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Periodic charging planning for a mobile WCE in wireless rechargeable sensor networks based on hybrid PSO and GA algorithm

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HIGHLIGHTS

- We model the periodic charging planning with limited travel energy.
- We propose a periodic charging planning based on realistic settings.
- A hybrid particle swarm optimization genetic algorithm is proposed to solve the problem.

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ABSTRACT

Previous studies of periodic charging planning in Wireless Rechargeable Sensor Networks (WRSNs) assumed that the traveling energy of a mobile Wireless Charging Equipment (WCE) has sufficient energy for charging travel and the energy depletion rate at each sensor is identical. These assumptions, however, are not realistic. In fact, the traveling energy of the WCE is limited by the energy capacity of the WCE and the energy consumptions at different sensor nodes are imbalanced. In this paper, a periodic charging planning for a mobile WCE with limited traveling energy is proposed. With the optimization objective of maximizing the the docking time ratio, this periodic charging planning ensures that the energy of the nodes in the WRSN varies periodically and that nodes perpetually fail to die. To deal with the problem, a Hybrid Particle Swarm Optimization Genetic Algorithm (HPSOGA) is proposed due to the NP-Hard of the problem. Extensive simulations have been conducted, the experimental results indicate that the proposed periodic charging planning can avoid node deaths and keep the energy of sensor nodes varying periodically. Compared with the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), the algorithm HPSOGA outperforms both of these two algorithms empirically.

1. Introduction

Wireless Sensor Networks (WSNs) are widely used in military, environmental monitoring, intelligent transportation, industrial and agricultural monitoring, etc [1]. In WSNs, energy problem is a key research of issue. The energy problems are as follows: (1) The sensor nodes are powered by batteries with limited energy, which is unacceptable in harsh environment where it is hard to implement batteries replacement. (2) The sensor nodes near the sink node undertake more data forwarding tasks and more communication load than the other nodes because of multi-hop wireless transmission, which causes the sensor nodes to die early. The phenomenon is called *Energy Hole*.

To prolong the lifespan of WSNs, there are two main ways to solve the energy problem, namely *saving methods* and *supplementary methods*. The saving methods reduce the energy consumption of sensor nodes through low power consumption technology and energy-saving algorithms. The supplementary methods provide the energy for sensor nodes by collecting wind energy, solar energy and vibration energy from the environment [2]. In recent years, a new supplementary method, using wireless energy transmission technology [3], has become a new focus in WSNs. In this method, the mobile Wireless Charging Equipment (WCE) is employed to charge the sensor nodes, and the networks are known as Wireless Rechargeable Sensor Networks (WRSNs) [4].

In WRSNs, to avoid node death, Shi and Xie et al. [5,6] proposed a periodic charging planning algorithm to keep the whole network operating properly during the charging cycle. Compared with non-periodic charging planning, the periodic method can guarantee the permanent work of the network. However, they assumed that

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the WCE has sufficient energy for charging travel and the energy depletion rate of each sensor node is identical. In fact, the traveling energy of the WCE is limited by the energy capacity of the WCE, and the energy consumptions of different sensor nodes are imbalanced.

On the other hand, in order to get the optimal charging planning solution, the optimization methods can be classified into two main categories-mathematical programming and heuristic algorithms. Mathematical programming is computationally fast for some applications, and even the optimality solution can be proven mathematically. However, mathematical programming usually has strict restrictions on the optimal objective function, and in some applications it only can solve differentiable and convex problems [7]. Heuristic algorithms, especially meta-heuristic algorithms, have great advantage in global searching ability and have fewer or no restrictions on the optimal objective function. However, as far as we know, little work has been performed to solve the charging planning problems by using meta-heuristic algorithms.

In this paper, the idea of limited energy of the WCE and imbalanced energy consumptions of sensor nodes is firstly strengthened by realistic settings on periodic charging planning. A hybrid meta-heuristic algorithm based on Particle Swarm Optimization and Genetic Algorithm is adopted for solving the periodic charging planning problem.

The main contributions of this paper are as follows.

1. In the view of the application, previous studies of charging planning problem assumed that the traveling energy of the WCE has sufficient energy. We assume that the traveling energy of the WCE is limited and the energy consumption of sensor nodes is imbalanced. A periodic charging planning based on realistic settings is proposed.

2. In terms of soft computing, there are few studies using the meta-heuristic algorithms to solve the charging planning problem. The optimal problem is formulated, targeting to maximize the docking time ratio of the mobile WCE. This problem is an NP-hard problem. A Hybrid Particle Swarm Optimization Genetic Algorithm (HPSOGA) is designed to solve this problem.

The rest of the paper is organized as follows. In Section 2, the related backgrounds are given. The problem statement is formulated in Section 3. Then, we analyze the shortcomings of the periodic charging planning for the WCE under ideal assumptions and design three periodic charging planning algorithms. In the end, the problem of the optimization objective of maximizing the docking time ratio of the mobile WCE is proposed. In Section 4, HPSOGA is adopted for solving this problem. Section 5 presents and analyzes the experimental results. Section 6 concludes the paper.

2. Related works

Xie [5,8] et al. elaborated on the development and classification of wireless energy transmission technology, and firstly applied the technology in WSNs by using the mobile WCE. Yuanyuan Yang et al. systematic explained on the related theory and technology of WRSNs in their book *Wireless Rechargeable Sensor Network* [9].

Intelligent mobile WCE carrying with batteries, such as mobile vehicle, mobile robot or unmanned air vehicle, is used to charge the sensor nodes in accordance with the established charging planning [10–12]. Xiao et al. [13] investigated the mobile charging planning problems. The key point of charging planning problems for the mobile WCE what the order of sensor nodes to be charged is, and how much energy the sensor nodes should be replenished. To maximize the utility of the network, the conditions of the network such as sensor node distributions, energy consumptions, and position of sensor nodes should be taken into consideration.

There are two methods to achieve charging planning, non-periodic charging planning and periodic charging planning. Furthermore, according to the charging range of the mobile WCE, it can be further separated into solo-WCE to a single-node (a mobile WCE can charge only one sensor node at a time) and solo-WCE to multi-nodes(a mobile WCE can charge multiple sensor nodes simultaneously). In this paper, we only use the type of solo-WCE to a single-node.

For non-periodic charging planning, Peng et al. [14] proposed a charging strategy for the WCE and designed a heuristic algorithm. Then, they conducted numerical simulation and a proto-system to demonstrate its feasibility. In [15], the Smallest Enclosing Space (SES) was introduced. They formulated a linear programming solution that contained the stop positions and charging time of the WCE with the optimization objective of minimizing the charging delay. Shu et al. [16] developed an approximation algorithm and linear programming to solve the maximum covering set problem to obtain the energy distribution sequence of sensor nodes. In [17,18], the method of on-demand charging planning was proposed, and queuing theory was applied in solving this problem. Lin et al. [19] proposed a cooperative charging model and demonstrated the existence of a Nash Equilibrium Point to deal with the cooperative charging problem of multiple WCEs. In summary, non-periodic charging planning can prolong the lifespan of the whole network as far as possible, but it cannot guarantee the perpetual network operation.

To avoid sensor nodes death, a few scholars proposed the periodic energy replenishment methods, which could keep the whole network operation properly during the charging cycle periodically. Shi et al. [5] proposed the concept of periodic charging planning , and they proved that maximizing the docking time ratio of the WCE was equal to shortening the traveling time of the mobile WCE. Thus charging planning problem can be reduced to a classic Travelling Salesman Problem (TSP). Then, Xie et al. [6] assumed that the mobile WCE can charge multiple sensor nodes simultaneously, and developed a provably near-optimal solution for the WCE.

From the point of view of the solution, the charging planning problems in WRSNs is similar to the Vehicle Routing Problems (VRP). The solution methods of the VRP can be introduced into the charging planning problem. VRP refers to distributing goods to a certain number of customers by using a vehicle. Each customer has different requirements on the quantity of goods. The vehicles start from the distribution center, move through appropriate routes, and then go back to the distribution center to achieve the goal of optimization under certain constraints (the shortest distance, minimum time cost, maximum benefit, etc.). This problem is NP-Hard [20,21].

In fact, if the mobile WCE is treated as a vehicle in the VRP and charging planning is treated as a moving strategy in the VRP, the charging planning for the mobile WCE in WRSNs is a variant of the VRP. However, it should be noted that the charging planning in WRSNs is essentially different from the VRP because of the coupling relati[illegible] the energy consumption of the sensor nodes. That is to say the arrival time of the mobile WCE has an effect on the energy demand of the other sensor nodes. The earlier the mobile WCE arrives at a sensor node, the less energy the mobile WCE needs to replenish for the sensor node. Then, the mobile WCE can serve other sensor nodes as soon as possible. Therefore, VRP is a special case of the charging planning problem, so the charging planning problem is also NP-Hard [22].

Many researchers have used the meta-heuristic algorithms to solve different VRPs [23–26]. However, there are few people using the meta-heuristic algorithm to solve the charging planning problems. The Genetic Algorithm (GA) [27], with the advantage of simple encoding, genetic operation, global searching ability and flexible search process, has been widely adopted for the TSP and VRP, but the basic crossover and mutation operation of the GA can easily lead to falling into local optimal solutions. In this paper, a Hybrid Particle Swarm Optimization Genetic Algorithm

(HPSOGA) is proposed to deal with the problem. Combined with the Particle Swarm Optimization (PSO) [28], the mutation operator is constructed. Based on the hierarchical genetic-particle swarm optimization in [29,30], HPSOGA is designed, in which we make some adjustments according to our problems.

3. Problem statement and modeling

In this section, we reformulate the model of periodic charging planning based on [5,6] and then analyze the shortcomings of existing studies when the traveling energy of the mobile WCE is limited and the energy consumption rate of different sensor nodes is imbalanced. Moreover, we then design charging planning strategy for the above assumption.

3.1. Network model

A WRSN is deployed over a two-dimensional area with a series of characteristics as follows. There are n sensor nodes distributed over the area. The position of each node is known and fixed. In WRSN, a base station B is deployed to serve as a sink node for all data generated by all nodes. A service station S is also set into this network as a dock to charge the mobile WCE. Each node is equipped with a wireless rechargeable battery of the same size, that possesses the same calculation and communication level. The maximum capacity of each battery is denoted by E_{max}. To keep the sensor nodes working properly, the minimum capacity of each battery is denoted by E_{min}. In the very beginning, each battery is fully charged. Single-hop routing and multi-hop routing are applied for transferring all data steams to the base station B. The mobile WCE in the WRSN sets off from the service station S and travels to charge each sensor node one by one. After a whole charging cycle, the mobile WCE comes back to the service station S to prepare for the next charging cycle. The network model is shown in Fig. 1.

The set of sensor nodes is denoted by $SN = \{s_1, s_2, \ldots, s_i, \ldots, s_n, i \in [1, n], i \in \mathbb{Z}\}$, where s_i is the ID of the ith sensor node. Assume that the energy consumption rate of sensor node s_i is p_i, which is a constant [5,6]. The notations in this paper are shown in Table 1.

3.2. Periodic charging planning

Periodic charging planning is that the mobile WCE charges sensor nodes in a WRSN to keep the energy of the sensor nodes varying periodically, which avoids sensor nodes deaths. As shown in Fig. 2, every charging cycle time is T. The charging path of the mobile WCE, the charging order and the charging time for each node are the same in every charging cycle. In this paper, the periodic charging planning is divided into two parts, the initial charging cycle and the general charging cycle.

