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Demand-based charging strategy for wireless rechargeable sensor networks

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A wireless power transfer technique can solve the power capacity problem in wireless rechargeable sensor networks (WRSNs). The charging strategy is a widespread research problem. In this paper, we propose a demand-based charging strategy (DBCS) for WRSNs. We improved the charging programming in four ways: clustering method, selecting to-be-charged nodes, charging path, and charging schedule. First, we proposed a multipoint improved K-means (MIKmeans) clustering algorithm to balance the energy consumption, which can group nodes based on location, residual energy, and historical contribution. Second, the dynamic selection algorithm for charging nodes (DSACN) was proposed to select on-demand charging nodes. Third, we designed simulated annealing based on performance and efficiency (SABPE) to optimize the charging path for a mobile charging vehicle (MCV) and reduce the charging time. Last, we proposed the DBCS to enhance the efficiency of the MCV. Simulations reveal that the strategy can achieve better performance in terms of reducing the charging path, thus increasing communication effectiveness and residual energy utility.

KEYWORDS
charging, charging programming, energy balance, wireless rechargeable sensor network

1 | INTRODUCTION

Wireless sensor networks (WSNs) are composed of many finite energy sensors and several sink nodes, where the sensor nodes can sense events such as the temperature, humidity, and content of pollutants in the atmosphere. In particular, the performance of a WSN is constrained by the capacity of the battery [1]. To extend the lifetime of a WSN as much as possible, many researchers have proposed various approaches.

Generally, there are two kinds of methods to solve the problem. The first one is a resource-saving method that uses an optimization method to improve the WSN's efficiency. For example, efficient routing protocols such as low-energy adaptive clustering hierarchy (LEACH) [2], energy aggregation of medium access control (MAC) protocols [3], clustering algorithm [4,5], controlling topology [6], and data fusion [7] have been put forward. Although these intensive efforts were developed to a high degree of efficiency, the limitation of energy has not been resolved. The finite lifetime is still the key factor that affects the wide-scale deployment of a WSN.

Some scientists devoted their efforts to finding harvesting energy for WSNs. They conducted extensive studies that included harvesting energy from the surrounding environment such as wave energy, solar energy, and thermal energy [8–10]. The harvested energy is unstable and uncontrollable by these methods. A recent breakthrough by Kurs et al. [11] is called the magnetic resonance technique. Energy can be wirelessly transferred by inexpensive controllable mobile charging vehicles (MCVs) and can be replenished to proactively meet application requirements. Xie et al. [12] coined the term "wireless rechargeable sensor network" (WRSN) based on this technique. This technique can provide sensor nodes with steady, controllable, and highly effective recharging velocity energy. Therefore, the fundamental problem is to design the charging schedule for nodes in an energy-balanced manner. This plays a crucial role in achieving high charging efficiency.

To address this issue, we investigate an on-demand mobile charging strategy in which the node is charged only when necessary. When the energy is inadequate, the node sends the charging request to the MCV. The MCV replenishes the energy to the node according to the received request. We aim to design a novel mobile charging strategy that is guided by the advantages of existing designs while minimizing the impacts of their limitations.

The contributions of this work are summarized as follows:

- To decrease the charging times and shorten the traveling time of the MCV, we propose a demand-based charging strategy (DBCS). The energy consumption of nodes in a WRSN is not balanced. DBCS charges only the emergency node, which can effectively improve the efficiency of the MCV. The energy utility of DBCS is greater than nearest-job-next with preemption (NJNP) [13] and first-come first-served (FCFS) [14] schemes.
- An improved hierarchical clustering method called multipoint improved K-means (MIKmeans) clustering is adopted. This method is utilized to construct a distance-energy core set of each cluster. The communication within the cluster is improved, and the residual energy of the nodes is better balanced compared to improved distributed energy efficient clustering (IDEEC) [15]. For an on-demand charging strategy, the more balanced the residual energy of the nodes, the higher the efficiency of the MCV.
- To further increase the efficiency of charging, the dynamic selection algorithm for charging nodes (DSACN) was offered to select sensors with critical lifetimes. The energy consumption of the node is varied; therefore, the residual energy is time varied. This new dynamic threshold algorithm can adapt the time-varied energy consumption of the node.
- Annealing based on performance and efficiency (SABPE) is designed to select the traveling tour of the MCV in each charging round. Thus, both the MCV travel distance and the charging delay of the sensors are reduced.

This paper is organized as follows. Section 2 briefly reviews the literature. We introduce our problem statement in Section 3. In Section 4, the DBCS algorithm is proposed in detail. Simulations and analysis are given in Section 5. Last, Section 6 concludes this work.

2 | RELATED WORK

With the progress of wireless energy transfer technology, prolonging the lifetime of WRSNs has been investigated. However, this technology is still in its initial stages. Based on different situations, WRSNs can be categorized as periodical WRSN [16] and event-driven WRSN [17].

