 doi:10.20944/preprints202209.0402.v1

Article

UAV-assisted WRSN Online Charging Strategy Based on Dynamic Queue and Improved K-means

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Abstract: Aiming at the problem of low charging efficiency caused by the scattered sensor nodes in traditional wireless rechargeable sensor networks (WRSNs), a UAV-assisted WRSN Online Charging Strategy Based on Dynamic Queue and Improved K-means (UOCS) is proposed. The scheme assumes that the energy consumption of nodes is unpredictable, and only generates charging requests when the energy is lower than a threshold, and performs on-demand responses to nodes that issue charging requests. The scheme combines the characteristics of one-to-one charging of UAVs, the selection and allocation timing of waiting queues and the number of UAVs, and the improved K-means partitioning based on space-time coordination(SPKM), which simplifies the problem of coordinated charging of multiple UAVs and maximizes energy. Using the efficiency and charging success rate, the optimal charging trajectory can be found under the constraint that the node will not starve to death due to power shortage. Finally, a simulation comparison experiment is carried out with the existing UAV charging scheduling strategy. UOCS achieves the optimal node survival rate with low algorithm complexity.

Keywords: Wireless Rechargeable Sensor Network; Unmanned Aerial Vehicle; One-to-one Charging; Space-time Collaboration; Optimal Charging Trajectory

1. INTRODUCTION

With the rapid development of wireless technology, wireless sensor networks have avery important status in real life, especially in the field of sensing monitoring applications, including environmental perception, target tracking and health monitoring [1]. In the traditional Wireless Sensor Network (WSN), the sensor node is generally driven by battery, but the limited energy of the battery not only hinders large-scale deployment of the sensor, but also affects the work life of the entire network. In response to this problem, researchers have proposed energy saving [2] and energy extraction [3], attempting to reduce or balance the energy consumption of the sensor, but it is impossible to solve this problem. For energy-saving methods, it can only effectively extend the life of the network, and prevent the sensor node from exhausting energy, the network will eventually die. Taking into account the unpredictability of the environment, the extraction efficiency will be greatly affected, causing the sensor node to operate continuously. Kurs et al. [4][5] proposes a problem that the Wireless Power Transfer (WPT) technology can solve the problem of limited energy in the traditional wireless sensor network, thereby further developing wireless rechargeable sensor networks (WRSN).

Domestic and foreign scholars have conducted a lot of research and practice on the node energy replenishment of wireless rechargeable sensor networks, among which the most commonly used is the use of mobile charging trolleys [6][7][8] (Mobile Charger, MC) for energy replenishment of WRSNs. However, the charging car is difficult to play its role in some areas with limited conditions and harsh environments, such as natural disaster areas, war areas, etc. Even in conventional environments, path planning may fail due to many obstacles.

To solve this problem, we proposed a UAV-assisted non-deterministic WRSN charging scheduling scheme. In this article, UAVs refer to aircraft that carry charging equipment and can be charged wirelessly. Its advantages include high speed, strong flexibility,

 doi:10.20944/preprints202209.0402.v1

easy to pass through general obstacles and fixed-point hovering. Therefore, the non-deterministic charging scheduling scheme based on UAV proposed in this paper can make up for the deficiency of MC.

Deterministic charging scheduling [9] considers that under ideal conditions, the energy consumption of all nodes in the sensor network is known and constant. Charge to avoid node power failure and death. The determination here refers to the determination of the overall energy state of the network, based on constant node energy consumption and the control center knowing the energy state of the network at any time; after the scheduling strategy, the charging sequence and charging time of each round is the same, and the energy state of each node also decreases at a constant rate and is periodically replenished. Therefore, in some works, deterministic WRSN charging scheduling is also called periodic WRSN charging scheduling.

The deterministic scheduling scheme is only suitable for small-scale sensor networks, because the energy demand of a single charge is not high, and a single UAV can be used to complete the charging of the entire network. In previous research[10][11], path planning is often used in the focus of periodic charging scheduling. It is similar to the Traveling Salesman Problem (TSP). It is necessary to construct an optimal charging access sequence for all nodes, which is an NP-hard problem, and factors such as charging effect and charging efficiency need to be comprehensively considered. And there are many constraints, such as the limited energy of the mobile charger, and the need to avoid node power failure and death as much as possible. Secondly, in the one-to-many charging scheduling[12] based on the UAV, not only the path, but also the one-to-many coverage characteristics of the UAV should be further considered, and the determination of the flight height should be considered. However, in the existing related research work, there are limitations in the planning of the charging path, such as insufficient search space and poor scalability, and most of them use one-to-one[13] charging method or a charging method with a fixed charging beam size.

