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Multi-MC Charging Schedule Algorithm With Time Windows in Wireless Rechargeable Sensor Networks

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ABSTRACT The limited lifespan of the traditional Wireless Sensor Networks (WSNs) has always restricted the broad application and development of WSNs. The current studies have shown that the wireless power transmission technology can effectively prolong the lifetime of WSNs. In most present studies on charging schedules, the sensor nodes will be charged once they have energy consumption, which will cause higher cost and lower networks utility. It is assumed in this paper that the sensor nodes in Wireless Rechargeable Sensor Networks (WRSNs) will be charged only after its energy is lower than a certain value. Each node has a charging time window and is charged within its respective time window. In large-scale wireless sensor networks, single mobile charger (MC) is difficult to ensure that all sensor nodes work properly. Therefore, it is propoesd in this paper that the multiple MCs which are used to replenish energy for the sensor nodes. When the average energy of all the sensor nodes falls below the upper energy threshold, each MC begins to charge the sensor nodes. The genetic algorithm has a great advantage in solving optimization problems. However, it could easily lead to inadequate search. Therefore, the genetic algorithm is improved by 2-opt strategy. And then multi-MC charging schedule algorithm with time windows based on genetic algorithm is proposed and simulated. The simulation results show that the algorithm designed in this paper can timely replenish energy for each sensor node and minimize the total charging cost.

INDEX TERMS Wireless rechargeable sensor networks, charging schedule, time windows, multiple mobile chargers, energy threshold.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) consist of various distributed sensor nodes (SNs) that collect useful information from their ambiance. Sensor nodes then transmit sensed data to the Base Station (BS) by either single-hop communication or multi-hop communication. The extensive applications of WSNs include intelligent medical care, industrial control, and intelligent transportation, etc., which have flourishing application prospects. A key constraint is that the sensor nodes in WSNs are powered by batteries that have limited energy storage, therefore, the lifetime of traditional Wireless Sensor Networks (WSNs) is usually limited. In order to prolong the lifetime of the networks, scholars have carried out a large number of studies, including the rational deployment of sensor nodes and obtaining energy from the surrounding environment. However, they can not solve the problem from the root, and the lifetime of networks is still a bottleneck that limits the widespread application of WSNs. For example, the method of replacing batteries can prolong the lifetime of the sensor nodes [1]. However, in large-scale wireless sensor networks, these energy-limited nodes may be deployed in remote areas, even in hostile environments, so it is difficult to maintain once deployed. Additionally, it is not convenient to replenish energy by replacing the battery of the sensor nodes, so energy harvesting technologies have been proposed

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to extract environmental energy, such as solar energy, wind energy and heat energy [2]. Although the energy harvesting technology can provide energy effectively, the energy replenishment still has lots of shortcomings, such as unpredictable value, uncontrollable capacity and great influence by the environments. It has great challenges in real applications. The recent breakthrough in the Wireless Power Transmission (WPT) technology based on the magnetic coupling harmonic resonance provides improved schemes to prolong the lifetime of WSNs [3]–[5]. In these schemes, one or more vehicles possessed with the WPT equipment follow the charging path to wirelessly charge the sensor nodes in the WSNs. The wireless power transmission can be achieved without contact, therefore, it is not affected by the surrounding environment and can provide continuous and stable energy supplement for nodes [6]. Based on these benefits, WPT that adds a new dimension to prolong the lifetime of WSNs has attracted a lot of attention. The WSNs that can be recharged wirelessly are called Wireless Rechargeable Sensor Networks (WRSNs) and the charging vehicle is named Mobile Charger (MC).

Most existing studies on WRSNs assumed a MC to charge the sensor nodes in the networks. However, it is not suitable for the large scale WRSNs. Therefore, multiple MCs need to be employed, and multi-MC charging strategies are studied [7]–[9]. However, most multi-MC charging strategies assumed that a sensor node can be charged as long as its energy is consumed. That may cause a higher cost of MC and lower network utility. To solve this problem, the charging time windows of each sensor node are given in this paper. The lower bound of time window means it is unnecessary to charge the sensor node when the time is less than this lower bound. And the sensor node not be charged before the upper bound of the time window will be die. Therefore, the sensor nodes can be charged within its own time window. The deviation from the time window will generate a certain penalty. And then our multi-MC scheduling problem can be transformed into a classical Vehicle Routing Problem with Time Windows (VRPTW). Moreover, many researches assumed that the mobile charger (MC) has infinite energy. However, the MC is powered by batteries and the energy of the MC is limited in reality. Under this condition, finding an optimal tour for the MC to charge the sensor nodes before their energy expirations poses a great challenge. In this paper, we will track this challenge, and multiple MCs are prepared to charge all sensor nodes in the networks. Furthermore, the limited energy influences the working hours of the MC, therefore reducing movement energy consumption is considered. And then the objective is to minimize the total cost after charging the WRSNs one time, including minimizing the total moving distance of the MCs under limited energy of the MC, the number of MCs, and the violation of the time windows.

Most existing researches have used the heuristic or the approximate algorithm to solve multi-MC scheduling problem, which can only obtain heuristic or near-optimal solution. The multi-MC scheduling problem is similar to the Vehicle Routing Problem (VRP). To deal with VRP, many scholars use meta-heuristic algorithms, which have great advantages in global searching ability and have fewer or no restrictions on the optimal objective function. However, little work has been done to solve the multi-MC scheduling problem with meta-heuristic algorithm. The genetic algorithm (GA) is a kind of meta-heuristic algorithms. GA has the advantage of simple encoding, genetic operation and flexible search process. Moreover, it has been widely adopted for the VRP [10]–[12]. Therefore, GA is adopted in this paper. However, it could easily lead to inadequate search, thus, the GA is improved by 2-opt.

The main contributions of this paper are as follows.

1) In large scale networks, a multi-MC scheduling problem with Time Windows is investigated. In this paper, each sensor node has its own charging time window, and multiple MCs are prepared to prolong the lifetime of the networks and minimize the total charging cost under the limited energy.
2) The improved Genetic Algorithm (GA) is proposed due to the NP-hard of the problem. GA has a great advantage in solving optimization problems. However, it may easily lead to inadequate search. Therefore, GA is combined with 2-opt strategy to further enhance its search ability.