In a periodical WRSN, it is supposed that the sensors generate data periodically and that the energy consumptions are almost equal. Thus, the sensor needs to be charged cyclically [16], [18–20]. The MCV periodically visits and charges the node in the field. To efficiently utilize its charging cycle, the MCV travels the optimized path along the shortest Hamiltonian cycle. The charging strategy can be converted into a traveling salesman problem (TSP) [16]. The periodical charging strategy can be divided into the single-node charging strategy and multi-node charging strategy [18–20]. In the single-node charging strategy, only one MCV is working at a particular moment, the charging efficiency is low, and the number of nodes is low.

To increase the charging efficiency, a multi-node charging strategy in which several sensors can be charged at the same time was proposed. In [18], the MCV was regarded as a mobile base station (BS) with the smallest enclosing space disk for communication. The work in [19] modeled the on-demand charging problem as scheduling the MCV to charge life-critical sensors in a network. In [20], the authors considered the minimum number of MCV problems in a general 2D network to keep the network running indefinitely. Most of these studies assumed that the sensing data and the energy consumption velocity of each sensor were fixed and provided in advance. However, in terms of realistic scenarios, the velocity of sensing and energy consumption will vary over time. A periodical energy replenishment strategy does not suit actual applications.

Some researchers proposed a charging strategy for efficient stochastic event captures [17], [21–26]. In [17], the authors proposed a framework of wireless energy replenishment based on mobile data gathering by considering the time-varying nature of energy replenishment. Angelopoulos [21] posed the charging decision problem and proved its complexity. In [22], the objective was to jointly determine the MCV movement and sensor activation schedules to maximize the quality of monitoring (QoM). Dai et al. [23] considered two closely related subproblems of mobile charging for stochastic event capture. One was a way to select the node for charging, and the other was how to schedule the node's activation according to its received energy. To deal with multisensor and multi-event problems, the authors used a weighted sum method to transform a multi-objective problem into general linear programming [24]. In [25], the authors concentrated on a scenario in which the MCV visited a selected subset of sensors in a predetermined path and charged and collected data from them simultaneously. Wang et al. [26] assumed that a mobile charger followed a random walk on the grid of sensors. The mobile charger conducted two battery-aware energy replenishment strategies to recharge the sensors.

These methods can indeed increase network performance. However, the charging of a node is a long process in a WRSN, and continuous optimization system parameter combinations are required. The performance of a system is affected by some uncertainty factors. A time-varied charging strategy needs to be established. In this work, we propose a time-varied clustering and charging algorithm DBCS for WRSNs, aiming at enhancing performance by increasing the energy utility, shortening the journey time, and decreasing the average charging time.

3 | SYSTEM MODEL

In this section, we introduce the framework of a WRSN, a sensor energy charging paradigm, and the problem definition.

3.1 | Framework of WRSN

In the framework of an on-demand charging WRSN, there is one maintenance station, one BS, only one MCV, and many rechargeable sensors, as shown in Figure 1. The maintenance station can meet the charging demand. The BS collects and aggregates the sensing data from sensors and does not have an energy constraint. After the nodes are deployed, the location of each node can be determined [27]. A set of nodes with a random battery capacity is distributed over a square field with length L. Nodes are grouped into several clusters based on their position and the residual energy. The sensor collects data and relays them to the cluster heads. When the power is lower than the threshold φ, the node will send a real-time charging request to the MCV. The request delivery time is assumed to be negligible when compared with the MCV's traveling time [28].

3.2 | Energy consumption model

In WRSN, most of the energy is consumed during the sending and receiving process. In this work, we adopt a simple energy model to obtain the energy consumption

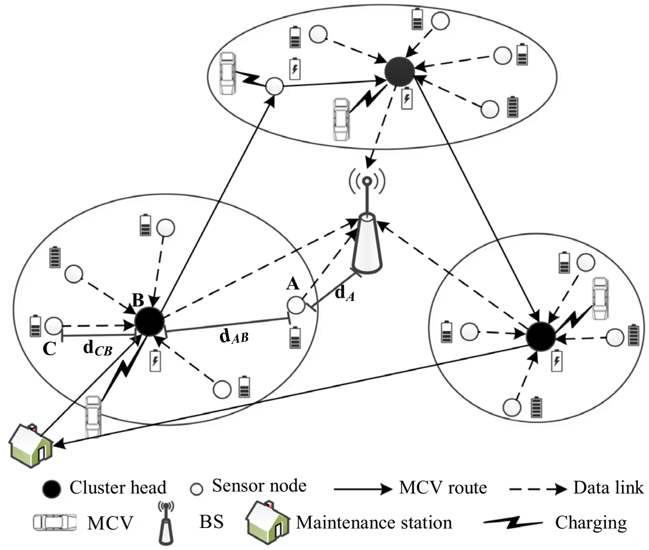

FIGURE 1 Framework of WRSN

of a normal node [29]. When sending or receiving a message with l bits, the energy consumption is shown in (1).

$$E = E_{\text{tx}}(l,d) + E_{\text{rx}}(l) = 2 \times E_{\text{elec}} \times l + \varepsilon_{\text{amp}} \times d_{ij}^2 \quad (1)$$

where E_{elec} indicates the energy consumption for sending or receiving each bit; d_{ij} denotes the distance between the sender; and receiver; ε_{amp} is the energy consumption for transmitting amplifier. The radio dissipates 50 nJ/b to run the transmitter or receiver circuitry.