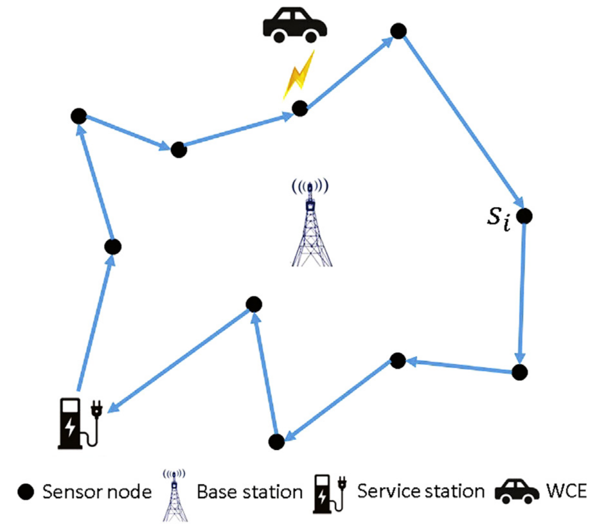

Fig. 1. Network model.

As shown in Fig. 3, for an general charging cycle, the charging power is U(W). The arrival time when the mobile WCE arrives at s_i is $\omega T + t_i (\omega \in \mathbb{Z})$, and the charging time for s_i is τ_i. Then, the departure time when the mobile WCE leaves from s_i is $\omega T + t_i + \tau_i$, where $t + i$ is a time duration from the beginning of a charging cycle to the arrival of the WCE. During general charging cycle ($t \in [T, +\infty]$), the energy variation of sensor node s_i with time t is shown as follows.

$$E_i(t) = \begin{cases} E_i(\omega T) - p_i \cdot (t - \omega T) \\ \quad t \in [\omega T, \omega T + t_i] \\ E_i(\omega T + t_i) + (U - p_i) \cdot (t - \omega T - t_i) \\ \quad t \in [\omega T + t_i, \omega T + t_i + \tau_i] \\ E_{max} - p_i \cdot (t - \omega T - t_i - \tau_i) \\ \quad t \in [\omega T + t_i + \tau_i, (\omega + 1)T] \end{cases} \tag{1}$$

Table 1
Related notation in this paper.

Symbol	Definition
B, S	communication base station and charging service station
SN	the set of sensor nodes
p_i	energy consumption rate of sensor node
E_{max}, E_{min}	maximum capacity and minimum capacity of battery of sensor node
$R_i, R_{i,j}, R_{i_B}$	data generation rate of sensor node s_i, data transmission rate between s_i and s_j, data transmission rate between s_i and B
$\rho, c_{i,j}, c_{i,B}$	energy consumption of receiving data per 1kbps for each sensor node, energy consumption of transmission data from s_i to s_j per 1kbps, energy consumption of transmission data from s_i to B per 1kbps
$T, \tau_i, \tau_{tsp}, \tau_{vac}$	time of a charging cycle, charging time for sensor node s_i, total traveling time of mobile WCE, docking time of mobile WCE
$E_i(t)$	function of energy variation of sensor node s_i with time
P_M, V, E_M	traveling power of mobile WCE, traveling speed, traveling energy carried by mobile WCE
U, U'	charging power of mobile WCE in an general charging cycle, charging power of mobile WCE in an initial charging cycle
Q, π_0, π_j	traveling path of mobile WCE, mark of charging service station in traveling pat h, mark of the jth sensor node that the mobile WCE has been to in a traveling path
$D_{\pi_j,\pi_{j+1}}, D_{\pi_j,\pi_0}$	distance between neighbor nodes or between a sensor node and the charging service station along the traveling path
τ_{tsp}^{min}	traveling time of the mobile WCE traveling through all the sensor nodes in a Hamilton loop
c_ξ, M, G_m, L_m	minimum charging times of bottleneck node l_ξ, total dispatching times of a charging cycle, set of sensor nodes that have been visited in the mth dispatching, distance of traveling path in the mth dispatching
η_{vac}	docking time ratio
p, η	cross operator adjustment factor of HPSOGA algorithm
c_1, c_2	mutation operator and adjustment factor of Particle Swarm Optimization
N, G	number of population and largest generation of evolution

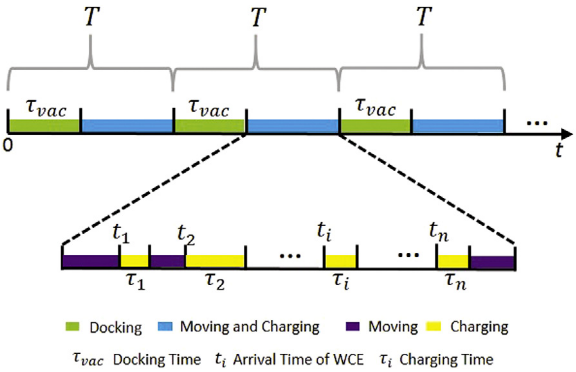

Fig. 2. Diagram of periodic charging planning.

For the initial charging cycle, t_i , τ_i and T are the same as those in the general charging cycle. The energy of sensor node s_i is $E_i(\omega T)$ at the beginning of every general charging cycle, which satisfies $E_i(\xi T) = E_i(\psi T), \forall \xi \neq \psi, \xi, \psi \in \mathbb{Z}$. However, the energy of sensor node s_i at the beginning of the initial charging cycle is E_{max}. To maintain the the energy of sensor node s_i at the end of the initial charging cycle equals to that at the beginning of the 1st general charging cycle, the charging power should be adjusted, the charging power is U'(W), and it will be discussed later. Then, the energy variation of sensor node s_i with the time t is as follows.

$$E_i(t) = \begin{cases} E_{max} - p_i \cdot t & t \in [0, t_i] \\ E_i(t_i) + (U' - p_i) \cdot (t - t_i) & t \in [t_i, t_i + \tau_i] \\ E_{max} - p_i \cdot (t - t_i - \tau_i) & t \in [t_i + \tau_i, T] \end{cases} \tag{2}$$

During each charging cycle, the mobile WCE works at three modes:

(1) Moving Mode: During the moving mode, the mobile WCE travels at a speed v(m/s) and driving power P_M(W) to the next node that will be charged or to the service station. The total travel time is denoted as τ_{tsp} in each charging cycle. Denote $Q = (\pi_0, \pi_1, \pi_2, \ldots, \pi_j, \ldots, \pi_0)(\pi_j \in SN, j \in [1, n], j \in \mathbb{Z})$ as the physical path of the mobile WCE, where π_0 is the service station and π_j is the jth sensor node. In particular, it is a Hamilton loop when the WCE travels each node only once. Denote $D_{\pi_i,\pi_{i+1}}$ as the distance between neighbor nodes or between the last node and the service station S. When the mobile WCE travels through every nodes only once, τ_{tsp} satisfies the following equation.

$$\tau_{tsp} = \sum_{j=0}^{n-1} \frac{D_{\pi_j,\pi_{j+1}}}{v} + \frac{D_{\pi_n,\pi_0}}{v} \tag{3}$$

(2) Charging Mode: During the charging mode, the mobile WCE charges each node until the battery is full in any cycle. That is, after the mobile WCE spends time τ_i charging sensor node s_i, the remaining energy of this node is E_{max}.

(3) Docking Mode: During the docking mode, the mobile WCE returns the service station S to replenish its energy. τ_{vac} is the docking time, $\tau_{vac} \geq 0$. Then, we have

$$T = \tau_{tsp} + \tau_{vac} + \sum_{i=1}^{n} \tau_i \tag{4}$$

For the general charging cycle, The ωth general charging cycle is same as the 1st general charging cycle, so we only need to analyze the 1st general charging cycle as representative. During the 1st general charging cycle, the energy consumption of sensor node s_i equals the energy replenished by the mobile WCE.

$$p_i \cdot T = U \cdot \tau_i \tag{5}$$

From Eqs. (4) and (5), the relation among T, τ_{tsp}, τ_{vac} and p_i is established as shown in Eq. (6)

$$(U - \sum_{i=1}^{n} p_i) \cdot \frac{T}{U} = \tau_{tsp} + \tau_{vac} \tag{6}$$

We then have constraint Eq. (7).

$$U > \sum_{i=1}^{n} p_i \tag{7}$$

When the WCE arrives at node s_i, the remaining energy of node s_i is $E_i(T + t_i)(E_i(T + t_i) \geq E_{min})$ when the WCE leaves. The energy of node s_i is E_{max}. We have

$$E_i(T + t_i) + U \cdot \tau_i - p_i \cdot \tau_i = E_{max} \tag{8}$$

From Eqs. (5) and (8), we have

$$(U - p_i) \cdot \tau_i \leq E_{max} - E_{min} \tag{9}$$

For the initial charging cycle, to realize a seamless transition of the energy between the initial charging cycle and the 1st general charging cycle, the remaining energy of node s_i at the end of the initial charging cycle must equal the energy at the beginning of the 1st general charging cycle. Thus, the charging power of the mobile WCE must be adjusted. The time durations between $[0, t_i]$ in the initial charging cycle and between $[\omega T, \omega T + t_i]$ in the general charging time are t_i. The relation between the remaining energy $E_i(t_i)$ and $E_i(\omega T + t_i)$ when the mobile WCE arrives at sensor node s_i satisfies

$$E_{max} - E_i(t_i) = E_i(\omega T) - E_i(\omega T + t_i) \tag{10}$$

The charging power is U' and the charging time is also τ_i during the initial charging cycle. Then, we have

$$E_i(t_i) + U' \cdot \tau_i - p_i \cdot \tau_i = E_{max}, \tag{11}$$

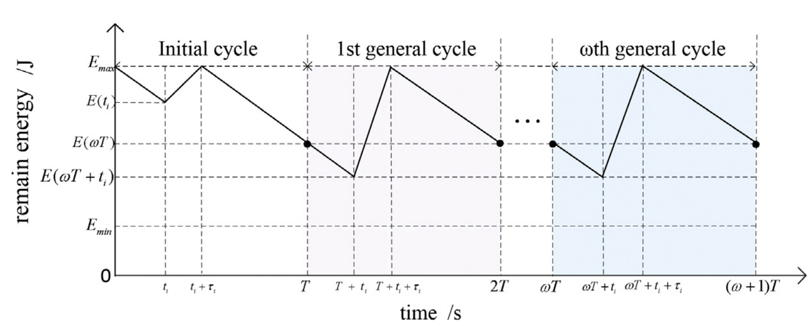

Fig. 3. Diagram of energy variation of sensor node s_i in periodic charging planning.