The rest of this paper is organized as follows: Section II introduced the related works. Section III states the network model, the charging model and the time window model. Section IV describes the multi-MC charging schedule algorithm with time windows. To meet the time windows corresponding to the sensor nodes, the objective of optimization problem is to minimize the total cost. Section V concretes the process of solving charging schedule problem. The superiority of the proposed charging schedule algorithm is proved through the simulations and experiments in Section VI.

II. RELATED WORK

In recent years, many scholars have done a lot of researches on wireless energy transmission technology to prolong the lifetime of WRSNs [13]–[16]. Shi *et al.* [17] studied the sensor networks based on the wireless energy transfer system for the first time. They introduced a mobile charger with enough energy into wireless sensor networks and proposed the concept of energy cycle. They used a MC to periodically charge all sensor nodes along the shortest Hamilton circuit. They investigated the optimization problem to maximize the percentage of station time in a cycle and constructed a feasible charging scheme. Peng *et al.* [18] assumed that the time and energy consumption of MC can be ignored when MC charges the sensor nodes. They combined the considerations of the network routing and single MC charging strategy together and proposed a heuristic algorithm and a joint optimization algorithm to maximize the lifetime cycle of networks. Different from traditional charging scheduling policies where sensor nodes passively wait for the arrival of mobile vehicles, Liu *et al.* [19] proposed a novel dynamic clustering based mobile-to-cluster (M2C) scheme to optimize the service process for both sensor nodes and the vehicle in an active way. In [20], the MC was regarded as a mobile sink which not only charges sensor nodes but also collects data from them. Thus, a distributed solution is proposed to maximize the utility of the sensor networks. However, the above literatures ignored the limited energy of the MC, and the schemes are not realistic. To solve this problem, Lyu et al. considered the limited energy of MC. And [21] studied a periodic charging planning with the optimization objective of maximizing the docking time ratio. Moreover, a Hybrid Particle Swarm Optimization Genetic Algorithm (HPSOGA) is proposed. And in [22], a multi-node charging planning algorithm with energy-limited MC is proposed. Besides, three charging planning models and their corresponding charging planning algorithms are proposed based on the different real energy conditions of the MC. Unlike existing studies that assumed a mobile charger must charge a sensor to its full energy capacity, [23] assumed that each sensor can be partially charged so that more sensors can be charged before their energy depletions. And a charging scheme with objectives to maximize the sum of sensor lifetimes and to minimize the travel distance of the mobile charger is proposed. In WRSNs, the MC is expensive in cost. If a MC can complete all the charging tasks, there is no more MCs to improve the charging service quality. Therefore, single MC charging strategy is mainly used in small-scale sensor networks with relatively simple charging schedule. However, the capacity of a MC is usually limited. Although a MC can charge some sensor nodes at the same time, it is still unable to meet the charging task of large -scale sensor networks.

Therefore, many scholars began to study multiple MCs charging scheme of sensor networks [24]–[26]. Lu *et al.* [27] assumed that the sensor nodes are deployed in one dimensional plane and multiple MCs with limited energy are used to make collaborative charging. In the case of equal power consumption of sensor nodes, push-wait schedule algorithm is proposed to obtain the optimal solution. The article [28] proposed a collaborative charging algorithm based on the clustering information. Xu *et al.* [29] considered multiple MCs charging schedule, so that the sensor nodes can work continuously in the cycle and a guaranteed performance approximation algorithm is proposed to ensure the MC traveling in the smallest distance. The article [30] firstly put forward the charging on-demand strategy based on the decoupling charging schedule and routing strategy. The problem of minimizing the number of MC is proved to be NP-hard, and an approximate algorithm is proposed to solve the problem. The article [31] studied the upper and lower bounds of single and multiple sources of Quality of Energy Provisioning in one dimension. Dai *et al.* [32], [33] proposed using multiple MCs to charge large-scale networks in a two-dimensional plane, as well as using minimum number of MCs to keep the persistent work of each node. The Min MCP problem was proved to be the classical Dynamic Vehicle Routing Problem (DVRP) which is NP-hard and an approximation algorithm was put forward to solve it. The article [34] and [35] gave a multi-MC cooperative charging strategy, which is different from the previous multiple MCs charging issue. Hu et al. [36] proposed that each MC can periodically charge the sensor nodes on multiple charging circuits, and independently execute its own charging tasks. This article divided the multi-MC charging schedule problem into two steps: Firstly, solve the charging Tour Construction Problem (TCP) to cover the whole WRSNs. According to the greedy charging scheme, the energy of each sensor node can be timely replenished. Secondly, a heuristic algorithm is proposed to solve the charging loop assignment Tour Assign Problem (TAP), which enables the MC to charge as many charging circuits as possible, so as to use the minimum number of MCs.

However, these charging schedules did not fully consider the energy condition of networks after charging. Some nodes' energy in the networks is sufficient, while others may be very limited or even depleted, and the distribution of energy in the whole network is extremely uneven. The existing research assumed that sensor nodes would be charged once energy consumed. They may cause a higher cost and lower network utility. Considering the actual and economic circumstances, this paper proposes a multiple MCs charging schedule strategy with time windows. We assume that the sensor nodes will be charged when the average energy of the network is less than a certain level. The remaining lifetime of each sensor node when the energy decreases to the upper threshold E_{high} is treated as the lower limit of the time window, and the remaining lifetime of each sensor node when the energy decreases to the lower threshold E_{min} is treated as the upper limit of the time window. The time window includes the lower charging time and the upper charging time for each sensor node in WRSNs, and the sensor nodes will be charged in their own time windows. In large-scale wireless rechargeable sensor networks, service station periodically sends out multiple MCs to provide one-to-one charging for sensor nodes. The MC leaves immediately after a full charge. Each MC carries limited energy, and it returns to the service station waiting for the next round of charging schedule when all sensor nodes are charged or the energy of MC is exhausted. The MC should try to charge the sensor nodes within the time windows, and the deviation from the time window will generate a certain penalty. In principle, the farther the deviation is, the higher the penalty cost is. Considering the actual situation, this paper aims to minimize the total cost used in each round of charging schedule.