3.3 | Energy charging model

The energy charging model is defined as a Friis free space model in (2).

$$P_r(d) = \frac{G_{\text{tx}} G_{\text{rx}} \eta}{L_{\text{p}}} \left(\frac{\lambda}{4\pi(d+\delta)} \right)^2 P_{\text{tx}} \quad (2)$$

where G_{tx} is the source antenna gain, G_{rx} is the receiver antenna gain, η represents the rectifier efficiency, L_{p} indicates the polarization loss, λ is the wavelength, d is the charging distance, δ is assigned a value of 0.2316 [8] as the parameter to adjust the Friis' free space equation for short-distance transmission, and P_{tx} is the source power of the MCV.

4 | CHARGING STRATEGY

The charging strategy for the WRSN is developed in this section. There are four parts to discuss: the MIKmeans clustering algorithm, which can balance the load of the network; DSACN, which selects the emergency charging node to improve the efficiency of the MCV; SABPE, which takes an optimal path planning method for the MCV; and the fact that the MCV operates on a charge-on-demand schedule DBCS.

4.1 | MIKmeans clustering algorithm

We proposed the MIKmeans clustering algorithm based on the K-means algorithm [5] to balance the load of the network and to prevent some special nodes from exhausting their energy quickly. Two improvements were proposed.

4.1.1 | Improve communication model within cluster

To decrease the relay task of the cluster head, the communication model within the cluster was improved. First, nodes group several clusters based on a K-means algorithm. The node in the cluster will cover a certain area where the cluster head is located near the center. The member node sends the sensing data to the cluster head, and then the cluster head relays data to the BS. Therefore, there are some special member nodes that are nearer to the BS than to the cluster head, such as A in Figure 1. To decrease the transmission consumption, these special member nodes communicate with the BS directly (e.g., A in Figure 1). The common member nodes communicate with the cluster head directly (e.g., C in Figure 1).

4.1.2 | Improve operation of cluster head

The cluster head is used to relay the communication between the BS and member nodes. Thus, the velocity of the energy consumption will be faster than the others. To balance the load of the cluster head, we design a dynamic operation. Some special nodes act as cluster heads based on the residual energy, location, and data volume. The purpose is to balance the energy consumption of the nodes. Some specific improvements are as follows:

- The node located nearest to the center of the cluster is chosen as the head. We assume that the radius of the cluster is r, and there is a concentric circle whose radius is $0.5r$. The node located in a concentric circle is labeled the candidate cluster head. These nodes will possibly be the cluster head in the next round.

To balance the load of the WRSN, we put forward the rotation parameter of the node. The rotation parameter is composed of three parts: the residual energy, the location, and the number of times as a cluster head. The rotating condition of the cluster head is that the residual energy is less than the threshold, or the mean square value of the residual energy of the candidate cluster head nodes is less than the threshold. The rotation parameter is calculated by (3). The node that has the maximum of the rotation parameter will be the cluster head in the next charging round.

$$\text{Rotation}(i) = \alpha \frac{E_i(m)}{E_{\text{aver}}(m)} + \beta \frac{D_{\text{aver}}(m)}{D_i(m)} + \gamma \frac{1}{A_i(m)+1} \tag{3}$$

where m denotes the cluster, $E_i(m)$ is the residual energy of the ith sensor node, $E_{\text{aver}}(m)$ indicates the average residual energy of the cluster, $D_i(m)$ is the distance between the node and the center of the cluster, $D_{\text{aver}}(m)$ denotes the mean of $D_i(m)$, and $A_i(m)$ indicates the times as the cluster head of the ith sensor. α, β, γ are the normalized parameters that represent the importance of the residual energy, location, and historical contribution, and $\alpha \geq 0$, $\beta \geq 0$, $\gamma \geq 0$. α will be larger when the total residual energy is smaller. Similarly, when the density of a cluster is higher, β will larger. When fairness is considered, γ will be close to 1. The dynamic setting of the factor can be seen as the Pareto solution for a multi-objective optimization problem [30].

4.2 | Select charging nodes

Although MIKmeans clustering can balance the load, the energy consumptions of the nodes show tremendous variations in WRSNs. We only charge the node for which the residual working time is lower than the threshold. This is the key to selecting the appropriate threshold. The exact threshold not only can reduce the charging time but can also ensure the node works all of the time. We propose a dynamic algorithm to ensure the threshold DSACN. DSACN is based on the minimum residual working time of the node and the residual working time of the MCV.