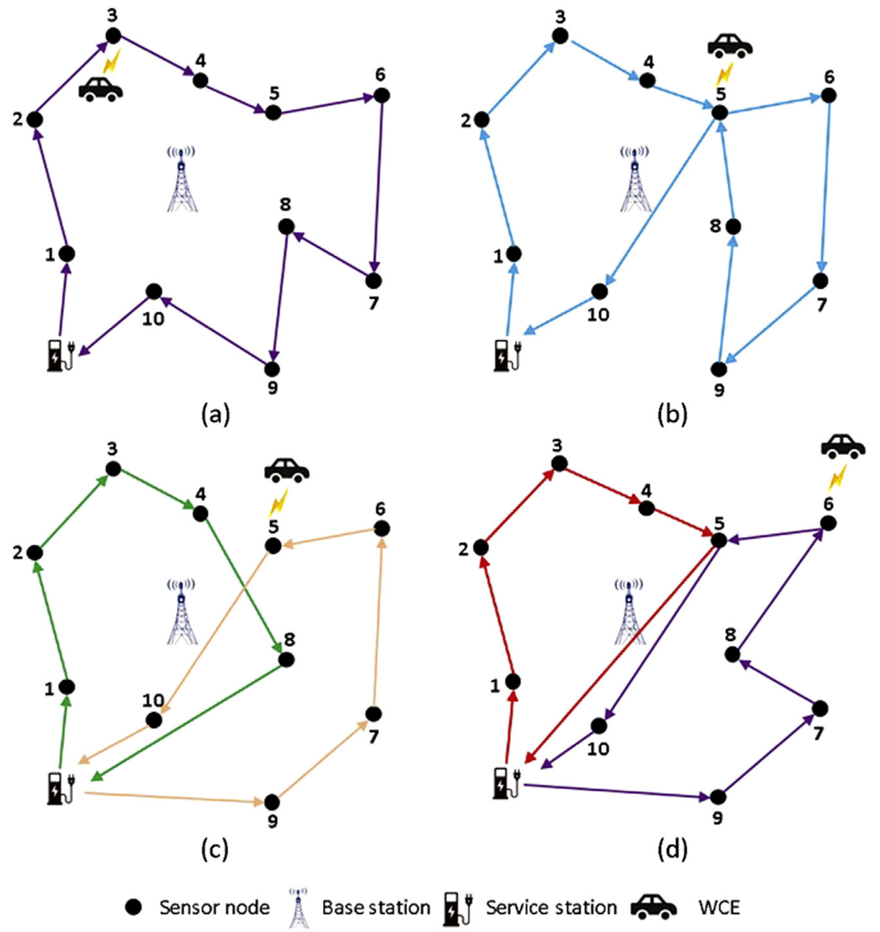

Fig. 4. Illustrative charging planning in different situations. (a) shows the shortest Hamilton loop in an ideal situation in previous studies. (b) shows an example of situation 1, when sensor node 5 is a bottleneck node, the WCE charges this node twice. (c) shows an example of situation 2, when the WCE finished charging the sensor node 8, it's traveling energy is insufficient, and the WCE should return to the service station, then continue to charge the other nodes. (d) shows an example of situation 3, sensor node 5 is a bottleneck node, and the WCE return to the service station twice.

Then, we have

$$U' = U - \frac{E_{max} - E_i(\omega T)}{\tau_i} \tag{12}$$

According to Eq. (12), we obtain the charging power U' in the initial charging cycle. Therefore, we get the whole charging planning.

3.3. Three situations with limited energy and imbalanced energy consumption

In the following, we will discuss three situations of periodic charging planning, when the traveling energy of WCE is infinite and the energy consumption of sensor nodes is imbalanced. Previous studies are unable to deal with these situations.

(1) Situation 1: The energy consumption of the nodes is imbalanced, and bottleneck nodes exist in the WRSN. Some bottleneck nodes may die if these nodes are charged only once in a cycle.
(2) Situation 2: The traveling energy of the mobile WCE is limited. Denote E_M as the traveling energy of the mobile WCE. In this situation, it is impossible for the mobile WCE to travel through all the sensor nodes by a Hamilton loop. Instead, the mobile WCE must travel many times to charge all nodes.
(3) Situation 3: In this situation, Situation 1 and Situation 2 happen at the same time.

In Situation 1, the sensor node $s_\beta (s_\beta \in SN)$ is denoted as a bottleneck node if the remaining energy of the node is E_{min} when the WCE arrive at it. In a cycle time T, the used energy and charged energy of node s_β satisfies Eqs. (13) and (14), respectively.

$$p_\beta \cdot (T - \tau_\beta) = E_{max} - E_{min} \tag{13}$$

$$(U - p_\beta) \cdot \tau_\beta = E_{max} - E_{min} \tag{14}$$

Therefore, we can get the relation between the cycle time T and the energy consumption of node s_β in Eq. (15), where E_{max}, E_{min}, and U are constants.

$$T = \frac{E_{max} - E_{min}}{U - p_\beta} + \frac{E_{max} - E_{min}}{p_\beta} \tag{15}$$

Then, the maximum cycle time T for all the nodes in the WRSN can be obtained, which is denoted as T_{max}. If $T > T_{max}$, the bottleneck node goes to death because its energy is below E_{min}.

From Eq. (5), the total charging time can be obtained by following equation.

$$\sum_{i=1}^{n} \tau_i = \sum_{i=1}^{n} \frac{p_{i \cdot T}}{U} \tag{16}$$

From Eq. (4), we have the docking time τ_{vac} of the mobile WCE.

$$\tau_{vac} = T - \tau_{tsp} - \sum_{i=1}^{n} \tau_i = T - \tau_{tsp} - \sum_{i=1}^{n} \frac{p_i \cdot T}{U} \tag{17}$$

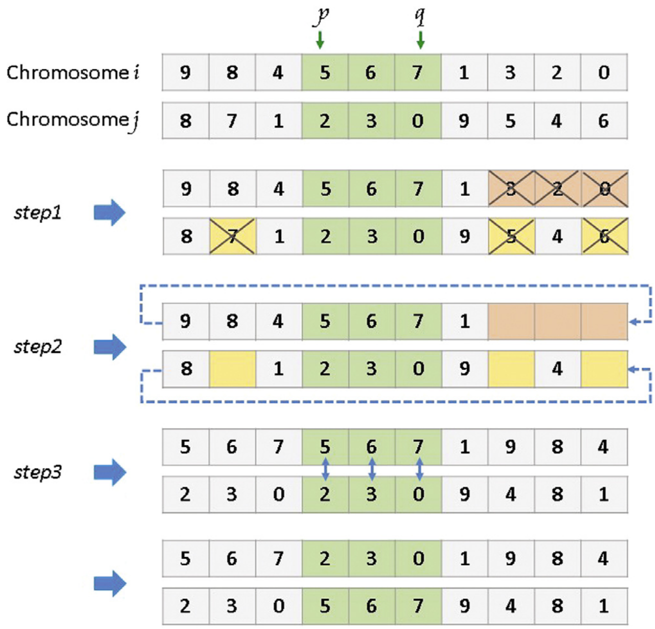

Fig. 5. Illustrative steps of crossover operation.

From Eq. (17), it may lead to $\tau_{vac} < 0$, even if $T = T_{max}$ and $\tau_{tsp} = \tau_{tsp}^{min}$. That is, it cannot guarantee the docking time $\tau_{vac} > 0$, even if the cycle time T is the maximum value T_{max} and the total traveling time is the minimum.

In Situation 2, when the area covered by the WRSN is relatively large and the distribution of the sensor nodes is sparse, the mobile WCE fails to travel through all the nodes with the traveling energy E_M. So, the traveling energy by Hamilton loop is greater than that taken by the WCE(i.e., Eq. (18)), we have

$$P_M \cdot \tau_{tsp} > E_M \tag{18}$$

In Situation 3, the bottleneck nodes and the limited traveling energy should be taken into account together.

3.4. Improved periodic charging planning

In this section, the improved periodic charging planning is proposed to deal with above situations. The charging planning diagram in different situations are shown as Fig. 4. To deal with situation 1, the WCE should charge the bottleneck nodes more than one time. The WCE should return to the service station S many times to replenish energy in situation 2. To solve the problem in situation 3, the WCE not only charges the bottleneck nodes many times but also returns to the service station S many times.

To solve the problem in Situation 1, in a cycle T, the mobile WCE charges the bottleneck node more than one time. First, renumber n sensor nodes from $\{s_1, s_2, \ldots, s_j, \ldots, s_n\}$ to $\{l_1, l_2, \ldots, l_\theta, \ldots, l_n\}$. The relation between l_θ and $l_{\theta+1}$ satisfies Eq. (19), where $l_\theta, l_{\theta+1} \in SN$, $1 \le \theta \le n-1, \theta \in \mathbb{Z}$.

$$\frac{E_{max}-E_{min}}{U-p_\theta} + \frac{E_{max}-E_{min}}{p_\theta} < \frac{E_{max}-E_{min}}{U-p_{\theta+1}} + \frac{E_{max}-E_{min}}{p_{\theta+1}} \tag{19}$$

Then, to obtain the corresponding docking time $\{\tau_1, \tau_2, \ldots, \tau_\theta, \ldots, \tau_n\}$, put $\{l_1, l_2, \ldots, l_\theta, \ldots, l_n\}$ into Eqs. (15)–(17) in order. It is clear that the docking time sequence is an increasing sequence,$\tau_1 \le \tau_2 \le \cdots \le \tau_\theta \le \cdots \le \tau_n$. Then, find a docking time τ_β that satisfies $\tau_{\beta-1} < 0, \tau_\beta \ge 0, 1 \le \beta \le n-1, \beta \in \mathbb{Z}$ from this sequence. Meanwhile, the docking time in set $\{\tau_1, \tau_2, \ldots, \tau_{\beta-1}\}$ is below zero, and the corresponding set of bottleneck nodes is $\{l_1, l_2, \ldots, l_{\beta-1}\}$.

Next, we will obtain the charging times for the bottleneck nodes. The bottleneck node will die because of low power if it is charged only once in a cycle. To obtain the minimum charging times for the bottleneck node under the condition that the node fails to die, the strategy of minimum charging times is proposed. For the bottleneck node $l_\xi \in \{l_1, l_2, \ldots, l_{\beta-1}\}$, p_ξ and τ_ξ are the corresponding power consumption and docking time, respectively. The minimum charging times m for the bottleneck node is obtained by Eq. (20).

$$(m-1)\cdot(E_{max}-E_{min}) < (T-\tau_\xi)\cdot p_\xi \le m\cdot(E_{max}-E_{min}) \qquad m \in \mathbb{Z} \tag{20}$$

To solve the problem in Situation 2, the sensor nodes in the WRSN are divided into several groups. The service station S is still the starting point and end point of the mobile WCE. In every group, we figure out the Hamilton loop, which is described as one scheduling. During each scheduling, the consumption of traveling energy is controlled below E_M. For the sensor nodes in a network, the total times of scheduling is M during a cycle T. During the mth scheduling, the charging path is $Q_m = (\pi_0, \pi_1, \pi_2, \ldots, \pi_l, \pi_0)$, $\pi_l \in SN$, $0 < l < n, l \in \mathbb{Z}$. The set of sensor nodes that have been visited in this scheduling is denoted as G_m. Obviously, all the sensor nodes can be charged through M scheduling. Each sensor node is charged only once in a scheduling, which satisfies Eq. (21).

$$\bigcup_{m=1}^{M} G_m = SN, \quad G_i \bigcap G_j = \varnothing \text{ if } i \ne j \tag{21}$$

The distance of the charging path in the mth scheduling is L_m. According to the speed V and traveling power P_M of the mobile WCE, the consumption of the traveling energy in the mth scheduling should be less than or equal to the energy carried by the mobile WCE, which satisfies Eqs. (22)–(24).

$$L_m = \sum_{k=0}^{l-1} D_{\pi_k,\pi_{k+1}} + D_{\pi_l,\pi_0}, \tag{22}$$

$$\tau_{tsp} = \frac{L_m}{v} \tag{23}$$

$$P_M * \tau_{tsp}^m \le E_M \tag{24}$$

Then, cycle T made up of M scheduling should satisfy Eqs. (25)–(27),

$$\tau_{tsp} = \sum_{m=1}^{M} \tau_{tsp}^m = \sum_{m=1}^{M} \frac{L_m}{v}, \tag{25}$$

$$\tau_{vac} = \sum_{m=1}^{M} \tau_{vac}^m, \tag{26}$$

$$T = \sum_{m=1}^{M} \frac{L_m}{v} + \sum_{m=1}^{M} \tau_{vac}^m + \sum_{m-1}^{M} \sum_{k=1}^{l} \tau_{\pi_k}^m \tag{27}$$

where the docking time in the mth scheduling is denoted as τ_{vac}^m and $\tau_{\pi_k}^m$ is the charging time for $\tau_{\pi_k}^m$ in the mth scheduling.