III. PROBLEM STATEMENT AND MODEL

We consider a rechargeable wireless sensor network consisting of n sensor nodes. The nodes are randomly distributed over a two-dimensional area. Without considering the impact of obstacles, a fixed sink base station (BS) and a charging service station (CS) are located in the center of the region. Sensor nodes, the base station and the service station will not move after deployment. There is enough number of MCs

TABLE 1. Symbol and definition.

Symbol	Definition
BS	Base Station in a WRSN
CS	Charging service Station in a WRSN
N	Set of sensor nodes
L	Set of sensor nodes positions
E	Residual energy set of all sensor nodes
n	Number of sensor nodes
$d_{i,j}$	Distance between sensor node s_i to s_j
E_{max}	Maximum battery capacities of sensor nodes
E_{high}	The upper energy threshold of the sensor node
E_{min}	The lower energy threshold of the sensor node
$E_{av}(t)$	Average energy of the sensor nodes
p_i	Power consumption of s_i
t_i^l	The lower limit of the time window of s_i
t_i^u	The upper limit of the time window of s_i
E_M	Maximum battery capacity of mobile charger k
v	Moving velocity of MC
q_c	Charging power of the MC
q_m	Mobile power of MC
η	Charging efficiency of MC
R_k	Charging circuit corresponding to mobile charger k
D_k	Total traveling distance of mobile charger k in R_k
τ_m^k	Total traveling time of mobile charger k in R_k
π_i^k	The ith sensor node in R_k
t_{ai}^k	The time when mobile charger k arrives at π_i^k
E_{ai}^k	Energy of mobile charger k at t_{ai}^k
$e_i(t_{ai}^k)$	Energy of π_i^k at t_{ai}^k
E_{di}^k	Energy of mobile charger k when k leaves π_i^k
T^k	Cycle time T^k of mobile charger k includes R_k and D_k
y_i^k	Visited flag of s_i indicates whether s_i is charged by mobile charger k
$x_{i,j}^k$	Flag indicates whether mobile charger k moves from s_i to s_j
p_l	Penalty coefficient when the MC reaches before t_i^l
p_u	Penalty coefficient when the MC reaches after t_i^u

at CS, and CS periodically dispatches MCs to charge the sensor nodes in WRSNs, and MC returns to the service station when the charging schedule is completed or the energy of the MCs is nearly running out. Each sensor node is equipped with battery whose initial capacity is E_{max}. In the very beginning, each sensor node has corresponding upper and lower limit of charging time. The sensor node requires to be charged within the time window, where the location of each sensor node is fixed and can be located accurately. Denote E_{min} as the minimum energy of battery. When the energy is below E_{min}, the nodes cannot work normally. Denote $p_i(1 \leq i \leq n)$ as the power consumption of each sensor node s_i, and p_i is a constant during the whole charging cycle. Denote E_M as initial energy of each MC, the energy is used to move along the charging path and replenish energy for the sensor nodes. The symbols used in this paper are shown in Table 1.

A. NETWORK MODEL

It is assumed that CS can get the residual energy and energy consumption rate of all sensor nodes at the initial time. N stands for the set of sensor nodes, and L stands for the set of nodes positions. $N = \{s_0, s_1, \cdots, s_i, \cdots, s_n, s_{n+1}\}$ and $L = \{l_0, l_1, \cdots, l_i, \cdots, l_n, l_{n+1}\}$, s_i and l_i refer to the ith sensor node and the position of the ith sensor node respectively. $s_0 = s_{n+1}$ and $l_0 = l_{n+1}$, where s_0 represents the location of the charging service station and l_0 represents the location of the CS in the network. As shown in Figure 1, each MC

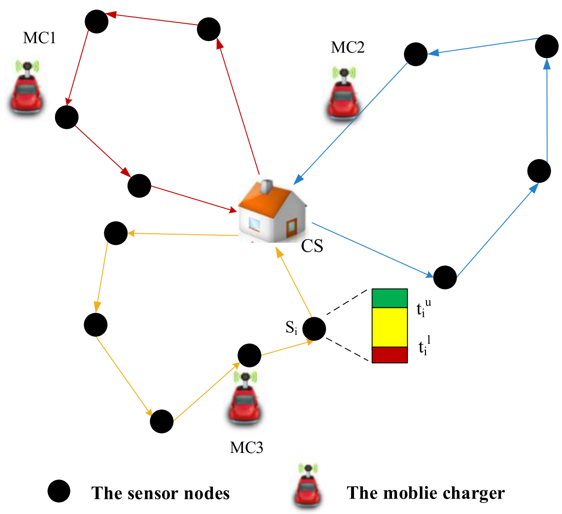

FIGURE 1. Diagram of multi-MC charging path planning in WRSNs.

starts from CS and returns to CS after the charging task is completed. Denote $D = \{d_{i,j} = d(l_i, l_j)|l_i, l_j \in L\}$ as the set of distance between any two sensor nodes and denote $d_{i,0}$ as the distance between the ith sensor node and CS, and $d_{0,j}$ is the distance between CS and the jth sensor node. The residual energy set of all sensor nodes is expressed as $E = \{e_1, e_2, \cdots, e_i, \cdots, e_n\}$. Denote e_i as the residual energy of the sensor node i, and the time window of sensor node is $[t_i^l, t_i^u]$, we assume that the initial time is $t = 0$, and the ith sensor node can be charged between time t_i^l and time t_i^u.

B. CHARGING MODEL

It is assumed that in WRSNs, there is only one charging service station CS. All MCs start from CS and return to CS after completing a charging schedule. The MC charges sensor nodes in one-to-one way. Each sensor node should be charged only once in a charging cycle and the time window of each sensor node is set at the beginning time. If the MC arrives outside the time window, a certain penalty will be given. Each MC used for charging in WRSNs is the same with the constant speed v during the moving process. Denote q_c as the charging power of the MC, q_m as the mobile power and η as the charging efficiency. Unlike the previous research which assumed the sensor node be charged immediately when energy consumed, we assume that charging only happens when the energy of the node is lower than E_{high}, and the energy of each node should never be below E_{min}.