Different from the assumption[14][15] that the energy consumption of nodes is known and constant in deterministic charging scheduling, in non-deterministic WRSN charging scheduling, considering that the energy consumption of nodes in sensor networks in most practical scenarios is affected by environmental changes, routing algorithms and other factors are random and unknown, so each node needs to actively report to the base station and send a charging request message when the energy is lower than the threshold[16]. After receiving the charging requests, the base station schedules the mobile charging device to respond to these requests. The research focus of non-deterministic charging schedule and deterministic schedule is different. First, non-deterministic assumptions are generally aimed at large-scale sensor networks[17][18]. At this time, it is difficult for a single UAV to meet the energy requirements of all nodes and it is necessary to design a mode of coordinated charging of multiple UAVs. Secondly, the non-deterministic charging scheduling strategy has high real-time requirements, and it is obviously unreasonable to spend more time for calculation and lead to charging delay, so there is a certain limit to the time complexity of the scheduling algorithm.

The existing non-deterministic charging schedules of related researches[19][20][21] have some shortcomings, most of them have high algorithm complexity, and cannot guarantee the real-time scheduling, and do not fully consider the task allocation problem when multi-UAV cooperative charging is performed. It is difficult to distribute charging tasks fairly by geographical location and other methods, resulting in unbalanced task allocation and inability to make full use of charging resources. In addition, most of the work [22][23] follow the concept of charging rounds in the deterministic charging scheduling strategy, which is not based on dynamic number of UAVs allocates charging tasks, resulting in long UAVs idle time.

Using UAV as a mobile charging device, a non-deterministic on-demand charging scheme UOCS (UAV-assisted WRSN Online Charging Strategy Based on Dynamic Queue and Improved K-means) based on UAV is proposed to maximize the energy utilization

 doi:10.20944/preprints202209.0402.v1

efficiency of UAV and maximize the charging success rate is the optimization target. The main work and innovations include: 1) A new mode of charging scheduling based on the number of dynamic UAVs is proposed, and the overall energy consumption is estimated with the help of the minimum spanning tree, and then the appropriate scheduling time is determined to reduce the number of unmanned aerial vehicles and overall idle time of the machine. 2) An improved K-means algorithm for space-time partitioning is proposed to allocate charging tasks, balance the charging tasks undertaken by each UAV, and ensure the rationality of task allocation. 3) The online algorithm based on the greedy strategy plans the charging trajectory of each UAV, and takes into account the goals of maximizing energy efficiency and charging success rate with low algorithm complexity, and realizes the planning and online update of each UAV charging path.

2. SYSTEM MODEL

2.1. Problem Model

The considered UAV-assisted wireless rechargeable sensor network consists of a base station, a set S of UAVs of size K, and a set of wireless sensor nodes O of size N deployed on a two-dimensional plane, $O = \{o_1, o_2, \dots, o_N\}$. The base station is the control center of the entire network, responsible for the collection of sensor node sensing data, the replacement of UAV batteries, and the scheduling of UAVs to perform charging tasks. The sensor nodes are randomly deployed in the monitoring area P. For the node o_i numbered i, its position in the area is defined as (xi, yi) in the plane Euclidean coordinate system, and the node battery capacity is Ei, as pointed out, the energy consumption qi of each node can be estimated based on the amount of data or obtained according to the statistics of charging records. The real-time power e_i can be detected and reported to the base station by the corresponding circuit. When the power of the node reaches the threshold θ_i, it will report its own status information $\gamma(T_{ci}, e_i)$ to the base station, where T_{ci} is the moment when the status information message is sent.

Since one-to-many charging method is suitable for a network with relatively dense charging nodes, in on-demand charging scheduling, the nodes that issue charging requests are relatively scattered, and the one-to-many charging method is less efficient. In addition, in on-demand charging, it is often necessary to estimate the schedule ability of the charging path, that is, to determine whether the energy of the UAV is sufficient to support the charging demand on the path. Node charging will bring additional and difficult-to-estimate power consumption to the UAV, and bring about the difficulty of schedule ability estimation. Therefore, in the non-deterministic charging scheduling, a one-to-one charging method is adopted.

2.2. Network Model

The network and charging model of this paper are shown in Figure 1.