4.2.1 | Compute residual working time of MCV

First, we compute the residual working time of the MCV according to (4).

$$\text{duration}_{\text{MCV}} = \left(\sum_{i=1}^{n} d_{i-1,i} + d_{n,0} \right) \Big/ v + \sum_{i=1}^{n} \tau_i \tag{4}$$

where $d_{i-1,i}$ denotes the distance between two nodes, 0 indicates the maintenance station, v is the travel velocity of the MCV, and τ_i denotes the duration of the MCV when it stays near the ith node. When the residual working time is longer than $\text{duration}_{\text{MCV}}$, the node will ensure it works all the time [28].

4.2.2 | Compute minimum residual working time of sensor

The minimum residual working time of the sensor in the WRSN is computed by (5).

$$\mathrm{re}T_{\min} = \min\left(\frac{E_i(m)}{p_i(m)}\right) \quad 1 \le i \le n \tag{5}$$

where $E_i(m)$ is the residual energy of the ith sensor node in the mth cluster and $p_i(m)$ denotes the power of the ith node.

$\mathrm{re}T_{\min}$ represents the residual working time of the earliest possible dead node. When the charging cycle is shorter than $\mathrm{re}T_{\min}$, no sensors will die. If the residual working time of the sensor is longer than $2 \times \mathrm{re}T_{\min}$ and the charging cycle is shorter than $\mathrm{re}T_{\min}$, the node in the WRSN can be sure not to die.

We design a strategy to select the charging node and record: $\mathrm{ChargeRound}^k = \{r_0, \ r_1, \ \ldots, \ r_k, \ \ldots, \ r_0\}$ where r_0 denotes the maintenance station and r_k represents the kth node that needs to be charged. First, in a charging round, we compute the residual working time of the MCV and the minimum residual working time of the sensor. The smaller one will be chosen as the threshold. A sensor is chosen for which the residual working time is lower than the threshold. The threshold is dynamic.

4.3 | Plan MCV charging route

When some nodes are selected, the MCV will move near them and charge them one by one. We take a full charging strategy for each node because the cost of the MCV moving is high. Thus, the total moving distance should be as short as possible to prevent excessive mobile overhead. The routing planning problem transformed the TSP for the charging nodes. We put forward SABPE based on the simulated annealing (SA) algorithm [31] to solve the traversal paths problems of the charging nodes.

4.3.1 | SA algorithm

The SA algorithm is a local search method that finds its inspiration in the physical annealing process studied in statistical mechanics. When a new traversal path $P(n)$ is produced, the length $D(P(n))$ should be computed. If $D(P(n)) < D(P(n-1))$, then $P(n)$ becomes the new path; if not, we accept $P(n)$ by the SA probability and then cool down. We repeat this process until we meet the end condition. Then, we output the solution $D(P)$. The SA probability can be solved by (6).

$$p(dE) = \exp\left(\frac{dE}{k_b T}\right) \tag{6}$$

where $dE < 0$ because it simulates the annealing process, T is the temperature, k_b is the Boltzmann constant, and $0 < p(dE) < 1$ because $dE/k_b T < 0$.

4.3.2 | SABPE algorithm

The SA algorithm is a method for a local optimal solution. To find the optimal solution faster and out of the local optimum solution, the SABPE algorithm is proposed. The solution procedure for SABPE is described in Algorithm 1.

Algorithm 1 SABPE algorithmtgroup1

1: Initialization the coordinate and order of nodes, number of iterations and swap nodes, initial temperature, final temperature, cooling coefficient;
2: while $temperature > 0.01$ do
3: Sensor nodes compute the distance of charging nodes with random order;
4: Exchange pairs of nodes order and compute the new distance;
5: if $\Delta dis\tan ce < 0$ then
6: Accept the new order and save it to the structure;
7: else if $p(temperature) > p(random)$ then
8: Accept the new order and save it to the structure;
9: else
10: $temperature = temperature/0.951$;
11: if $p(temperature) > p(random)$ then
12: Accept the new order and save it to the structure;
13: else
14: Keep the previous order;
15: end if
16: end if
17: if the iterations times satisfies the reservation then
18: if *distance* < *shortest distance* in structure then
19: if the result is convergence then
20: Significantly cooling and get new distance;
21: else if $accepttimes \le 5$ then
22: Slowly cooling, reset iteration times, return to step 3;
23: else
24: Substantial cooling, reset iteration times, return to step 3;
25: end if
26: else
27: Reduce the iteration times;
28: end if
29: end if
30: end while
31: Return final order and distance

- Add a stage that is named "elite reserve." The best solution in each period is recorded and updated in real time, which avoids a situation where the poor solution is accepted in the probability.
- Add the disturbance intensity. The number of exchanging nodes is increased from one to several. Thus, the intensity of perturbation is increased.
- A reheating process is inserted. To avoid only finding the local optimum and stagnation, a reheating step is interspersed during the cooling process.
- To improve the algorithm efficiency, the cooling velocity is adjusted according to the number of times of acceptance.
- After the optimal solution is obtained, the result will be the initial solution again and the algorithm is iterated for several steps to ensure that the solution does not change. This improvement can ensure the result will not fall into the local optimal.