For the kth MC, it starts from CS at time $t = 0$, and charges the sensor node $S_k(\subseteq N)$, then returns to the service station after the charging schedule has been completed. Denote $R_k = \{\pi_0^k, \pi_1^k, \pi_2^k, \cdots, \pi_i^k, \cdots, \pi_{|S_k|}^k, \pi_{|S_k|+1}^k\}$ as a charging circuit corresponding to mobile charger k. Denote both π_0^k *and* $\pi_{|S_k|+1}^k$ as the CS, and π_i^k as the ith sensor node in R_k. During the entire process, the MC charges the sensor node immediately after arriving at the node.

Denote D_k as the total traveling distance of mobile charger k in R_k and $D_k = \sum_{i=0}^{|S_k|} d_{\pi_i^k, \pi_{i+1}^k}$, so $\tau_m^k = D_k/v$ is the traveling time. To reduce the moving distance of MC under the same replenished energy, a greedy charging strategy is adopted, i.e., the node is charged to maximum energy each time. Denote t_{ai}^k as the time when mobile charger k arrives at the ith sensor node, and the energy of the ith sensor node is $e_i(t_{ai}^k)$. The MC leaves the sensor node at time t_{di}^k, and the energy of the node is E_{max}. Denote E_{di}^k as the energy of mobile charger k when it leaves sensor node i, and denote τ_i^k as the charging time for sensor node i. So we have

$$\tau_i^k = (E_{max} - e_i(t_{ai}^k))/(q_c\eta - p_i), \quad 1 \le i \le n \tag{1}$$

For the kth MC, the cycle time T^k includes traveling time τ_m^k and charging time for nodes in corresponding path. We have

$$T^k = \tau_m^k + \sum_{i=1}^{|S_k|} \tau_i^k, \quad \forall k \in K \tag{2}$$

For each MC, the effective charging power should be higher than the power consumption p_i of any sensor node. Thus

$$p_i < q_c\,\eta, \quad i = 1, 2, \cdots, n \tag{3}$$

In the whole process, the charging energy for each sensor node should not be less than the minimum energy required for normal work. We have

$$E_{max} - (T^k - \tau_i^k)p_i \ge E_{min} \tag{4}$$

In the charging schedule, y_i^k indicates whether the sensor node is charged by mobile charger k. If mobile charger k charges the node, its value is equal to 1, otherwise it will be 0. And y_i^k can be written as follows:

$$y_i^k = \begin{cases} 1, & mobilechargerchargesfornodei \\ 0, & otherwise, \end{cases} \qquad i = 1, 2, \cdots, n;\ \forall k \in K \tag{5}$$

The energy consumed by the mobile charger k during the whole charging process cannot exceed its initial energy E_M, so we have

$$q_m D_k + q_c \sum_{i=1}^{|S_k|} (\tau_i^k\, y_{i,k}) \le E_M, \quad \forall k \in K \tag{6}$$

Replace τ_i^k into the upper equation, the constraint (6) can be rewritten as

$$q_m D_k + q_c \sum_{i=1}^{|S_k|} (\frac{E_{max} - e_i(t_{ai}^k)}{q_c\eta - p_i}\, y_{i,k}) \le E_M, \quad \forall k \in K \tag{7}$$

Denote E_{ai}^k as the energy of mobile charger k when it arrives at sensor node i, and then denote E_{di}^k as the residual energy of mobile charger k after the completion of charging for sensor node i and $E_{di}^k = E_{ai}^k - \frac{1}{\eta}(E_{\max} - e_i(t_{ai}^k))$. When k arrives at sensor node i, the energy of MC should guarantee that MC can return to CS after charging for node i. Then we have

$$E_{ai}^k - \frac{1}{\eta}(E_{\max} - e_i(t_{ai}^k)) \ge q_m d_{i,0} \tag{8}$$

$x_{i,j}^k$=1 means that mobile charger k moves from sensor node i to j, otherwise $x_{i,j}^k$=0. That can be written as

$$x_{i,j}^k = \begin{cases} 1, & mobilecharger\ fromitoj \\ 0, & otherwise, \end{cases} \qquad i, j = 1, 2, \cdots, n;\ \forall k \in K \tag{9}$$

When the mobile charger k arrives at sensor node i, the time window constraint should also be considered. The traveling time from the sensor node i to node j must satisfy the condition that the time window is lower than the upper time limit, so we have

$$\sum_{i=1}^{n} \sum_{k=1}^{K} x_{i,j}^k (t_{ai}^k + \tau_i^k + \tau_{i,j}) \le t_j^u, \quad j = 1, 2, \cdots, n \tag{10}$$

C. TIME WINDOW MODEL

The start time of each charging schedule cycle is set as $t = 0$. The initial energy of each sensor node is e_i. According to the upper and lower threshold of the energy, the corresponding time window $[t_i^l, t_i^u]$ can be obtained. It means that the sensor node should be charged between the lower time t_i^l and the upper time t_i^u. We have

$$\begin{aligned} t_i^l &= \begin{cases} \dfrac{e_i(t_0) - E_{high}}{p_i}, & E_{high} \le e_i(t_0) \\ 0, & E_{min} \le e_i(t_0) < E_{high}, \end{cases} \\ t_i^u &= \frac{e_i(t_0) - E_{min}}{p_i} \end{aligned} \tag{11}$$

In a cycle of charging schedule, the MC charges sensor nodes in the time windows of the sensor nodes by satisfying the upper and lower constraints of the charging time. Meanwhile, it realizes the energy supplement with the minimum total cost of the distance, the number of MCs and violation of time windows, so that the sensor nodes can work continuously.