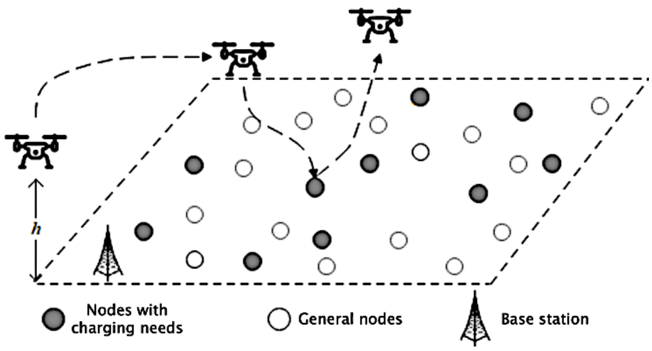

Fig. 1: UAV-assisted WRSN Charging on Demand.

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WRSNs can be recharged by multiple UAVs equipped with wireless charging modules. The UAV starts from the base station, determines the next charging node based on the scheduling strategy, rises vertically to a certain height h, and then flies horizontally to the next node at a constant speed v. And land to charge the node, complete a charging response, and repeat the above process after completing the response, until all assigned charging responses are completed or the UAV itself is exhausted and returns to the base station to replace the battery. It is assumed that the UAV always carries enough energy to support it to complete the charging task and return to the base station.

2.3. UAV Charging Space Model

One-to-one wireless charging is currently commonly used electric field coupling technology or magnetic coupling induction technology [24]. The power Pc of the charging device and the energy transmission efficiency η of the charging device to the node can be regarded as a constant, and $0 < \eta < 1$, the energy received power of the node Pr is expressed as:

$$Pr = \eta \cdot Pc \qquad (1)$$

From this, the UAV can calculate the node energy demand E_{qi} and the time required to fully charge the power in this charging request before performing the charging task on the node oi t_e^i:

$$E_{qi} = \begin{cases} E_i - [\theta_i - (T - T_{ci}) \cdot q_i], \theta_i \leq (T - T_{ci}) \cdot q_i \\ E_i, \theta_i > (T - T_{ci}) \cdot q_i \end{cases} \qquad (2)$$

$$t_e^i = \frac{E_{qi}}{P_r} \qquad (3)$$

2.4. Determination of the Number of UAVs

This paper studies the problem of multi-UAV collaborative charging planning. The number of UAVs is also a key factor affecting the charging effect. If the number of UAVs is too small, it is difficult to meet the energy demand of the entire network, but due to its cost, it is obviously also unlimited deployment is not possible. Therefore, it is a big difficulty to choose the appropriate number K of UAVs. The more UAVs in a certain range, the better the charging effect, but when the number exceeds a certain number, there will be a phenomenon of diminishing marginal utility, which often needs to be combined with the use of sensor networks. In different scenarios, there is a trade-off between cost and charging effect. The principle of energy neutrality can be applied here, that is, at any time T, the total energy consumption of nodes should not be greater than the sum of the energy charged to the sensor network and the initial energy of the network [25].

$$\sum_{i=1}^{N} q_i T \leq \frac{KP_r}{Q} T + E_0 \qquad (4)$$

Among them, q_i represents the energy consumption rate of a single sensor node, which is mentioned in Chapter 2 as a known quantity, and the left side of the inequality as a whole represents the total energy consumption of all sensor nodes from the start to time t. E_0 represents the initial energy of the network, q_u is the energy consumption rate of a single UAV, and the energy efficiency Q fluctuates little with the number of UAVs, so it is regarded as a constant here, so there is:

$$K \geq \frac{(\sum_{i=1}^{N} q_i T - E_0) \cdot Q}{P_r \cdot T} \qquad (5)$$

The above formula is the minimum number of UAVs that can theoretically support all nodes without dying under a given network energy consumption rate. The specific optimal number of UAVs can be compared with multiple experiments to make sure.