Algorithm 1 proceeds as follows. The initialization of some parameters occurs in Line 1. The basic SA algorithm is described in lines 5–16. Lines 7–10 realize the reheating process. In lines 6–12, a better solution is reserved and is called the elite reserve stage. In line 4, disturbance intensity is increased. A reheating process is inserted in the program. Lines 21–25 realize the 4th improvement. In lines 17–29, the research process is achieved. The SABPE algorithm can guarantee to find the shortest charging path as soon as possible. Thus, the charging delay can be effectively decreased.

4.4 | MCV charging schedule

We propose a DBCS charging schedule to determine the operation of the MCV. The timer controls the working time of the MCV when the WRSN operates. The charging schedule lasts until the MCV returns to the maintenance station, the timer goes to zero, and the new charging schedule is started.

The status of the MCV can be described by (7–10).

$$\tau_i^k q_c \eta = E_{oi} - E_i^k + p_i(t_i^k - t_0^k + \tau_i^k), \tag{7}$$

$$E_i^k \geq p_i(t_i^k - t_0^k), \tag{8}$$

$$t_i^k = t_0^k + \sum_{j=1}^{i-1} \tau_i^k + \sum_{j=1}^{i} \frac{d_{j-1,j}}{v}, \tag{9}$$

$$t_{i+1}^k = t_i^k + \tau_i^k + \frac{d_{i,i+1}}{v}, \tag{10}$$

where E_{oi} denotes the original energy of the ith sensor node. When the WRSN has already worked k charging rounds, the residual energy of the ith sensor node is E_i^k. p_i indicates the energy consumption rate of the ith sensor node, which is invariable during charging. τ_i^k denotes the duration when the MCV works for the ith node in the kth charging round, q_c denotes the power of MCV charging, η indicates the efficiency of MCV charging, and $d_{j-1,j}$ denotes the distance between two nodes; the speed of MCV is v, and the duration of the MCV recharging is $\tau_0^k = \tau_{\text{station}}$.

Equations (7) and (9) indicate that the sum of the residual energy and replenished energy is equivalent to the energy consumption of the node in one working round. Equation (8) indicates the residual energy that can support the normal operation of the node at the beginning of the kth charging round. Equation (10) indicates the time of the MCV charging for the $i+1$ node, which is related to the time and the duration of the MCV charging for the ith node and the distance between the two nodes. The charging schedule of the WRSN is described in Algorithm 2.

Algorithm 2 DBCS charging scheduletgroup1

Initialization: $n, area, E_{oi}, \eta, E_W, q_W, q_c, k, \tau_{\text{station}}$;
Set up the WRSN with random distribution;
Uses MIKmeans algorithm to cluster the network;
Sensors communicate with each other and consume energy;
for $j = 1$ to k **do**
  while $t > \tau_{\text{station}}$ **do**
    Calculate $\text{duration}_{\text{MCV}}$;
    for $i = 1$ to n **do**
      Collect residual energy and energy consumption;
      BS calculate $\text{re}T_{\min}$ and $\text{duration}_{\text{MCV}}$;
      if $E_i^k \leq \min(2\text{re}T_{\min}, \text{duartion}_{\text{MCV}})$ **then**
        puts sensor and S into *ChargeRound*;
      end if
    end for
    use SABPE algorithm to find the shortest distance of *ChargeRound*;
    The nodes in the *ChargeRound* are recorded;
    MCV charges for N_i node at $t = t_i^k$ in new order;
    MCV leaves N_i node at $t = t_i^k + \tau_i^k$ for next one;
    MCV returns to S at $t = chargeD^k / v + \sum_{i=1}^{S} \tau_i^k$;
    $t = 0$;
  end while
end for

The DBCS charging schedule is an on-demand charging schedule for the WRSN. The charging round starts when the MCV is located in the maintenance station. The BS can calculate the threshold of the residual working time based on the location, residual energy, and power consumption of the node. When the residual working time is lower than the threshold, the node will send a request to the BS. After the BS makes a path plan, the MCV sets out from the maintenance station and charges the node in turn. When the charging task is scheduled to end, the MCV returns to the maintenance station.

5 | SIMULATION RESULTS

In this section, we conduct extensive simulation experiments to evaluate the performance of the WRSN.