D. PENALTY FUNCTION MODEL

In this paper, multi-MC charging schedule strategy with time window constraints is studied, and the charging path construction problem can be transformed into a classical Vehicle Routing Problem with Time Windows (VRPTW). However, charging schedule is not like the VRPTW problem. VRPTW problem only assumed that the vehicle capacity constraints do not include the walking distance constraints and each demand is a fixed value. For the charging schedule problem, the energy of sensor nodes gradually decreases with time, and the charging time increases gradually, and the current residual energy of the MC used to charge the sensor nodes is also related to the travelling time. Moreover, the charging problem can be derived from the m-TSP problem, and the article [29] proves that m-TSP is a NP-hard problem, and so is the charging problem.

Unlike the traditional charging schedule that the sensor nodes are charged once they have energy consumption, we assume that the sensor nodes start to be charged when the energy of sensor nodes is below E_{high}, which effectively prevents the frequent charging for those nodes with sufficient energy. The initial time is set to 0, and then the time used to charge for the node i is between t_i^l and t_i^u. In order to efficiently use the energy of MC, the MC should avoid charging the sensor nodes once the node's energy is lower than E_{high}, but when the number of nodes whose energy is less than E_{high} reaches a certain scale, they begin to dispatch more MCs to charge sensor nodes. Denote $E_{av}(t)$ as the average energy of nodes and $E_{av}(t) = \sum_{i=1}^{n} e_i(t)/n$, if $E_{min} \leq E_{av}(t) \leq E_{high}$, then the CS starts to dispatch MCs to replenish energy for sensor nodes. To fully utilize the energy of MCs to achieve the purpose of minimizing the total cost of the charging schedule, each MC should charge as many sensor nodes as possible, and the residual energy of MC should be enough to return to the charging service station.

When the MC arrives at the sensor node, it starts to charge the nodes immediately. Each MC tries to reach the sensor nodes within the time windows. If there is a deviation from the time window, certain penalty will be given, the principle of penalty is that more deviation get higher cost. The charging schedule allows the MC's arriving before the lower limit time with some penalty but does not allow the MC to arrive after the node's energy is totally consumed. Assume that the penalty function increases linearly. Denote p_l as penalty coefficient when the MC reaches before the lower limit of the time window and denote p_u as penalty coefficient when the MC reaches after the upper limit time. To avoid the arrival of the MC when the sensor nodes deplete its energy, it is assumed that the penalty coefficient is infinitely large in this case, set $p_u \rightarrow \infty$. The penalty function is expressed as follows:

$$PF_i(t_{ai}^k) = \begin{cases} p_l(t_i^l - t_{ai}^k), & t_{ai}^k < t_i^l \\ 0, & t_i^l \leq t_{ai}^k \leq t_i^u \\ p_u(t_{ai}^k - t_i^u), & t_{ai}^k > t_i^u \end{cases} \tag{12}$$

The penalty function can be transformed into:

$$PF_i(t_{ai}^k) = p_l\, max(t_i^l - t_{ai}^k, 0) + p_u\, max(t_{ai}^k - t_i^u, 0) \tag{13}$$

IV. OPTIMIZATION OBJECTIVE

The objective of this paper is to minimize the total cost (Total Rechargeable Cost, TRC) of sensor nodes on the basis of meeting time window constraints in WRSNs. The corresponding objective function value is f. Considering the actual situation in WRSNs, the problem can be stated formally as:

$$OPT: minTRC = \alpha \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{K} d_{i,j}x_{i,j}^k + \beta \sum_{j=1}^{n}\sum_{k=1}^{K} x_{0,j}^k + \gamma \sum_{i=1}^{n}\sum_{k=1}^{K} PF_i(t_{ai}^k) \tag{14}$$

s.t. (4),(5),(7),(8),(10)-(13),

$$\sum_{k=1}^{K} y_{ik} = 1, \quad i = 1, 2, \cdots, n \tag{15}$$

$$\sum_{i=1}^{n} x_{0,i}^k = \sum_{j=1}^{n} x_{j,0}^k \leq 1, \quad \forall k \in K \tag{16}$$

The formula (14) shows that the optimization goal is the total cost minimization of the distance, the number of MCs, and the violation of the time windows. Denote α as the unit distance cost, β as single MC cost and γ as unit time window cost. The constraint (15) indicates that each sensor node is only charged by one MC in a cycle. The constraint (16) indicates that all MCs must go back to the service station after leaving it, and it can also indicate whether mobile charger k is used in the charging schedule.

V. CHARGING SCHEDULE ALGORITHM

This paper studies the multi-MC charging schedule problem, in which each sensor node has a time window in WRSNs. This problem is NP-hard. Genetic algorithm and 2-OPT strategy are combined to solve the problem. Suppose the population has a number of chromosomes. The main idea of genetic algorithm is as follow, in each iteration, the offspring population is generated by performing selection, crossover and mutation operation on chromosomes in parent population. The process will repeat until the number of iterations satisfy the termination condition. And then the chromosome in latest population with lowest objective function value is the optimal solution. As for the proposed charging schedule algorithm, the final result is obtained after the optimal solution obtained by genetic algorithm is exchanged by 2-OPT strategy. As described above, the flow chart of our charging schedule algorithm is shown below. Details of each step will be discussed in section A to section D.

A. CHROMOSOMES CODING AND DECODING

The population size affects the implementation efficiency and the final result of genetic algorithm. In this paper, a set of different chromosomes $G_h(h = 1, 2, \cdots, m)$ is generated randomly, where m is the number of chromosomes in the initial population.