To solve the problem in Situation 3, combining the analyses of Situations 1 and 2, Eq. (28) is also correct.

$$\bigcup_{m=1}^{M} G_m = SN \tag{28}$$

The bottleneck node should be charged multiple times and the other nodes only once. Assume that sensor node $s_i \in SN$ is charged $h_i (h_i \in \mathbb{Z})$ times. For the bottleneck node, $h_i > 1$, while for

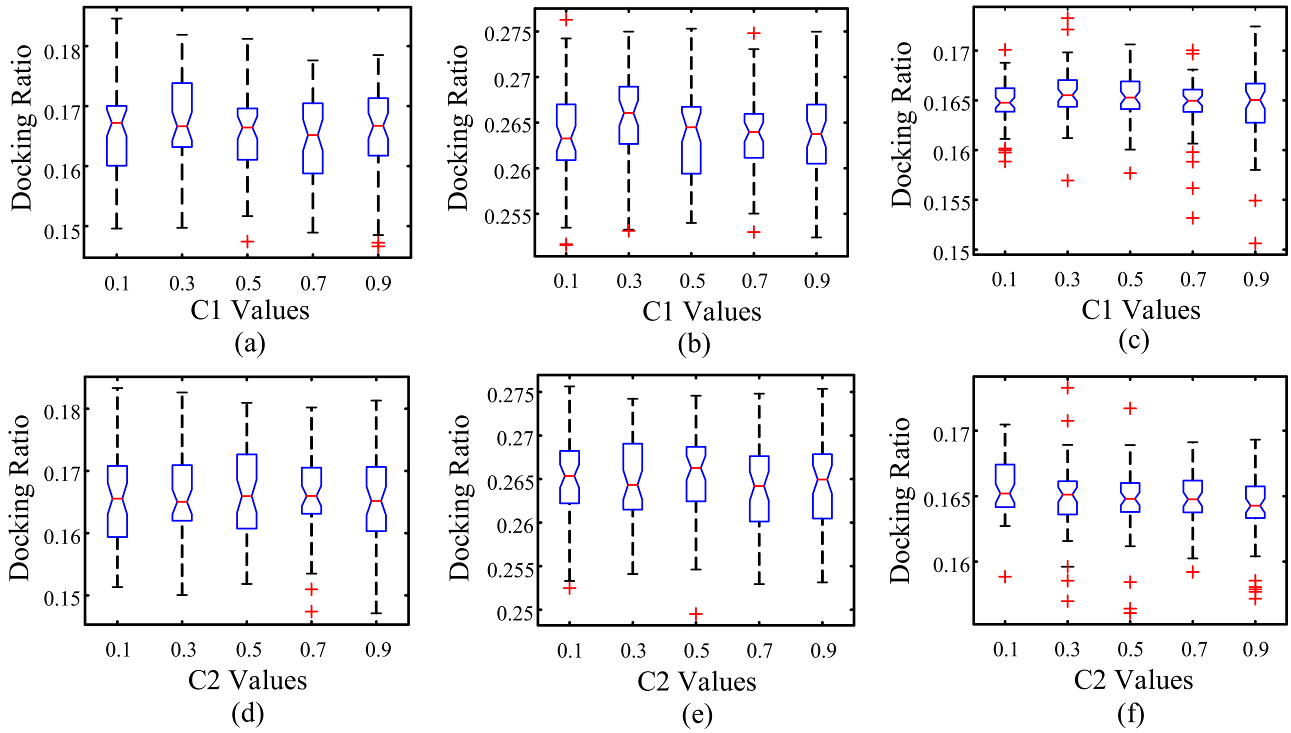

Fig. 6. Effect of c_1, c_2 on the performance of the algorithms under three situations.

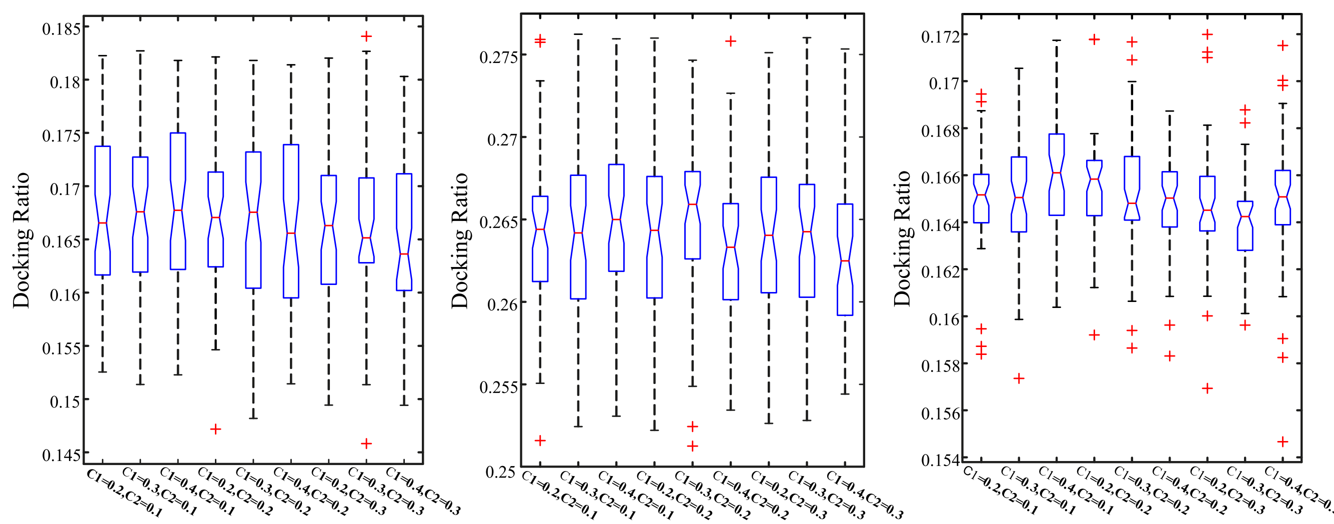

Fig. 7. Combinational effect of c_1 and c_2 under the three situations.

the others, $h_i = 1$. The charging time for sensor node s_i for the bth$(1 \leq b \leq h_i, b \in \mathbb{Z})$ charging is denoted as τ_i^b. Then, the total charging time is shown in Eq. (29).

$$\tau_i = \sum_{b=1}^{h_i} \tau_i^b \tag{29}$$

The remaining energy of a sensor node when the mobile WCE arrives at it for the bth time is $e_i^b, e_i^b \geq E_{min}$, which satisfies Eqs. (30) and (31).

$$e_i^b + \tau_i^b \cdot (U - p_i) \leq E_{max} \tag{30}$$

$$p_i \cdot T = U \cdot \tau_i \tag{31}$$

Table 2
The coordinate of each sensor node in WRSN.

Node index	Location (m)	Node index	Location (m)
1	(50,950)	11	(750,150)
2	(590,480)	12	(360,900)
3	(450,900)	13	(850,700)
4	(100,200)	14	(980,50)
5	(650,750)	15	(470,700)
6	(560,560)	16	(100,600)
7	(100,500)	17	(420,20)
8	(520,540)	18	(400,750)
9	(800,700)	19	(200,550)
10	(300,100)	20	(800,480)

Meanwhile, cycle T made up of M scheduling should satisfy Eq. (32).

$$T=\sum_{m=1}^{M}\frac{L_m}{v}+\sum_{m=1}^{M}\tau_{vac}^{m}+\sum_{i=1}^{n}\sum_{b=1}^{h_i}\tau_i^b \tag{32}$$

In summary, the total times of scheduling in Situation 1 is once, and the bottleneck node can be charged many times. In Situation 2, the total times of scheduling is more than once, and each sensor node is charged only once. In Situation 3, the total times of scheduling is also more than once, and each sensor node can be charged many times.

3.5. Optimization problem

To evaluate the working efficiency of the mobile WCE with limited traveling energy [5,6], we use the docking time ratio of the mobile WCE as an optimization objective. The docking time ratio is the proportion of docking time in a cycle. The larger the docking time ratio, the higher the working efficiency of the mobile WCE. The optimization objective is to obtain the maximum docking time ratio, and then the optimal charging path is found and the optimization problem OPT-D thus is formulated as follows.

$$arg\ \max_{Q,\tau_i}\ \eta_{vac}=\frac{\tau_{vac}}{T}\qquad s.t.\,(1)\sim(9),(20)\sim(32)$$

In this problem, we adjust the charging path Q and the charging time τ_i to obtain the maximum docking time ratio. Parameters n, p_i, E_M, E_{max} and E_{min} are known in advance. This problem is a combinatorial optimization problem which is an NP-Hard problem. It can be solved by a meta-heuristic algorithm.

4. Periodic charging planning algorithm based on the hybrid particle swarm optimization genetic algorithm

In this section, we design a Hybrid Particle Swarm Optimization Genetic Algorithm (HPSOGA) to solve our problem. First, we describe the steps of the HPSOGA, then, we introduce the framework of the periodic charging planning algorithm based on HPSOGA.

4.1. HPSOGA algorithm

The basic GA to solve combinatorial optimization problems has the following steps, chromosome encoding, selection, crossover and mutation. In HPSOGA, the PSO mutation operation is introduced into the mutation of GA [31]. The reasons are as follows: (1) The basic GA and PSO can use binary encoding, sequential encoding and integer encoding, thus, they can be unified in encoding. (2) The basic GA has good global search capability, but the blindness and randomness of the genetic operation cannot preserve the good genes of the optimal solution. As a result, it will lead to a decline in the ability of local searching later. However, the evolutionary process of finding the optimal solution by PSO is cooperative and directional. (3) The basic GA does not have a function of memory, but the PSO has and so can converge faster to the optimal solution. Next we will introduce the four steps of the HPSOGA separately.

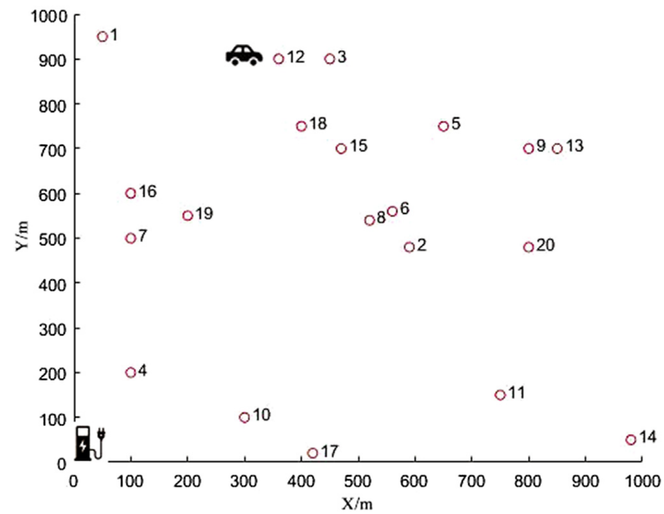

Fig. 8. Distribution of the network.

(I) Chromosome Encoding

The population in the GA represents a set of feasible solutions. A population consists of a lot of individuals. The individual, through a combination of multiple genes of the chromosome, displays the character. The main method of chromosome coding for path planning is order, adjacent, and side representation etc.. We here use the sequential encoding [32]. In sequential encoding, a chromosome represents a charging path of the WCE, and gene in the chromosome represents a sensor node. n sensor nodes are numbered in order, and then the traversal path of the sensor network is an arrangement. For example, there are six sensor nodes. Firstly, use $1\sim6$ to number the sensor nodes, and then the chromosome

Table 3
The statistics results using different algorithms under different situations.