5.1 | Simulation setup

As shown in Table 1, we randomly deploy {50, 60, 70, 80, 90, 100} nodes into a 100 m × 100 m square field. The BS was placed at the center of the field. The BS coordinate is at (50, 50), and the maintenance station coordinate is at (0, 0). The environment information, after being captured by individual nodes, is relayed to the BS. The sensor node sends a charging request to the BS when the remaining energy is below the threshold. In our event-driven simulator, the sensing data is simulated as events occur at random times and in random locations. Whenever an event occurs

TABLE 1 Simulation parameters

Parameters	Values
Node number	{50, 60, 70, 80, 90, 100}
Field size (m^2)	100 × 100
Initial energy (J)	(500 + rand(1) × 10)
Amount of transmitting information (bit)	4,000k
Communication consumption per bit of node (nJ/bit)	50
MCV speed (m/s)	3
MCV charging efficiency (η)	0.5
MCV moving consumption (J/m)	8
MCV charging power (W)	10
MCV recharging duration (min)	10
α, β, γ	{0.6, 0.3, 0.1}

in the range of the sensor node, the node captures the event and transmits it to the BS via the constructed route. The mobile charging process is simulated using C++.

5.2 | Communication topology

Figure 2 shows the communication topology of the WRSN, which has 50 nodes.

In Figure 2, the star denotes the BS, and the nodes are grouped into five clusters that are marked by different symbols (square, triple, cross, diamond, and snowflake). The clusters are grouped according to the MIKmeans algorithm. The lines in Figure 2 indicate the communication links. In Figure 2, some special nodes located near the BS will communicate with the BS instead of the cluster head.

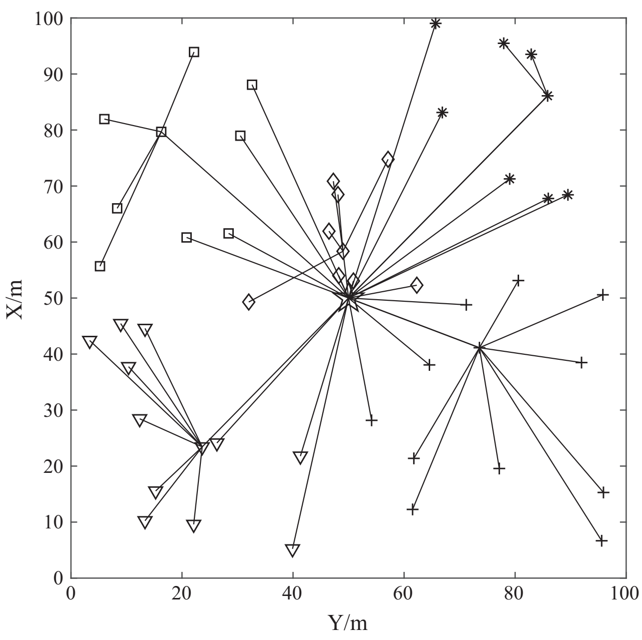

FIGURE 2 Communication topology of WRSN

5.3 | Traveling path of MCV

Figure 3 describes the traveling paths of the MCV in different charging rounds.

Figure 3A shows the traveling path of the MCV in the 1st charging round. There are only five nodes to be charged, and each is a cluster head that loads a lot of transfer work. The energy consumption is high. Figure 3B shows the traveling path of the MCV in the 24th charging round. As long as the workload becomes heavy, the number of charging nodes is increased. Because the MIKmeans algorithm operates in the WRSN, the member nodes act as the cluster head rotates, and the energy consumption also increased. The charging queue is expanded. The MCV need to replenish its energy for more nodes.