The multi-MC schedule problem in WRSNs with time window constraints is related to the charging order of sensor nodes. The charging path of MC and the charging time that sensor nodes take are combinatorial optimization problems based on sequence. Therefore, this paper uses natural number coding to sequentially encode the sensor nodes charged in all

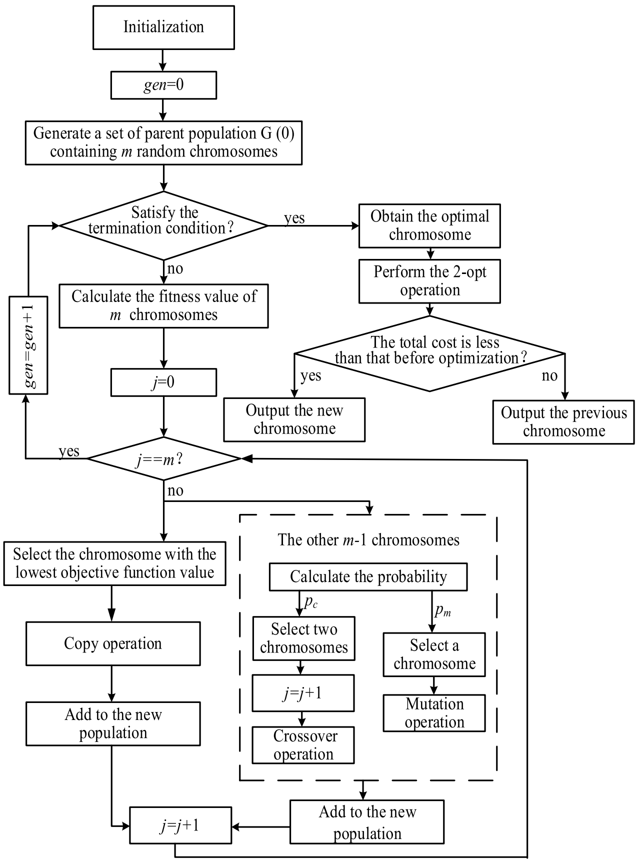

FIGURE 2. The flow chat of the proposed algorithm.

paths into a chromosome, and the chromosomes are represented by denoting vector G_h. Denote G_h=$(g_1, g_2, \cdots, g_n)$, where each gene g_i is a natural number ranging from 1 to n without overlapping with each other. By adopting such a coding method based on direct arrangement of sensor nodes, it is possible to ensure that each sensor node is charged only once, and simplify the handling of constraints in mathematical models.

Detailed decoding operation process is given as follows: Firstly, we select the gene from left to right and insert it into the current path according to the gene sequence of a chromosome. If the insertion of a gene does not meet the energy constraints of MCs or the time windows of sensor nodes, we begin to construct a new charging path. The above process is repeated until all the sensor nodes are assigned to the corresponding charging path.

B. SELECTION, CROSSOVER AND MUTATION OPERATION

The purpose of selection is to choose better individuals from the current population and keep them to next generations as parents or create new individuals by mutation. In this paper, the selection strategy combines the elite choice with the expectation value, which is used to improve the performance of selection operation and maintain the individuals with the best fitness. And the individuals with larger fitness value are more likely to be passed on to the next generation. The specific process is given as follows: Firstly, we suppose the size of the population is n, the objective function value f_h of each chromosome G_h will be in ascending order, and the chromosome with the lowest f_h will be kept directly to the next generation. The remaining $n-1$ chromosomes in the next generation are selected by the roulette method.

The purpose of the crossover operation is to enable genetic algorithm to search for new gene space and this brings diversity to the new populations. This paper adopts the like-PMX (Partially Matched Exchange) crossover method, which is different from the method of direct exchanging chromosome segments. The like-PMX method first moves the crossover segment to the head of the other chromosome, and then removes the same genes and results in a new individual after the crossover. This crossover operation can still perform iterative optimization if two crossover individuals are the same, to get different individuals from their parents, jump out of the local optimum, and improve the global search capability.

The mutation operation can overcome the premature convergence phenomenon in the crossover process and improve the local search ability to a certain extent. In this paper, two mutation points are randomly selected from a chromosome in a population by using a basic mutation operator, and then the gene values corresponding to the two mutation points are exchanged with probability p_m to obtain mutated individuals.

C. TERMINATION RULE OF EVOLUTION

In this paper, the number of iterations is used as the termination rule to determine whether the number of iterations meets the prescribed level *Gen*. If so, evolution ceases and the charging schedule corresponding to the best performing chromosome G_h is selected as the final solution.

D. 2-OPT ALGORITHM

GA could easily lead to inadequate search. The solution obtained by genetic algorithm may not be optimal solution, and the corresponding charging path is not necessarily the optimal path. Some adjustments must be made to the obtained charging path for local optimization. In this paper, the efficient and simple 2-OPT local search algorithm proposed in [37] is used to optimize the charging path.

E. REALIZATION OF CHARGING SCHEDULE ALGORITHM

Based on the proposed genetic algorithm and 2-OPT algorithm, this paper solves the problem of multi-MC charging schedule in WRSNs. The concrete steps of its realization are given as follows

Algorithm 1 Minimize the Total Cost of Charging the Sensor Nodes in WRSNs, and Get the Corresponding Optimal Charging Schedule

input: $E_{max}, E_{high}, E_{min}, l_i(x, y), p_i, e_i, E_M, q_c, q_m, \eta, v, \alpha, \beta, \gamma, p_l, p_u$

output: The minimum total cost for charging nodes in the WRSNs, the corresponding charging schedule, the number of MCs, and the charging path corresponding to each MC