	The docking time ratio in Situation 1				
	PSO	GA	MMAS	DFWA	HPSOGA
BEST	0.1599	0.1792	0.1519	0.1822	**0.1827**
AVERAGE	0.1440	0.1736	0.1391	**0.1806**	0.1751
MEDIAN	0.1434	0.1742	0.1386	**0.1815**	0.1747
WORST	0.1316	0.1651	0.1338	**0.1739**	0.1640
	The docking time ratio in Situation 2				
	PSO	GA	MMAS	DFWA	HPSOGA
BEST	0.2634	0.2823	0.2600	0.2622	**0.2826**
AVERAGE	0.2559	0.2760	0.2544	0.2516	**0.2791**
MEDIAN	0.2558	0.2761	0.2543	0.2515	**0.2793**
WORST	0.2492	0.2716	0.2511	0.2456	**0.2751**
	The docking time ratio in Situation 3				
	PSO	GA	MMAS	DFWA	HPSOGA
BEST	0.1593	0.1701	0.1346	0.1682	**0.1714**
AVERAGE	0.1457	0.1657	0.1162	**0.1674**	0.1666
MEDIAN	0.1469	0.1651	0.1149	**0.1677**	0.1665
WORST	0.1168	**0.1632**	0.1077	0.1608	0.1607

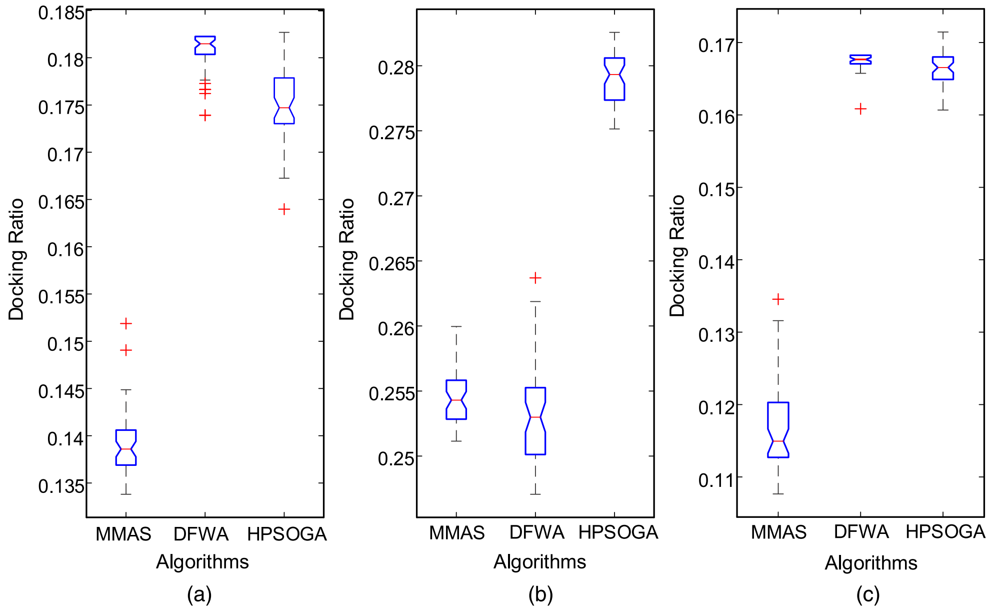

Fig. 9. Statistical box diagrams of optimization objective using PSO, GA and HPSOGA.

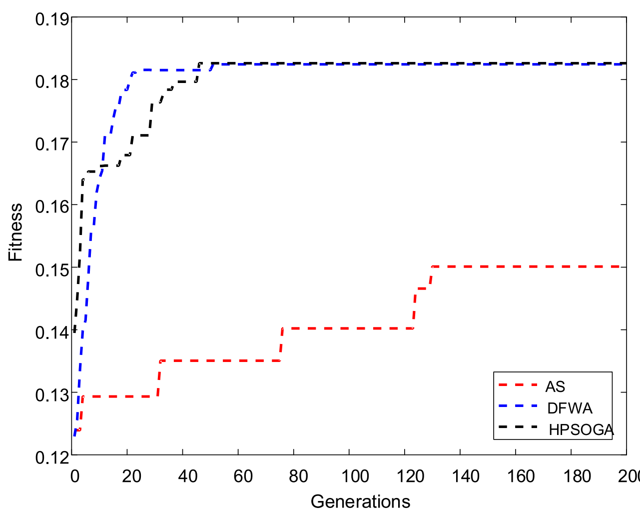

Fig. 10. Convergence of the average value of the optimization objective with the variation of the evolutionary generation in Situation 1.

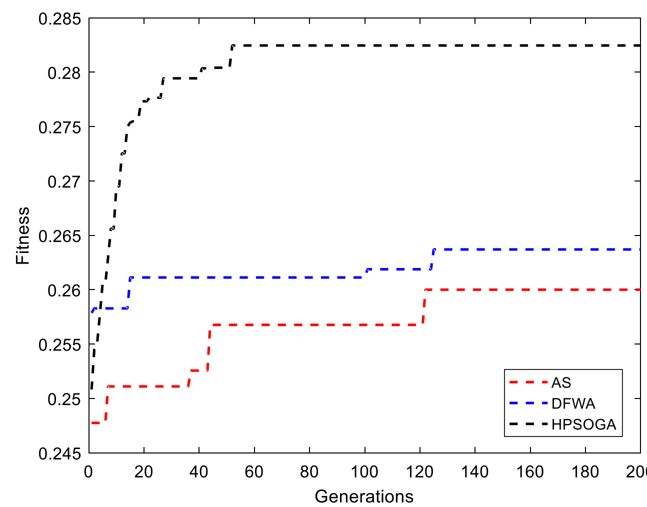

Fig. 11. Convergence of the average value of the optimization objective with the variation of the evolutionary generation in Situation 2.

(634215) represents a path sequence 0-6-3-4-2-1-5-0 (0 is service station).

In our problem, we first randomly arrange all the sensor nodes to generate initial sequences, then transform the initial sequences according to different situations. In situation 1, the bottleneck nodes need to be charged more than once, therefore, we insert the bottleneck node into the initial sequences to generate new individuals; For example, if the sensor node 3 need to be charged twice, a possible path is 0-6-3-4-2-3-1-5-0. In situation 2, the WCE has limited traveling energy, we should insert service station into the initial sequences; For example, if the WCE need to return to the service station twice, a possible path is 0-6-3-4-0-2-1-5-0. In situation 3, we insert bottleneck nodes and service station into the initial sequence to generates new individuals. For example, if the sensor node 2 need to be charged twice and the WCE need to return to the service station twice, a possible path is 0-6-3-2-4-0-2-1-5-0.

(II) Selection

The elitist strategy is adopted in the selection operation, to retain the highest fitness individual (elite individual) in the current population. The lowest fitness individuals in a population will be replaced by the individuals with the highest fitness. The specific process is as follows: In the iteration process, record individuals of the current population with the highest fitness and individuals with the lowest fitness. If the fitness of an individual is higher than the best fitness of individuals of the population in the previous iterations, record this individual as the globally best individual. Then, replace it by the lowest fitness of the current population using the global best individual. The fitness is the docking time ratio, $f = \eta_{vac}$.

(III) Crossover

Crossover includes crossover mode and crossover operation. We use the adaptive crossover mode [33]. In the early evolution of the population, the population size and population diversity are

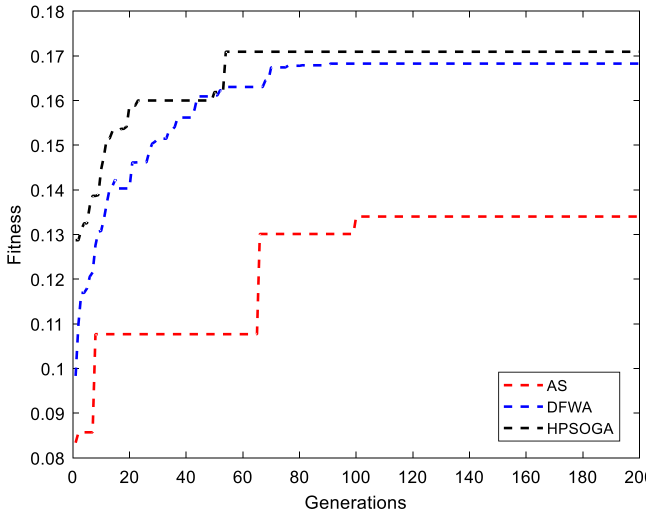

Fig. 12. Convergence of the average value of the optimization objective with the variation of the evolutionary generation in Situation 3.

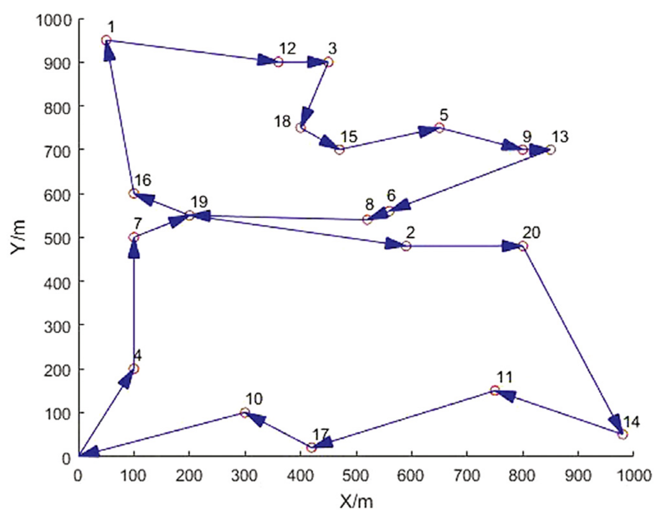

Fig. 13. Best charging path in Situation 1.

high; thus, we use a lower crossover probability to prevent high-fitness individuals from being destroyed to preserve the gene in the next-generation in population. Due to the survival of the fittest, the excellent individuals increase and the diversity of the population decreases; thus, we use a higher crossover probability to eliminate the lowest fitness individuals. The crossover probability here thus is

$$P_c = \begin{cases} k_1 - k_2 \dfrac{f_{max} - \widetilde{f}}{f_{max} - \bar{f}} & (if\, \widetilde{f} \geq \bar{f}) \\ k_1 & else \end{cases} \tag{33}$$

where f_{max} is the highest fitness, $\bar{f}$ is the average fitness of the population, and $\widetilde{f}$ is the higher one of the two parent individuals used to cross. $k1, k2$ are less than 1 to contain P_c to the range $0 \sim 1$.

We made minor adjustments based on Order Crossover (OX) [34] as the crossover operation. The new chromosome generated by OX preserves the ordered structural units of the original arrangement, and ordered structural units of different arrangements are produced. As shown in Fig. 5, two parent chromosomes are denoted as Chromosome i and Chromosome j. The crossover operation has the following three steps: (1) Make the alleles. In the interval $[p, q]$, make the alleles of Chromosome i and Chromosome j. Then, make the genes in interval $[p, q]$ of Chromosome i from Chromosome j. Likewise, make the genes in interval $[p, q]$ of Chromosome j from Chromosome i. The length of interval $[p, q]$ equals the number of genes that have been marked. p and q in step 1 are the sequence numbers of genes p and $q \in \mathbb{Z}, p < q$. (2) Delete the marked genes and then rotate Left. We should delete the genes marked in the previous step and rotate left for $(q - p + 1)$. (3) Exchange the intervals $[p, q]$ of the two chromosomes. In the end, child chromosomes are generated.

(IV) Mutation

We adapt the PSO mutation instead of GA mutation. The PSO mutation uses historic information to guide the mutation. The PSO mutation treats each chromosome as a particle, which is shown in Eqs. (34) and (35),

$$X_i^{r+1} = X_i^r + V_i^r \tag{34}$$

$$V_i^r = c_1(X_{pbest,i} - X_i^r) + c_2(X_{gbest} - X_i^r) \tag{35}$$

where X_i^{r+1} is the position of particle i in the $(r + 1)$th generation, X_i^r is the position of particle i in the rth generation, V_i^r is the speed of particle i in the rth generation, $X_{pbest,i}$ is the position of particle i with the best fitness historically, X_{gbest} is the position of the particle with the best fitness from all the particles in history, and c_1 and c_2 are adjustment factors. X_i^{r+1} is the new position of a particle after the mutation of X_i^r.