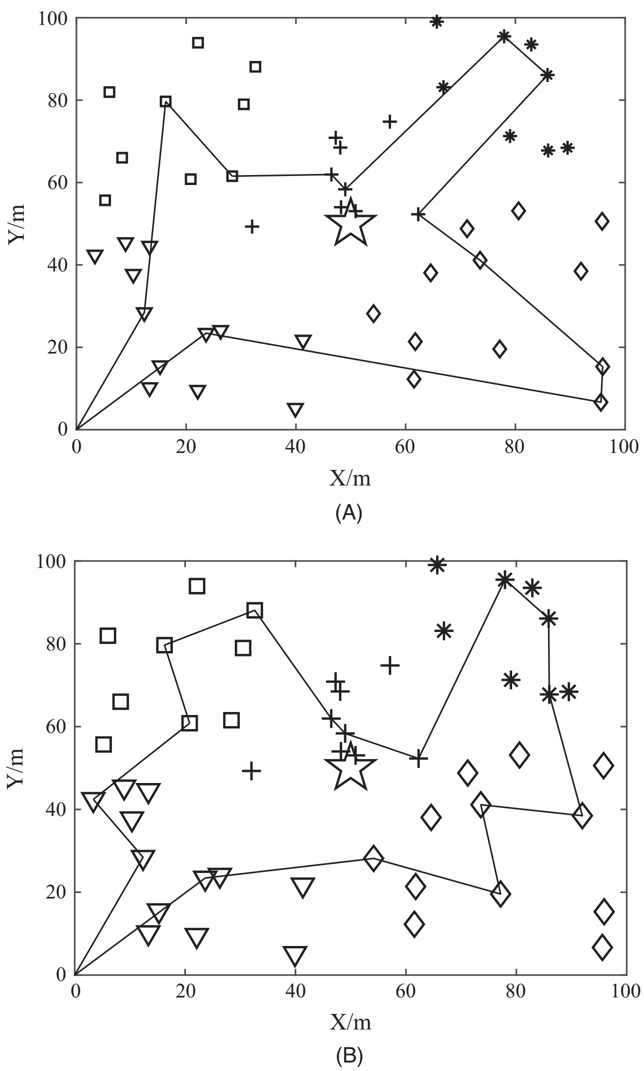

FIGURE 3 Traveling paths of different charging rounds: (A) traveling path in 1st charging round and (B) traveling path in 24th charging round

5.4 | Communication mode

To analyze the communication mode, we selected the residual energy mean square to characterize the equilibrium degree of the node residual energy in the WRSN, as shown in Figure 4. This indicator embodies the deviation degree of the residual energy of the special node and the average residual energy of the entire network. The residual energy mean square value is larger, which means that the deviation degree of the residual energy of the special node is greater and the network energy balance is worse.

In Figure 4, the curve of the K-means algorithm and IDEEC algorithm is reduced at 900 rounds. This indicates that there are some nodes that died by these two algorithms at this point. The K-means algorithm used the node closest to the center of the cluster as the cluster head, and the energy consumption is not balanced. The mean square value is the largest and grows faster. IDEEC takes in account the residual energy and the location. The balance of energy consumption is better than in the K-means algorithm. The MIKmeans algorithm proposed in this paper considers multiple factors, and the energy consumption of the network is the best balanced. When the value of MIKmeans increases slowly, there are no dead nodes, and the residual energy of the network is balanced.

5.5 | Efficiency of energy

We propose the energy utility as an index of the character of the efficiency of energy. The definition of energy utility is the ratio of the moving energy consumption of the MCV to the replenished energy of the node by the MCV in each charging round [32]. The calculation method is presented in (11).

$$\text{utility} = \frac{\sum_{i=1}^{s} q_c \tau_i \eta}{q_W D(P)}. \tag{11}$$

where q_c denotes the power of MCV charging, τ_i indicates the duration that the MCV charges for the ith node, η denotes the efficiency of the MCV charging, q_W indicates the MCV moving consumption, and the total distance of the MCV moving in a charging round is indicated by $D(P)$. In (11), we know that the higher value of "utility" means that the MCV requires more energy to charge the node. Less energy used to move the MCV indicates better performance of the WRSN.

Figure 5 is a comparison of the efficiency of energy by varying the charging round. There are also two typical comparison strategies (NJNP [13] and FCFS [14]), which are simulated. By using the FCFS strategy, the charging path is arranged by the order of the charging request, the first charging request will respond first, and the latter request will respond later. By using the NJNP strategy, the charging path is arranged by the location of nodes that send the charging demand. The MCV will first charge the nodes that are nearer to its location. We simulated 50 charging rounds and compared the DBCS strategy, NJNP strategy, and FCFS strategy, as shown in Figure 5.

It is obvious that the DBCS charging strategy designed in this paper is the best one. The energy utility of DBCS is obviously highest during the 50 charging rounds. The FCFS strategy is to charge the node that sends its request first. Thus, there are many repeated crossover routes in a charging round. The MCV will move along various redundant paths. This results in its energy utility being the worst in Figure 5. For the NJNP strategy, the nodes located nearest to the MCV are charged first in each charging round. When nodes decentralize, the effect is better. However, if the charging nodes are dense, redundant charging paths will easily occur.

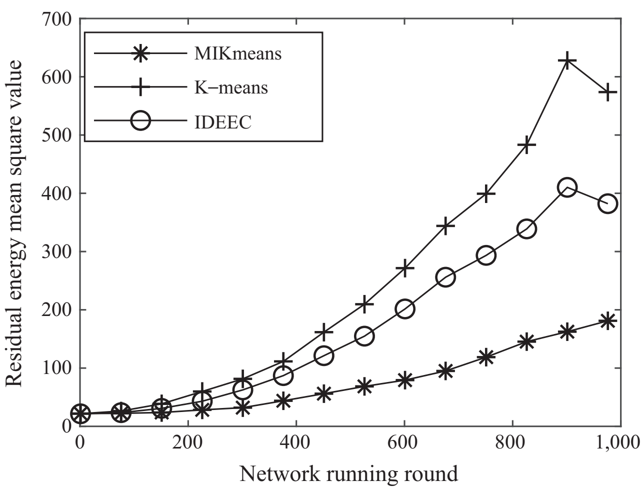

FIGURE 4 Residual energy mean square value of algorithms by varying network running round

