. Jafarkhani, "Movement-efficient sensor deployment in wireless sensor networks with limited communication range," *IEEE Transactions on Wireless Communications*, vol. 18, no. 7, pp. 3469–3484, 2019.

[2] M. Wang and J. Zeng, "Hierarchical clustering nodes collaborative scheduling in wireless sensor network," *IEEE Sensors Journal*, vol. 22, no. 2, pp. 1786–1798, 2022.

[3] C. Dai, X. Liu, H. Cheng, L. T. Yang, and M. Jamal Deen, "Compressing deep model with pruning and Tucker decomposition for smart embedded systems," *IEEE Internet of Things Journal*, vol. 9, no. 16, pp. 14490–14500, 2022.

[4] P. Gope and T. Hwang, "BSN-care: a secure IoT-based modern healthcare system using body sensor network," *IEEE Sensors Journal*, vol. 16, no. 5, pp. 1368–1376, 2016.

[5] Y. K. Tan and S. K. Panda, "Optimized wind energy harvesting system using resistance emulator and active rectifier for wireless sensor nodes," *IEEE Transactions on Power Electronics*, vol. 26, no. 1, pp. 38–50, 2011.

[6] A. Pirisi, F. Grimaccia, M. Mussetta et al., "Optimization of an Energy Harvesting Buoy for Coral Reef Monitoring," in *2013 IEEE Congress on Evolutionary Computation*, pp. 629–634, Cancun, Mexico, June 2013.

[7] P. Cheng, S. He, F. Jiang, Y. Gu, and J. Chen, "Optimal scheduling for quality of monitoring in wireless rechargeable sensor networks," *IEEE Transactions on Wireless Communications*, vol. 12, no. 6, pp. 3072–3084, 2013.

[8] C. Alippi and C. Galperti, "An adaptive system for optimal solar energy harvesting in wireless sensor network nodes," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 55, no. 6, pp. 1742–1750, 2008.

[9] M. Gorlatova, A. Wallwater, and G. Zussman, "Networking low-power energy harvesting devices: measurements and algorithms," *IEEE Transactions on Mobile Computing*, vol. 12, no. 9, pp. 1853–1865, 2013.

[10] W. Liang, Z. Xu, W. Xu, J. Shi, G. Mao, and S. K. Das, "Approximation algorithms for charging reward maximization in rechargeable sensor networks via a mobile charger," *IEEE/ACM Transactions on Networking*, vol. 25, no. 5, pp. 3161–3174, 2017.

[11] Z. Wei, F. Liu, X. Ding, L. Feng, Z. Lyu, and J. Ji, "K-CHRA: a clustering hierarchical routing algorithm for wireless rechargeable sensor networks," *IEEE Access*, vol. 7, pp. 81859–81874, 2019.

[12] L. Mo, A. Kritikakou, and S. He, "Energy-aware multiple Mobile chargers coordination for wireless rechargeable sensor networks," *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 8202–8214, 2019.

[13] G. Han, J. Wu, H. Wang, M. Guizani, J. A. Ansere, and W. Zhang, "A multicharger cooperative energy provision algorithm based on density clustering in the industrial Internet of things," *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 9165–9174, 2019.

[14] K. L. Ang, J. K. P. Seng, and A. M. Zungeru, "Optimizing energy consumption for big data collection in large-scale wireless sensor networks with mobile collectors," *IEEE Systems Journal*, vol. 12, no. 1, pp. 616–626, 2018.

[15] S. Zhang, Z. Qian, J. Wu, F. Kong, and S. Lu, "Wireless charger placement and power allocation for maximizing charging quality," *IEEE Transactions on Mobile Computing*, vol. 17, no. 6, pp. 1483–1496, 2018.

[16] D. Arivudainambi and S. Balaji, "Optimal placement of wireless chargers in rechargeable sensor networks," *IEEE Sensors Journal*, vol. 18, no. 10, pp. 4212–4222, 2018.

[17] S. Priyadarshani, A. Tomar, and P. K. Jana, "An efficient partial charging scheme using multiple mobile chargers in wireless rechargeable sensor networks," *Ad Hoc Networks*, vol. 113, no. 1, article 102407, 2021.

[18] K. Wang, L. Wang, M. S. Obaidat, C. Lin, and M. Alam, "Extending network lifetime for wireless rechargeable sensor network systems through partial charge," *IEEE Systems Journal*, vol. 15, no. 1, pp. 1307–1317, 2021.

[19] L. He, L. Kong, Y. Gu, J. Pan, and T. Zhu, "Evaluating the on-demand mobile charging in wireless sensor networks," *IEEE Transactions on Mobile Computing*, vol. 14, no. 9, pp. 1861–1875, 2015.

[20] Y. Wang, Y. Dong, S. Li, H. Wu, and M. Cui, "CRCM: a new combined data gathering and energy charging model for WRSN," *Symmetry*, vol. 10, no. 8, pp. 319–319, 2018.

[21] Y. Shu, H. Yousefi, P. Cheng et al., "Near-optimal velocity control for mobile charging in wireless rechargeable sensor networks," *IEEE Transactions on Mobile Computing*, vol. 15, no. 7, pp. 1699–1713, 2016.

[22] G. Han, X. Yang, L. Liu, and W. Zhang, "A joint energy replenishment and data collection algorithm in wireless rechargeable sensor networks," *IEEE Internet of Things Journal*, vol. 5, no. 4, pp. 2596–2604, 2018.

[23] G. Han, H. Guan, J. Wu, S. Chan, L. Shu, and W. Zhang, "An uneven cluster-based mobile charging algorithm for wireless rechargeable sensor networks," *IEEE Systems Journal*, vol. 13, no. 4, pp. 3747–3758, 2019.

[24] Y. Ma, W. Liang, and W. Xu, "Charging utility maximization in wireless rechargeable sensor networks by charging multiple

sensors simultaneously," *IEEE/ACM Transactions on Networking*, vol. 26, no. 4, pp. 1591–1604, 2018.

[25] N. Nguyen, B. Liu, V. Pham, and C. Huang, "Network under limited mobile devices: a new technique for mobile charging scheduling with multiple sinks," *IEEE Systems Journal*, vol. 12, no. 3, pp. 2186–2196, 2018.

[26] S. Zhang, J. Wu, and S. Lu, "Collaborative mobile charging," *IEEE Transactions on Computers*, vol. 64, no. 3, pp. 654–667, 2015.

[27] Q. Qian, A. Y. S. Pandiyan, and D. E. Boyle, "Optimal recharge scheduler for drone-to-sensor wireless power transfer," *IEEE Access*, vol. 9, pp. 59301–59312, 2021.

[28] M. Wang, L. Zhu, L. T. Yang, M. Lin, X. Deng, and L. Yi, "Offloading-assisted energy-balanced Iot edge node relocation for confident information coverage," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 4482–4490, 2019.

[29] B. Wang, X. Deng, W. Liu, L. T. Yang, and H. C. Zhao, "Confident information coverage in sensor networks for field reconstruction," *IEEE Wireless Communications*, vol. 20, no. 6, pp. 74–81, 2013.

[30] M. Wang and C. Zhai, "Node collaborative sensing-based redundant path construction for multi-area coverage in MWSNs," *IEEE Internet of Things Journal*, vol. 9, no. 11, pp. 8763–8773, 2022.

[31] M. Wang, X. Wang, K. Jiang, and B. Fan, "Reinforcement learning-enabled resampling particle swarm optimization for sensor relocation in reconfigurable WSNs," *IEEE Sensors Journal*, vol. 22, no. 8, pp. 8257–8267, 2022.