To calculating (34), we face the following challenges: (1) How to change the chromosome in the GA to the position of the particle; and (2) How to define the add operation of the speed and positions of the particles, the subtraction operation of the positions of the particles, the multiply operation of the speed of the particles and the add operation of the speed of the particles. Once the add and multiply operations are defined, the new position of a particle can be calculated.

To deal with the first challenge, we use edge encoding to transform the chromosome to the positions of the particle X. In particular, for n sensor nodes in the WRSN, we use an n-dimensional vector made up of edges to represent the position of a particle, $X = (x_1, x_2, \dots, x_j, \dots, x_n)$, $1 \leq j \leq n$, $1 \leq x_j \leq n$, $i, x_j \in \mathbb{Z}$. The jth dimension is an edge between the number of dimension j and the corresponding value x_j of this dimension, denoted as (j, x_j). That is to say, the mobile WCE moves from sensor node j to sensor node x_j. The coding of X is a circular linked list. For example, there are six sensor nodes in the WRSN. If the chromosome is 6-3-5-1-4-2, then the position of the particle is 4,6,5,2,1,3.

To deal with the second challenge, we should redefine the add operation and multiply operation. Define the add operation of the speed and positions of the particles. The new position of a particle is generated by the add operation of the speed and position of the particle. The speed of particle $V = (v_1, v_2, \dots, v_j, \dots, v_n)$ is an n-dimensional vector. Each dimension is a variation of the position of the particle. $v_j = 0$ is a null operation, which means that x_j keeps its valve. $v_j \neq 0$ means change x_j to v_j. If $v_j = x_j$, it is also a null operation. To make the coding of X a circular linked list, we should take the following alternation to generate the new position. If $v_j = 0$ or $v_j = x_j$, it is a null operation. If $v_j \neq 0$ and $v_j \neq x_j$, we use $x_{prev(v_j)} = x_{v_j}$, $x_{v_j} = x_j$, $x_j = v_j$ to operate.

Define the subtraction operation of the positions of the particles. The result of the subtraction operation of the positions of the particles is speed. $V = X_2 - X_1$ means the difference between X_2 and X_1. Compare the values of the jth dimension of X_2 and X_1. If $x_{2,j} = x_{1,j}$ then $v_j = 0$. If not, $v_j = x_{2,j}$.

Define the multiply operation of the speed of the particles. The speed of a particle is multiplied by a constant to get a new speed, denoted as $V_2 = c \cdot V_1$. Generate an n-dimensional random vector $Rand = (r_1, r_2, \ldots, r_j, \ldots, r_n)$ that has the same dimension as V_1. Each dimension is a random number $r_j (0 < r_j < 1)$. If $r_j < c$, $v_{2,j} = v_{1,j}$. Else, $v_{2,j} = 0$.

Define the add operation of the speed of the particles. The new speed of a particle is generated by the add operation of the speed of the particles, denoted as $V = V_2 + V_1$. If $v_{2,j} \neq 0$, $v_j = v_{2,j}$. If $v_{2,j} = 0$, $v_j = v_{1,j}$.

The HPSOGA is described in algorithm 1. First, initialize the parameters of the algorithm. Then, generate a population of solutions according to the chromosome encoding steps with three situations. Last, calculate the fitness value of the individuals and select the individuals by the selection strategy step, use the crossover step to generate new individuals, until the stop condition is satisfied. The details are described in the aforementioned steps.

Algorithm 1: HPSOGA

Input: *sit.flag:* the situation flag. *CN:* the set of charging number of bottleneck nodes; N: the population size; *pop*: the set of population;
Output: Q_{best}: the best moving path of WCE; τ_i: the charging time of sensor node s_i; η_{vac}^{best}: the best docking time ratio;

Initialize the parameters;
while $i = N$ **do**
  Chromosome code: generate an initial individual by arranging the nodes serial number randomly;
  if $sit.flag = 1$ **then**
    Insert the bottleneck nodes into the initial individual randomly to generate a new individual;
  end
  if $sit.flag = 2$ **then**
    Insert the service station into the initial individual randomly to generate a new individual;
  end
  if $sit.flag = 3$ **then**
    Insert the bottleneck nodes and service station into the initial individual randomly to generate a new individual;
  end
  if *the individual satisfied all the constraints* **then**
    Add the individual to the population pop;
    $i = i + 1$;
  end
end
while *the stop condition is not satisfied* **do**
  foreach $path \in pop$ **do**
    $f = \eta_{vac}$; //compute the fitness value;
  end
  Update the population by selecting the individuals through the selection strategy;
  Crossover: generate new individuals using crossover mode and operation;
  for *each mutational individuals* **do**
    Use edge encoding to transform the chromosome to the position of particles;
    Calculate particle velocity according to Eq. (35);
    Update particle position according to Eq. (34);
  end
end

4.2. The periodic charging planning algorithm

For a WRSN, when the positions and the energy consumption rates of sensor nodes and parameters of the network are given, the WCE is employed to periodically charge the network to avoid nodes death. To this end, the OPT-D is formulated, and the key point to get the best docking time ratio is to find the best traveling path of the WCE. If the travelling path is determined, the traveling time of WCE and the charging time of each sensor node can be successively calculated according to the order that the WCE visits. Therefore, to solve this problem, we first initialize the parameters of the WRSN and calculate the distance between sensor nodes. Then, we compute the minimum charging number of each sensor node to determine whether bottleneck nodes exist, and determine the situation of the network. Finally, we conduct the Algorithm.1 to get the best traveling path of the WCE, return the best docking time ratio. The framework of periodic charging planning algorithm by using HPSOGA is detailed in Algorithm. 2.

Algorithm 2: Framework of the Periodical Recharging Strategy Using HPSOGA

Input: $SN = \{s_1, s_2, \cdots, s_i, \cdots, s_n\}$: the set of sensor nodes; $\Omega = \{p_1, p_2, \cdots, p_i, \cdots, p_n\}$: the set of sensor nodes energy consumption rates; $pos = \{(x_i, y_j) | i \in \mathbb{Z}, i \le n\}$: the set of sensor nodes position coordinates; (x_0, y_0): the service station position coordinate; E_{max}, E_{min}: the maximum and minimum battery capacity of sensor nodes, respectively; E_M, v and P_M: traveling energy, speed and power of WCE, respectively; U: the charging power for sensor nodes of WCE; *btn.flag* : the bottleneck node flag; *sit.flag* : the situation flag; *CN* : the set of charging number of bottleneck nodes;
Output: Q_{best}: the best moving path of WCE; τ_i: the charging time of sensor node s_i; η_{vac}^{best}: the best docking time ratio;

Initialize the parameters of WRSN;
for $i \leftarrow 0$ *to* n **do**
  for $j \leftarrow i+1$ *to* n **do**
    $D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$;
  end
end
Compute the minimum Hamilton cycle length L_{tsp} of all sensor nodes (service station as a starting point and end point);
$\tau_{tsp}^{min} = L_{tsp}/v$; //compute the minimum moving time;
$E_M^{'} = \tau_{tsp}^{min} * P_M$; // get the minimum moving energy;
for $i \leftarrow 1$ *to* n **do**
  $T_i = (E_{max} - E_{min})/U + (E_{max} - E_{min})/(U - p_i)$; //compute the maximum cycle time of each sensor node;
  if $T \le T_i$ **then**
    $T \leftarrow T_i$; //get the maximum cycle time of all sensor nodes;
  end
  $P \leftarrow P + p_i$;
end
for $i \leftarrow 1$ *to* n **do**
  $\tau_{vac}^{i} = T - \tau_{tsp}^{min} - P * T/U$; //compute the vacation time of each sensor node;
  if $\tau_{vac}^{i} < 0$ **then**
    $btn.flag = 1$;
    Add s_i to the set of below zero vacation time nodes;
    $n_i = \lceil T * p_i * (U - p_i)/U \cdot (E_{max} - E_{min}) \rceil$; //compute the minimum charging number of each node;
    Add n_i to the set of charging number CN of s_i;
  end
end
if $btn.flag = 1$ *and* $E_M > E_M^{'}$ **then**
  $sit.flag = 1$;
  else if $btn.flag = 0$ *and* $E_M < E_M^{'}$ **then**
    $sit.flag = 2$;
    else if $btn.flag = 1$ *and* $E_M < E_M^{'}$ **then**
      $sit.flag = 3$;
    end
  end
end
HPSOGA($sit.flag, CN$**)**; // conduct Algorithm.1.

5. Simulation analysis

5.1. Simulation settings

We consider a WRSN that consists of 20 sensor nodes distributed over a 1000 m$\times$1000 m square area, randomly. The service station S is located at the origin (0 m,0 m), and the base station is located at origin (500 m,500 m). The whole simulation experiment is executed by MATLAB R2012a. The computer configuration, is a Core i7-6700K CPU (4.01 GHz) with 16G RAM. We choose a regular NiMH battery and its nominal cell voltage and the quantity of electricity is 1.2V/2.5 Ah. We have the maximum capacity of the battery $E_{max} = 1.2$ V$\times$2.5A $\times$3600 s $= 10800$ J [35]. We let the minimum capacity of the battery $E_{min} = 0.05 \times E_{max} = 540$ J, $E_M = 4000$ J, $v = 5$ m/s, $U = 5$ W and $P_M = 1$ W [5,6]. The energy consumption rate of node p_i is selected from 0.01 W to 1 W randomly. In HPSOGA, the population size is 50. The value of the adjustment factors are $k1 = 0.9$, $k2 = 0.3$.

Table 4
The charging planning of the general charging cycle in Situation 1.

Nodes no.	Power (W)	arrival (s)	charging (s)	departure (s)	Remaining energy at arrival (J)	Remaining energy at Departure (J)	Remaining energy of WCE (J)
4	0.33	44.72	1285.80	1330.52	4795.32	10800.00	5776.39
7	0.09	1390.52	352.96	1743.48	9067.15	10800.00	5476.39
19	0.60	1765.85	1248.76	3014.59	5303.27	10800.00	5364.59
16	0.18	3036.95	688.97	3725.92	7476.99	10800.00	5252.79
1	0.19	3796.63	752.56	4549.19	7182.55	10800.00	4899.23
12	0.10	4611.99	381.28	4993.27	8930.93	10800.00	4585.23
3	0.53	5011.27	2046.69	7058.03	1641.37	10800.00	4495.23
18	0.17	7089.65	659.87	7749.52	7612.41	10800.00	4337.11
15	0.24	7766.72	939.65	8706.37	6328.37	10800.00	4251.09
5	0.03	8743.73	118.24	8861.98	10212.37	10800.00	4064.27
9	0.14	8893.60	545.49	9439.09	8148.92	10800.00	3906.16
13	0.13	9449.09	508.48	9957.57	8323.98	10800.00	3856.16
6	0.13	10021.97	499.05	10521.02	8368.68	10800.00	3534.14
8	0.10	10529.96	382.81	10912.78	8923.54	10800.00	3489.41
19	0.60	10976.81	1082.05	12058.86	6037.00	10800.00	3169.26
2	0.33	12138.11	1285.80	13423.91	4795.32	10800.00	2773.03
20	0.07	13465.91	256.41	13722.32	9534.83	10800.00	2563.03
14	0.29	13815.55	1132.07	14947.62	5468.56	10800.00	2096.87
11	0.08	14997.78	292.43	15290.21	9359.81	10800.00	1846.07
17	0.09	15361.15	352.89	15714.03	9067.53	10800.00	1491.39
10	0.04	15742.88	160.53	15903.40	10003.99	10800.00	1347.17
0	0.00	15966.65	0.00	19535.85	0.00	0.00	1030.94