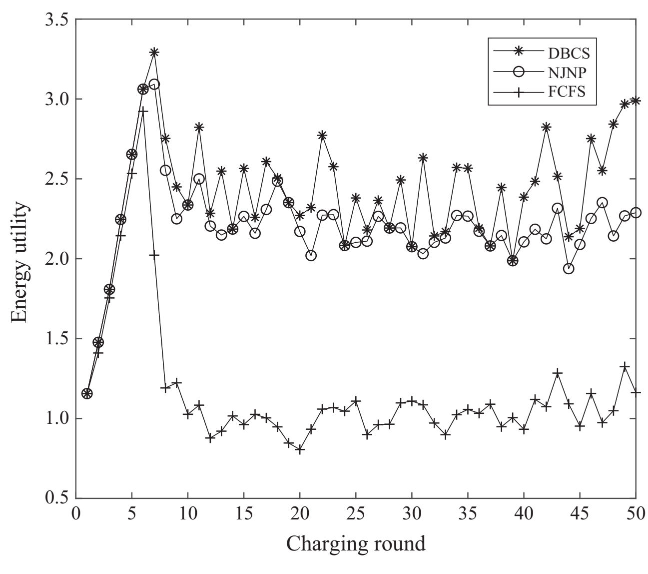

FIGURE 5 Energy utility by varied charging round

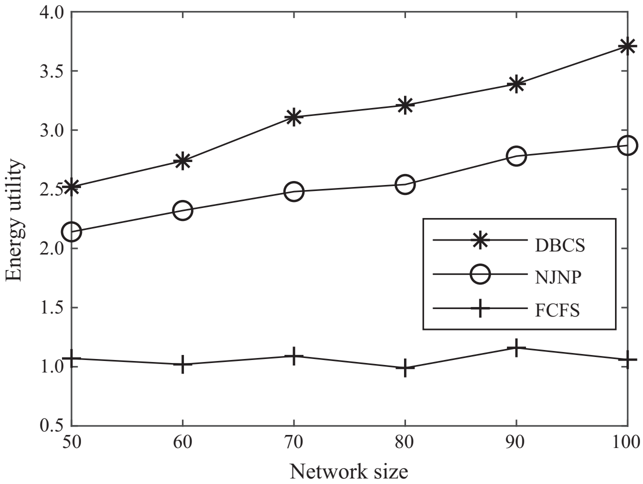

FIGURE 6 Energy utility varied by network size

As shown in Figure 3A, there are few nodes that need to be charged in the beginning, and the differences between the three strategies are not obvious. With the continuous operation of the network, in Figure 3B, more and more nodes need to be charged, and the density also increases. The shortcoming of NJNP and FCFS has been exposed. For DBCS, the output power and the loss of movement of the MCV are determined by the MCV itself. By the definition of energy utility, if the charging time is greater, the number of charging nodes is higher, the moving distance is shorter, and the energy utility is higher. Since the MCV runs longer and more nodes need to be charged in the WRSN, the advantage of the DBCS strategy is more obvious.

Figure 6 shows a comparison of energy utility by varying network sizes.

We simulated the DBCS, NJNP, and FCFS strategies by varying the network size from 50 nodes to 100 nodes. In the simulation, 10 rounds of charging were taken for each size of network, and the energy utility averages were compared. In Figure 6, the energy utility of the NJNP and DBCS strategies rises slowly with an increase in network size. However, the value of the energy utility and the rising range of the DBCS strategy are greater than those of the NJNP strategy, while the energy utility of the FCFS strategy does not change significantly. The energy utility of the DBCS strategy is the best one. Therefore, the energy utility of the DBCS strategy proposed in this paper proves the effectiveness and feasibility of the DBCS strategy for different network sizes.

6 | CONCLUSION

The WRSN, which introduces wireless energy transmission technology, is a brand-new approach to solving the WSN energy problem. To make WRSN operate in the long term, it is extremely important to design and study the charging program. We proposed a new on-demand charging strategy for WRSNs by ensuring the communication mode, choosing the charging nodes, optimizing the charging path, and ensuring the charging strategy in this paper. First, since the energy consumption characteristics of on-demand WRSNs are uneven, we designed the MIKmeans algorithm to group nodes and communicate in order to balance the energy consumption in a WRSN.

Then, according to the relationship between the MCV working time and the node minimum residual working time, we put forward a new algorithm (DSACN) to select the charging nodes. Next, we determined the shortest charging path and the charging time per round by the SABPE algorithm. Last, we proposed the DBCS algorithm to increase the efficiency of the MCV. To evaluate the performance of the charging strategy, we simulated and compared several typical charging strategies. We concluded that the on-demand charging strategy can obtain a better energy balance and higher charging energy utility than other charging strategies for WRSNs.

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