1: Calculate the time window $[t_i^l, t_i^u]$ of each sensor node at the initial time;
2: Set the terminate number of iterations Gen, crossover probability p_c, andmutation probability p_m;
3: Generate a set of initial population $G(0)$ containing N random chromosomes, define and initialize the number of iterations variables $gen = 0$;
// It is assumed that the charging completion time of $j-1$ th sensor node is $t_{d(j-1)}$, when the remaining energy of the MC is $E_{d(j-1)}$, the node distance and time corresponding to $j-1$ to j are $d_{j-1,j}$ and $t_{j-1,j}$
4: **for** $i = 1$ to N **do**
5: **for** $j = 1$ to L **do**
//It is assumed that the node corresponding to the gene $j-1$ is the last node of the current path, so the time of arrival at j is $t_{aj} = t_{d(j-1)} + t_{j-1,j}$. Then discuss whether the node corresponding to j can join the current path
6: **if** MC arrives at sensor node j **then**
7: Calculate the remaining energy of node j of this moment is $e_j(t_{aj}) = e_j(t_0) - p_j t_{aj}$. The remaining energy of MC is $E_{aj} = E_{d(j-1)} - q_m d_{j-1,j}$ when the MC arrives at j, and the energy of node j that needs to be replenished is $e_j^{ch}(t_{aj}) = E_{max} - e_j(t_{aj})$;
8: **if** $e_j(t_{aj}) > 0$ and $E_{aj} - \frac{1}{\eta}(E_{\max} - e_j(t_{aj})) \geq q_m d_{j,0}$ **then**
9: Add node j to the current path, update the charging time at j, energy value of j, the cost of distance and the violation of time windows corresponding to the current path after node j has been charged;
10: **else**
11: Add another charging path, update the current time $t = 0$;
12: **end if**
13: **end if**
14: **end for**
15: Calculate the total distance, the number of MCs, the total cost of violating the time windows and the total cost of the three individuals corresponding to chromosomes in the population;
16: **end for**
17: According to the elite selection strategy, select the chromosomes with the lowest f_h into the next generation. The other $N-1$ chromosomes are selected by the roulette strategy. Finally, we get N chromosomes belonging to the next generation;
18: Carry out like-PMX cross and basic reversal mutation operations and reorganize to generate new individuals;
19: Set the number of iteration variables $gen = gen + 1$;
20: **if** the termination condition of genetic algorithm is satisfied **then**
21: Go to step 17;
22: **else**
23: Go to step 5;
24: Use 2-OPT local algorithm to optimize the charging path to get a new charging schedule;
25: **if** the total cost is less than that before optimization **then**
26: Keep the optimized charging schedule;
27: **else**
28: Maintain the previous optimization;
29: **end if**
30: **end if**
31: **return** result

VI. NUMERICAL RESULTS

A. SIMULATION SETTINGS

In this section, MATLAB R2015a is adopted for simulation experiments and some numerical results are presented to demonstrate how our charging schedule achieved a less total cost. We randomly distribute 20 sensor nodes in a 1000 m × 1000 m square area. The BS and CS both are located at coordinate (500m, 500m). We here set $E_{\max}$=10.8KJ, $E_{\min} = 540J$, $E_M = 108KJ$, $v = 8m/s$, $q_c = 10W$, $q_m = 100J/m$ [38], [39]. The consumption rate of each node is randomly generated within [0.1, 1] J/s. The location of each sensor node was shown in table 2.

TABLE 2. Location of 20 sensor nodes.

Node No	Location(m)	Node No	Location(m)
1	(986,89)	11	(307,636)
2	(172,141)	12	(853,886)
3	(819,127)	13	(570,327)
4	(586,463)	14	(207,725)
5	(712,479)	15	(550,928)
6	(980,23)	16	(908,581)
7	(614,870)	17	(570,752)
8	(991,255)	18	(157,10)
9	(162,297)	19	(415,672)
10	(326,158)	20	(74,748)

B. RESULTS

The crossover and mutation probabilities are $p_c = 0.9$, $p_m = 0.05$ respectively. Set $Gen = 100$ as the terminate number of iterations. A WRSN consisting of 20 sensor nodes is analyzed in details. The results are shown in Table 3:

The first time in the table stands for the number of iterations that get the final solution for the first time. It can be seen from Table 3 that the obtained average value of the total charging cost is 328.7. Nine of the experimental results are higher than the average, the total cost of the optimal final solution is 304.8, the chromosome is [13,3,6,1,8,5,4,10,18,2,9,20,14,11,19,16,12,15,7,17]. As shown in Table 4, we can get its corresponding charging schedule path after the feasibility analysis.

It can be seen from Table 4 that the total cost of each charging path corresponding to the optimal charging schedule is similar, and the residual energy of the MC is less than 1/20 of the initial energy and smaller than the initial energy of

TABLE 3. Charging schedule results.

Index	Total cost	First time	Charger amount
1	346.1	48	3
2	304.8	77	3
3	349.8	49	3
4	339.9	45	3
5	342.9	58	3
6	336.8	62	3
7	335.5	60	3
8	324.6	70	3
9	340.8	73	3
10	315.1	77	3
11	308.2	58	3
12	334.2	63	3
13	323.5	75	3
14	316.8	77	3
15	329.6	68	3
16	306.4	70	3
17	354.3	49	3
18	319.7	74	3
19	330.1	78	3
20	315.9	77	3
Average	Totalcost: 328.7	First time to get final solution:65	Charger amount: 3

TABLE 4. Charging sequence.

Path Index	Charging sequence	Total cost of the path	Rest energy of MC
1	0-13-3-6-1-8-5-4-0	95.3	442.55
2	0-10-18-2-9-20-14-11-19-0	118.4	2485.95
3	0-16-12-15-7-17-0	91.1	5710.63

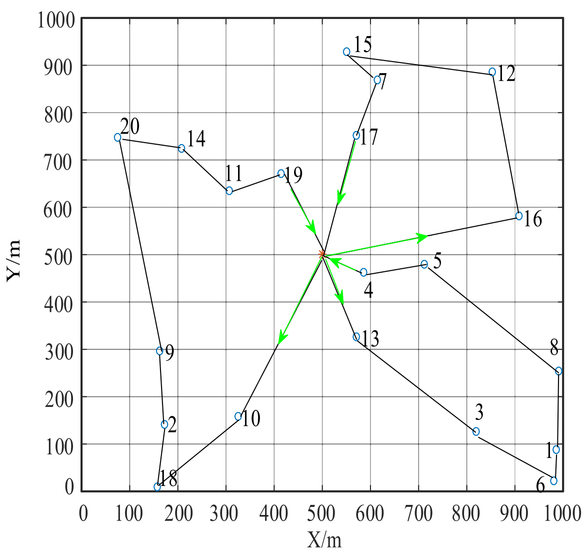

FIGURE 3. Best charging paths for the sensor network consisting of 20 nodes.