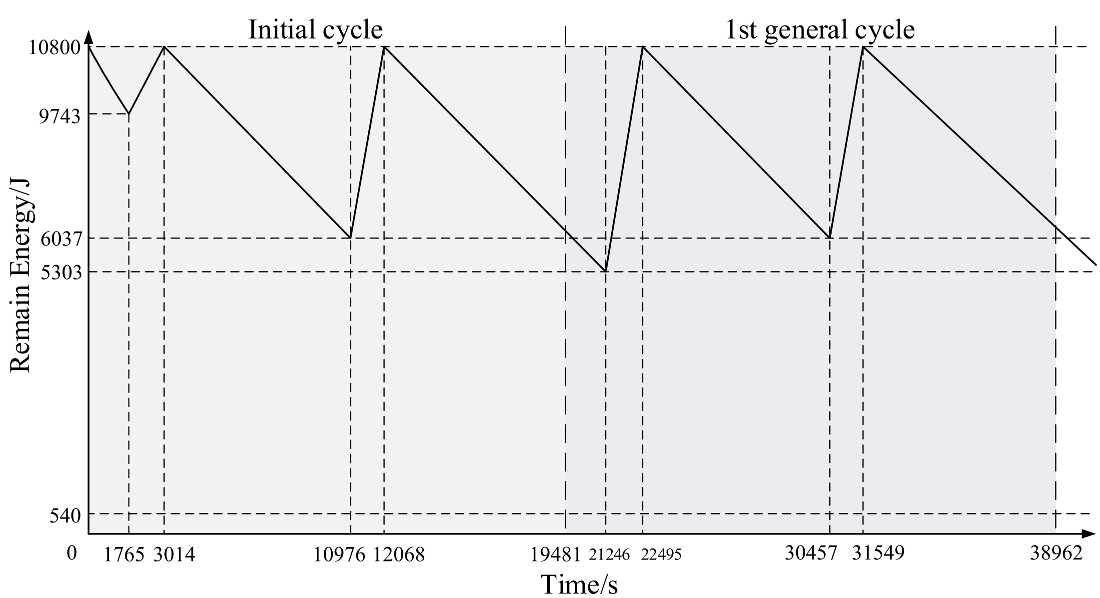

Fig. 14. Variation of remaining energy of bottleneck node 19.

5.2. Design of simulation

To evaluate the performance of algorithm HPSOGA, three experiments are performed. (i) The mutation factors of HPSOGA c_1, c_2 have effects on the performance of the HPSOGA. To obtain the best values of parameters c_1, c_2, 50 instances in three situations are executed. There are 20 sensor nodes in each instance. The coordinates and energy consumption rate of each node are different. (ii) Based on the best values of the parameters from (i), HPSOGA is compared with the PSO, GA, MMAS [36] and DFWA [37]. 50 independent runs are performed to compare the performance of the three algorithms. (iii) is based on the results from (ii). We show the optimal solutions corresponding to the charging planning in the three situations.

As for experiment (ii), to compare the HPSOGA with GA and PSO in our problem, we replace some steps of Algorithm.1 with GA or PSO, and the factors of corresponding algorithms are same. The steps of GA are as follow: (1) generate chromosomes by using sequential encoding, and randomly generate population with size according to the three situations; (2) calculate the fitness value of each individual, and the elitist strategy is adopted to selection operation; (3) use the adaptive crossover and Order Crossover operation [34] to generate new individuals; (4) use mutation operation [33] to generate new individuals; (5) repeat step (2) (4) until the stop condition is satisfied, and return the best solution. To contrast with PSO, we use discrete PSO [31] to solve our problem, and the steps are as follows. (1) Generate particle swarm with size by using sequential encoding according to the three situations. (2) Calculate the fitness value of each particles, record the best position of the particle and the best position of the particle swarm until now. (3) Calculate and update the position and velocity of each particle by Eqs. (34) and (35). (4) Repeat step (2) to (3) until the stop condition is satisfied, and return the best solution.

For the convenience of comparison with the HPSOGA, we adjust the MMAS in [36] and the DFWA in [37] to solve our problem. In [36], a non-periodic charging planning was designed to minimize the remaining energy of the WCE to prolong the lifespan of

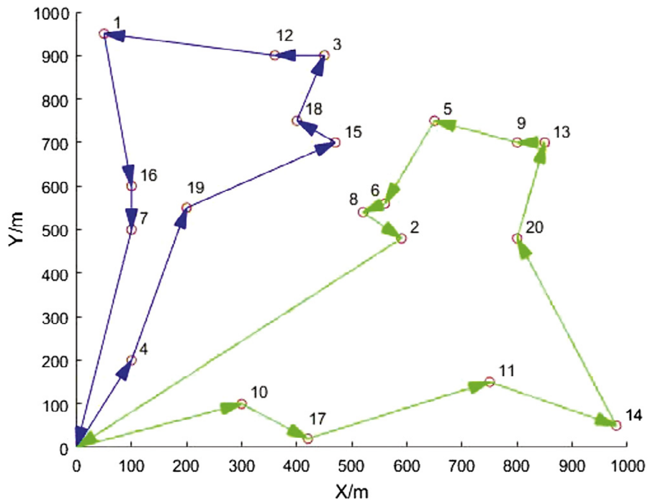

Fig. 15. Best charging path in Situation 2.

the network. The proposed algorithm to solve the problem was based on MAX–MIN Ant System (MMAS). Therefore, we replace the algorithm 1 of our method with the MMAS to test the performance in our scenario. As for the difference of the optimization objective, we modify the pheromone updating strategy as follows: $\sigma_{ij}^{k+1} = (1-\rho)\,\sigma_{ij}^{k} + \sum_{w=1}^{\varphi} \Delta\sigma_{ij}^{w} + \varphi\Delta\sigma_{ij}^{gb}$, where parameter $\rho\,(0 \le \rho < 1)$ is the pheromone volatilization coefficients, φ is the total number of elite ants, $\Delta\sigma_{ij}^{w} = (\varphi - w)\,\eta_{vac}$, $\Delta\sigma_{ij}^{gb} = \eta_{vac}$, and η_{vac} is the optimization objective in this paper. In [37], WCE had both charging and data collection functions. When the WCE arrived at a sensor node, the energy of the sensor nodes was replenished and the data was collected at the same time. Thus, a Multi-Objective Discrete Fireworks Algorithm (MODFA) based on grid was proposed to maximize the lifespan of the network and the amount of data collection. The MODFA was based on the Discrete Fireworks Algorithm (DFWA) [38] which was designed to solve the Travelling Salesman Problem (TSP). DFWA was a hybrid algorithm that introduced the 2-opt and 3-opt searching scheme. We replace the algorithm 1 of our method with the DFWA to test the performance in our scenario. The steps of the DFWA are as follows. (1) Generate fireworks according to the three situations. (2) Use fireworks explosion operation (2-opt and 3-opt) to generate new sparks. (3) Randomly select the spark to generate the better individual using variation operation. (4) Use the elite strategy to generate the next population. (5) Repeat (2) to (4) until the stop condition is satisfied.

5.3. Results and analysis of simulation

In Experiment (i), the results are shown in Figs. 6 and 7. Fig. 6(a), (b), (c) show statistic box diagrams of the optimization objective when parameter c_1 varies among 0.1, 0.3, 0.5, 0.7 and 0.9 under the three situations. The red line of each statistic box diagram is the median of the experimental data. The blue lines below and above the red line represent 75% and 25% of the experimental data, respectively. It can be seen from the diagrams that the experimental results obtained under the three situations are better when $c_1 = 0.3$. Therefore, the range of c_1 is 0.2–0.4. Fig. 6(e) (f) (g) show the statistic box diagrams of the optimization objective when parameter c_2 varies among 0.1, 0.3, 0.5, 0.7 and 0.9 under the three situations. It can be seen from the diagrams that the experimental results obtained under the three situations are better when $c_2 = 0.1$ or $c_2 = 0.3$. Therefore, the range of c_2 is 0.1–0.3.

After the range of c_1 and c_2 is obtained, we should determine the combinational effect of c_1 and c_2. Fig. 7 shows statistical box diagrams of the optimization objective when parameters c_1 and c_2 vary in different combinations under the three situations. It can be seen from the diagrams that the experimental results obtained under the three situations are better when $c_1 = 0.4$, $c_2 = 0.1$.

Based on Experiment (i), in Experiment (ii), we set $c_1 = 0.4$, $c_2 = 0.1$. A sensor network is generated randomly. The coordinate of each sensor node is shown in Table 2, and the distribution is shown in Fig. 8. In Situation 1, the energy consumption rate of sensor node 19 is larger, and it is a bottleneck node. The traveling energy carried by the mobile WCE is 6000 J. In Situation 2, there is no bottleneck node. The traveling energy carried by the mobile WCE is 4000 J. In Situation 3, the energy consumption rate of sensor node 15 is larger, and it is a bottleneck node. The traveling energy carried by the mobile WCE is 4000 J. Each situation instance is executed 50 times independently.

Table 5
The charging planning of the general charging cycle in Situation 2.

Nodes no.	power (W)	arrival (s)	charging (s)	departure (s)	Remaining energy at arrival (J)	Remaining energy at departure (J)	Remaining energy of WCE (J)
4	0.02	44.72	137.02	181.74	10117.64	10800.00	3776.39
19	0.08	254.54	548.08	802.62	8103.46	10800.00	3412.39
15	0.32	864.39	2192.31	3056.70	540.00	10800.00	3103.52
18	0.12	3073.90	822.12	3896.02	6788.08	10800.00	3017.50
3	0.12	3927.64	822.12	4749.76	6788.08	10800.00	2859.38
12	0.27	4767.76	1849.76	6617.52	2050.64	10800.00	2769.38
1	0.21	6680.32	1438.70	8119.02	3908.62	10800.00	2455.38
16	0.1	8189.73	685.10	8874.83	7443.03	10800.00	2101.82
7	0.28	8894.83	1918.27	10813.10	1745.77	10800.00	2001.82
0	0	10903.65	0.00	10903.65	0.00	0.00	1491.92
10	0.25	10966.90	1712.74	12679.64	2664.48	10800.00	3683.77
17	0.05	12708.48	342.55	13051.03	9104.39	10800.00	3539.55
11	0.32	13122.24	2192.31	15314.55	540.00	10800.00	3184.87
14	0.07	15364.71	479.57	15844.28	8435.73	10800.00	2934.07
20	0.26	15937.51	1781.25	17718.76	2356.88	10800.00	2467.91
13	0.21	15856.76	1438.70	19202.58	3908.62	10800.00	2242.30
9	0.12	19212.58	822.12	20034.70	6788.08	10800.00	2192.30
5	0.23	20066.33	1575.72	21642.04	3283.81	10800.00	2034.19
6	0.07	21684.09	479.57	22162.66	8435.73	10800.00	1823.95
8	0.17	22171.54	1164.66	23336.20	5174.68	10800.00	1779.23
2	0.19	23354.63	1301.68	24656.31	4538.91	10800.00	1687.04
0	0	24808.43	0.00	34591.03	0.00	0.00	926.44

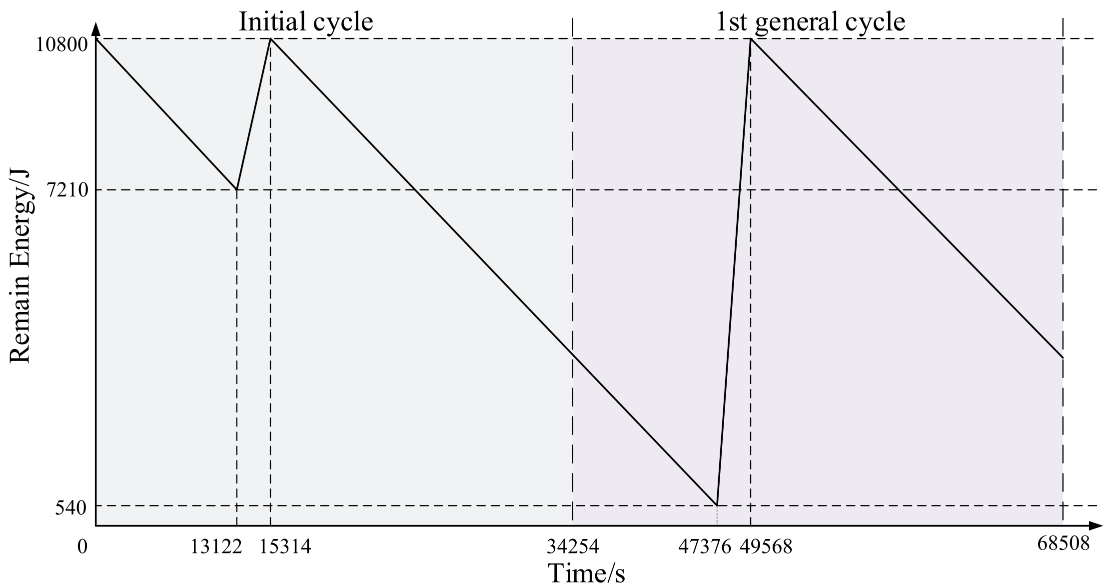

Fig. 16. Variation of remaining energy of node 11.