2. 5. Target Optimization

In the on-demand WRSN scheduling problem, the UAV energy utilization efficiency and the number of node deaths are also used as optimization goals. The total service request set R is recorded, and its quantity is |R|; the UAV energy efficiency Q is defined as

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the percentage of the power successfully charged into the node to the total power consumption in the charging scheduling, the latter includes the power consumption of the UAV charging module, and the travel distance. Power consumption and take-off and landing power consumption. Note the battery capacity E_i, the energy required for the charging request of the node o_i E_{qi}, the overall charging request energy $E_R = \sum_{i=1}^{|R|} E_{qi}$, remember the total energy consumption of all UAVs on the journey E_M, and the energy consumption of UAVs for a single take-off and landing E_L, the goal of maximizing energy utilization efficiency can be expressed as:

$$max\ Q = \frac{E_R \cdot \eta}{E_R + (E_M + E_L \cdot |R|) \cdot \eta} \tag{6}$$

The total number of nodes that need to be charged in on-demand scheduling is not constant, and the goal of minimizing the number of node deaths should not be simply considered. The goal of maximizing the charging success rate is expressed as:

$$max\ \delta = \frac{|R_S|}{|R|} \tag{7}$$

Among them, R_S is the set of successful charging requests, and $|R_S|$ represents its number. Same as the previous section, this section will be the weighted summation of the two objectives of maximizing the energy utilization efficiency and maximizing the charging success rate, and deal with it as a single-objective optimization problem:

$$max\ M_{target} = \frac{E_R \cdot \eta}{E_R + (E_M + E_L \cdot |R|) \cdot \eta} + \frac{|R_S|}{|R|}$$

$$= \frac{|R| E_R \cdot \eta + |R_S| (E_R + (E_M + E_L \cdot |R|) \cdot \eta)}{E_R + (E_M + E_L \cdot |R|) \cdot \eta} \tag{8}$$

$$s.t. \quad E_{Ri} \leq E_i \tag{9}$$

$$0 < E_R, E_M, E_L \tag{10}$$

$$0 < |R_S| \leq |R| \tag{11}$$

$$EM_K > E_{qi} + D_{(i,0)} \cdot P_{move} + E_L \tag{12}$$

Equation 9 constrains that the amount of electricity charged to each node must not be higher than its total capacity. Equations 10 and 11 are range constraints. Equation 12 is the schedule ability constraint. The UAV needs to ensure that there is enough power to return to the base station after each charging task is performed. Among them, $D(i,0)$ represents the distance between the node o_i and the base station, and P_{move} represents the energy consumption per unit distance of the node.

Table 1 lists the symbol identifications in the non-deterministic UAV-assisted WRSN charging scheduling problem:

TABLE I: Symbol Identifications.

Symbol	Mean
S_k	The kth UAV
O_i	The ith sensor node
E_u	Battery capacity of UAV
T	Current time
T_c^i	The time node i sends charge request
t_c^i	Node i fully charged time

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θ_i	Node i charge threshold
P_c	Wireless output power
P_r	Node received power
η	Wireless charging efficiency
Q	Energy efficiency
E_{qi}	Node i energy needs
E_i	Node i battery capacity
q_i	Node energy consumption rate
E_C	Wireless transmission energy consumption
E_M	UAV's journey energy consumption
E_L	UAV energy consumption per take-off and landing
R_S	Charge success request
R	All charge requests
|R|	Number of charging requests
$S_{i,k}$	Energy offset of Node i insertion partition k
$D_{i,j}$	Euclidean distance between nodes i and j
$D'_{i,j}$	Blend distance between nodes i and j

3. On-demand charging solution

In this section, we will discuss how to determine the scheduling timing, realize the assignment of tasks, and plan the charging sequence of each UAV based on the dynamic number of UAVs in the multi-UAV-assisted non-deterministic WRSN charging scheduling to achieve the optimization goal. The overall process of the non-deterministic charging scheduling strategy proposed in this paper is shown in Figure 2.

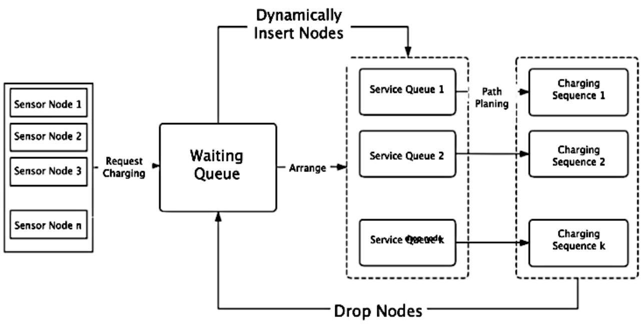

Fig. 2: Charging Request and Scheduling Process.