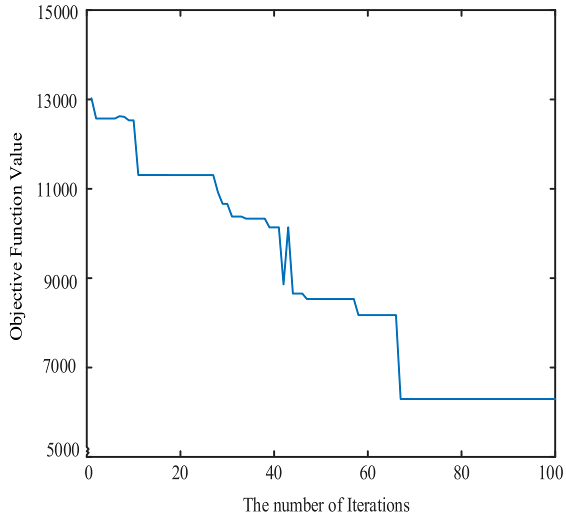

FIGURE 4. Effect of iteration on objective function value.

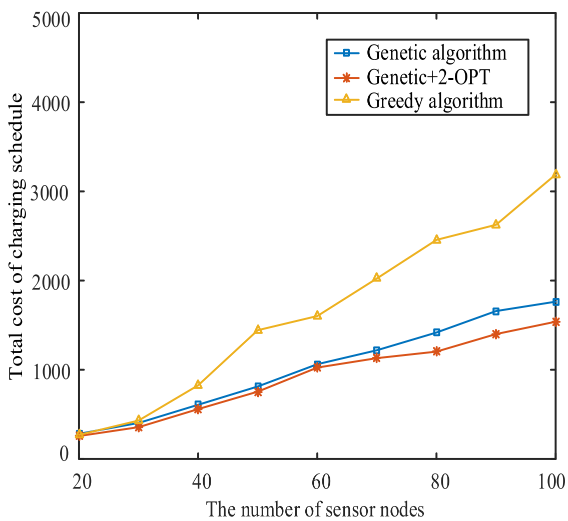

FIGURE 5. Effect of the number of sensor nodes on the total charging cost.

the sensor node when the MC finally returns to CS. This paper shows that the solution can indeed charge as many nodes as possible. Figure 3 shows the charging paths corresponding to the randomly distributed 20 nodes which are charged by 3 MCs respectively. The total cost of the moving distance, violation of the time windows and the number of the MCs corresponding to the charging schedule in this case is the lowest. It can be seen from Figure 4 that the proposed charging schedule algorithm shows a decreasing corresponding objective function value with the increasing of the number of iterations and a better and more reasonable result is achieved.

In the WRSNs' region, 20, 30,..., 100 nodes are respectively generated. Figure 5 and Figure 6 show the impacts on the total charging cost and the number of MCs as the number of sensor nodes changes in the charging schedule respectively. It can be seen that when the number of sensor nodes in the WRSNs increases, the total charging cost corresponding to the MC charging process increases, and the size of the network increases. However, the initial energy of each MC is limited. Therefore, without more MCs to charge the sensor nodes, the sensor nodes may not work perpetually. In this case, more MCs are needed. Overall, when the WRSNs become larger, the number of sensor nodes requiring to be charged and the corresponding total moving distance increase, unit distance and unit charger cost remain unchanged, and even if each sensor node is charged within a

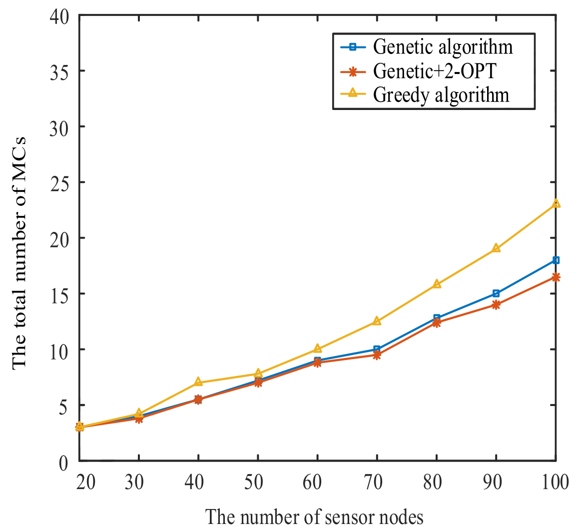

FIGURE 6. Effect of the number of sensor nodes on the total number of MCs.

time window, its corresponding total cost will also increase. After using 2-OPT local optimization algorithm, there is no obvious change in the number of MCs. This is because the WRSNs charging schedule is based on time window and each sensor node should satisfy the time window constraint. After the local adjustment, the corresponding total cost is reduced by 18% when compared with the genetic algorithm due to the reduction of the moving distance, while the greedy algorithm performs well under the condition that fewer nodes exist in the network. However, in the large-scale networks, the number of MCs corresponding to its solution is larger, and the total cost is about 29.4% higher than ours.

VII. CONCLUSION

This paper studies the problem of multi-MC charging schedule for WRSNs with time windows. When the average energy of the sensor networks is lower than a certain value, the MC begins to charge the sensor nodes. Compared with the charging strategy in which the sensor nodes are charged once they have energy consumption, our charging schedule can effectively prevent sensor nodes with sufficient energy from being charged frequently. Additionally, the energy carried by MC is limited, so more MCs are required to charge for large-scale sensor networks. The purpose of this paper is to minimize the total cost of moving distance, the number of MCs and violation of time windows. Due to the NP-hard of the problem, elite retention strategy and genetic algorithm are used together to get final solution, and then the 2-OPT local search algorithm is used to adjust the final solution, so as to achieve the optimal solution.

The simulation results show that the proposed algorithm can effectively reduce the charging consumption of MC and prolong the lifetime of the networks. Moreover, the final solution of the proposed algorithm is better than the basic genetic algorithm and greedy algorithm. This paper also has some limitations: the solution depends on the initial population overly and does not consider the priority of the sensor nodes, etc. We will study the charging schedule based on the prioritization of sensor nodes in our future research.

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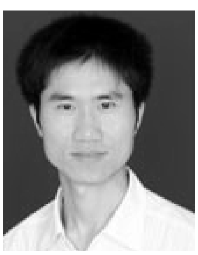

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