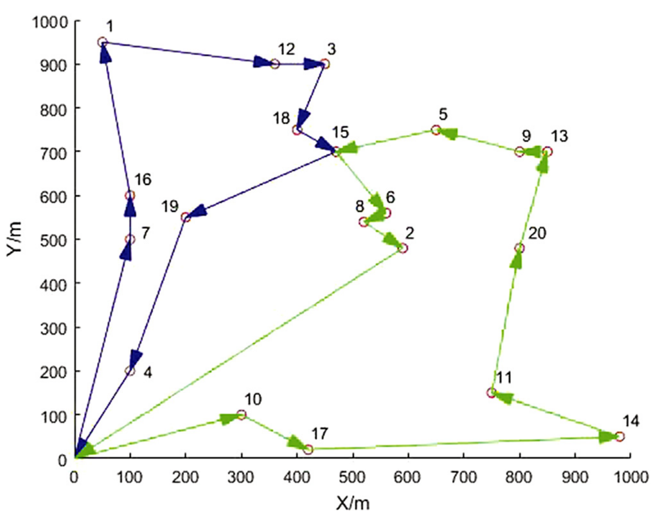

Fig. 17. Best charging path in Situation 3.

The best, average, median and worst values of the docking time ratio using PSO, GA, MMAS, DFWA and HPSOGA under three situations are shown in Table 3. The HPSOGA is outperform the PSO and GA, compared with PSO, the average value of HPSOGA improves significantly, and the improvements in three situations are 21.6%, 9.06% and 14.3%, respectively. Compared with GA, the average value improvements of the three situations are 0.8%, 1.12% and 0.54%, respectively. Fig. 9 shows the statistic box diagrams of the performance of MMAS, DFWA and HPSOGA, and Fig. 9(a) (b) (c) are the performance of Situation 1, Situation 2 and Situation 3, respectively. From Table 3 and Fig. 9 we can see, the best, average, median and worst values of the docking time ratio of HPSOGA is significantly higher than that of MMAS, and the improvements is 25.9%, 9.7% and 43.4%, respectively. Compared with DFWA, the average optimization value of HPSOGA is 9.9% higher than that of the DFWA in Situation 2, and the DFWA is 3.1% and 0.5% higher than that of HPSOGA in Situation 1 and Situation 3, but the best optimization value of HPSOGA is 0.27%, 7.78% and 1.9% higher than that of DFWA in three situations.

Figs. 10–12 show the convergence of the HPOSGA, MMAS and DFWA with the variation of evolutionary generations in three situations. From the Fig we can see, the HPSOGA converges faster than the other two algorithms. The optimal solution is better than the MMAS, and the difference performance is not huge between the HPSOGA and DFWA.

In Experiment (iii), the charging path with the best docking time ratio in different situations is shown as follows. Fig. 13, Table 4 and Fig. 14 show the best charging path, the charging plan of the general charging cycle and the variation of the remaining energy of the bottleneck node in Situation 1, respectively. The charging cycle T is 19535.85 s and τ_{vac} is 3569.2 s. The docking time ratio η_{vac} is 18.27%. The traveling energy consumed by the mobile WCE in a charging cycle is 4969.04 J. From Table 4, node 19 is a bottleneck node. Node 19 is charged twice in a cycle. When the mobile WCE reaches node 19 for the first time, its remaining energy is 5303.27 J. The mobile WCE replenishes its energy to 10800 J and then leaves. After charging node 8, the mobile WCE goes to node 19 for the second time and charges it to ensure that its remaining energy is not less than the threshold for working.

Fig. 15, Table 5 and Fig. 16 show the best charging path, the charging plan of the general charging cycle and the variation of the remaining energy of node 11 in Situation 2, respectively. The charging cycle T is 34581.03 s and τ_{vac} is 9972.6 s. The docking time ratio η_{vac} is 28.26%. The traveling energy consumed by the mobile WCE in the first Hamilton loop is 2508.08 J. The traveling energy consumed by the mobile WCE in the second Hamilton loop is 3073.56 J. Node 11 has the maximum power consumption. When the mobile WCE reaches node 11, its remaining energy is 540 J.

Fig. 17, Table 6 and Fig. 18 show the best charging path, the charging plan of the general charging cycle and the variation of the remaining energy of node 15 in Situation 3, respectively. The charging cycle T is 19469.51 s, and τ_{vac} is 3337.07 s, The docking time ratio η_{vac} is 17.14%. The traveling energy consumed by the mobile WCE in the first Hamilton loop is 2519.68 J. The traveling energy consumed by the mobile WCE in the second Hamilton loop is 3290.3 J. Node 15 is charged twice in a cycle and is charged in two Hamilton loops.

6. Conclusion

In this paper, we studied the problem of periodic charging planning in WRSNs. We first reformulated the model of periodic charging planning, and analyzed the shortcomings of previous

Table 6
The charging planning of the general charging cycle in Situation 3.

Nodes no.	power (W)	arrival (s)	charging (s)	departure (s)	Remaining energy at arrival (J)	Remaining energy at departure (J)	Remaining energy of WCE (J)
7	0.09	101.98	352.96	454.94	9067.15	10800.00	3490.10
16	0.18	474.94	688.97	1163.91	7476.99	10800.00	3390.10
1	0.19	1234.62	752.56	1987.18	7182.55	10800.00	3036.54
12	0.10	2049.99	381.28	2431.26	8930.93	10800.00	2722.54
3	0.53	2449.26	2046.69	4495.95	1641.64	10800.00	2632.54
18	0.17	4527.57	659.87	5187.44	7612.41	10800.00	2474.42
15	0.60	5204.65	1485.98	6690.63	4259.01	10800.00	2388.40
19	0.24	6752.40	939.65	7692.05	6328.37	10800.00	2079.53
4	0.33	7764.85	1285.80	9050.65	4795.32	10800.00	1715.53
0	0.00	9095.37	0.00	9095.37	0.00	0.00	1480.32
10	0.04	9158.62	160.53	9319.14	10003.99	10800.00	3683.77
17	0.09	9347.99	352.89	9700.87	9067.53	10800.00	3539.55
14	0.29	9813.03	1132.07	10945.11	5468.56	10800.00	2978.75
11	0.08	10995.26	292.43	11287.69	9359.81	10800.00	2727.95
20	0.07	11354.45	256.41	11610.86	9534.83	10800.00	2394.18
13	0.13	11655.98	508.48	12164.45	8323.98	10800.00	2168.57
9	0.14	12174.45	545.49	12719.94	8148.92	10800.00	2118.57
5	0.03	12751.57	118.24	12869.81	10212.37	10800.00	1960.46
15	0.60	12907.17	844.82	13751.99	7081.26	10800.00	1773.64
6	0.13	13785.28	499.05	14284.33	8368.68	10800.00	1607.21
8	0.10	14293.27	382.81	14676.09	8923.54	10800.00	1562.49
2	0.33	14694.52	1285.80	15980.32	4795.32	10800.00	1470.29
0	0.00	16132.44	0.00	19469.51	0.00	0.00	709.70

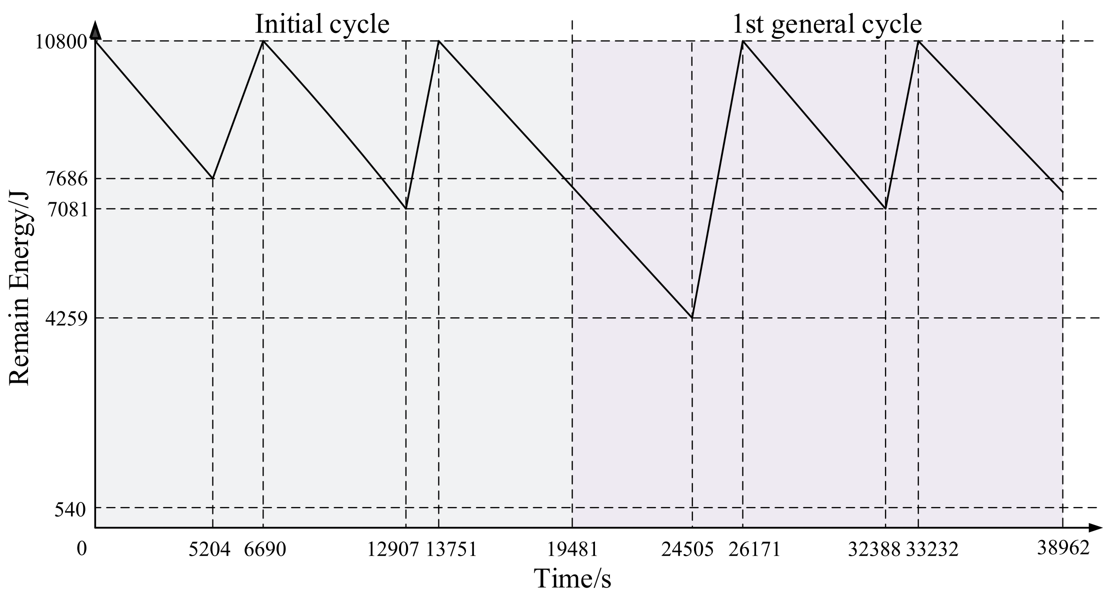

Fig. 18. Variation of remaining energy of node 15.

studies under ideal assumptions. Then, we proposed an improved periodic charging planning under realistic assumptions. A Hybrid Particle Swarm Optimization Genetic Algorithm was adjusted to achieve the solution of the improved periodic charging planning. The simulations show that the performance of HPSOGA is significantly improved compared with PSO and MMAS in three situations. Compared with GA, the improvements are 0.8%, 1.12% and 0.54%, respectively. Compared with DFWA, the improvement is 9.9% in Situation 2, and the performances between DFWA and HPSOGA are similar in Situation 1 and Situation 3. The charging planning is a complex combinational optimization problem, and the solution space is discrete and small. Our proposed algorithm outperforms these algorithms. As far as we know, this is the first attempt to use hybrid meta-heuristic algorithm to solve the charging planning problem in WRSNs, which provides a new idea for this field.

Some interesting directions are worthy of further study in the future. First, one-to-many charging planning should be investigated under realistic assumptions if the WCE can charge more than one sensor nodes at the same time. Second, multi-WCE charging planning should be studied in a large-scale network. Third, some new meta-heuristic algorithms should be adopted to deal with the charging planning problems.

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