3.1. Waiting for Queue Maintenance

Before all charging requests are assigned to specific UAVs to perform services, they first enter the waiting queue, and the waiting queue maintenance algorithm performs the scheduling of requests. The waiting queue maintenance algorithm mainly consists of two parts, namely partition timing decision and urgent request insertion. The former is used to dynamically select the appropriate task assignment timing in combination with the number of real-time UAVs in the base station, and the latter is used to insert scattered urgent tasks into the service queue. In the on-demand WRSN, charging requests are constantly generated, and at the same time, multiple UAVs continue to go back and forth between the base station and the network. The selection of charging task allocation timing is particularly important. If the allocation is too early, it may lead to incomplete task division, each UAV is assigned less tasks, and after completing the charging task, it returns to the base station too early, and frequent round trips between base stations lead to waste of energy. If the allocation is too late, it may cause the node to wait for a long time and cause the node to die.

The more intuitive solution is to estimate the energy requirement to respond to all charging request tasks in the current waiting queue based on energy information, and combine the UAV battery capacity to perform scheduling when the current total energy of all UAVs just meets the energy required by the charging request. Achieving higher energy utilization efficiency, expressed as:

$$\frac{\sum_{i=1}^{|Qw|} E_{qi}}{\eta} + E_M + E_L \cdot |Q_w| \geq KE_U \quad (13)$$

Except for the path energy consumption E_M, all parameters are fixed hardware parameters, which can be directly calculated or obtained from real machine tests, while E_M is related to the real-time charging node distribution and the flight path of each UAV, and the optimal charging path for multiple UAVs can be approximated as a multi-travel salesman problem, which is a NP-hard problem and cannot be solved in polynomial time, but its lower bound can be roughly calculated with a relatively low time complexity with the help of the minimum spanning tree. Let the minimum spanning tree path length be H, then estimated path energy consumption $E_M = H \cdot P_{move}$. For the waiting queue Q_w, the maintenance algorithm estimates the energy consumption required by the multi-UAV charging task according to the relevant information of the charging request, and then decides the appropriate time to perform the task assignment. The waiting queue also needs to avoid the death of the node due to the unresponsiveness of the charging request for a long time.

Define the request that the node's power exhaustion time is earlier than the earliest UAV return time as an emergency charging request, record the power q_i of the node o_i, its current remaining power Eri, and the UAV U_i's expected return time T_{bj}, if the node is expected to die early due to lack of electricity at the earliest UAV return time, namely:

$$\frac{E_{qi}}{q_i} < min\{T_{bj}\} \quad (14)$$

Considering that the charging task has a risk of power shortage, the emergency task insertion algorithm inserts the task into the charging queue of the UAV in the partition where the node is located. If the latter is put back into the waiting queue again because it cannot be scheduled, it will be marked and no longer inserted. Algorithms that avoid round-robin scheduling. The overall description of the waiting queue maintenance algorithm is shown in algorithm 1.

Algorithm 1 Waiting queue maintenance
Input: waiting queue Q_w, UAV set S, charging request R, partition set C

1 assignFlag←false; C←null; H←null;//H is Minimum spanning tree's path length
2 **while** running do
3   **while** request Added
4   **if** (assign Flag = true) **then**
5   **break;**
6   **end if**
7   update MST(R, H)//Update minimum spanning tree

doi:10.20944/preprints202209.0402.v1


```
            /*calculate schedule ability of current
        Q_w based on formula(10)*/
        assign Flag =calSchedulable(R,H,S)
    end while
    SPKM(Q_w, S)//space-time partitioning based
    on K-Means
        /*determine charging urgency based on.
    formula(11)*/
    for r in Q_w:
        if (isUrgentRequest(r)) then
            insert r into C
        end if
    end for
end while
```

3.2.Improved K-means Algorithm

UAV charging task assignment is a major difficulty in multi-UAV charging scheduling. The assignment of tasks needs to comprehensively consider multiple factors such as equal distribution of tasks and avoidance of task conflicts. By dividing the charging area into several non-overlapping zones, it is an intuitive and effective way for UAVs to be responsible for charging tasks in their respective zones, and has also been used in many studies. The K-means algorithm was originally used for clustering problems in unsupervised learning. After determining the number of clusters K in advance, based on the similarity of feature vectors, find K centroids, and divide all samples into the nearest ones. The core idea is to divide the closest points into the same cluster in each round, and iteratively update the centroids based on the clustering results until it converges to a specified degree. In WRSN multi-UAV charging scheduling, the use of K-means clustering algorithm to partition the charging tasks of nodes has achieved good results [26,27,28], and the clustering results obtained based on the clustering algorithm are used as the charging of each UAV. The schematic diagram of partition and multi-UAV partition charging is shown in Figure 3.

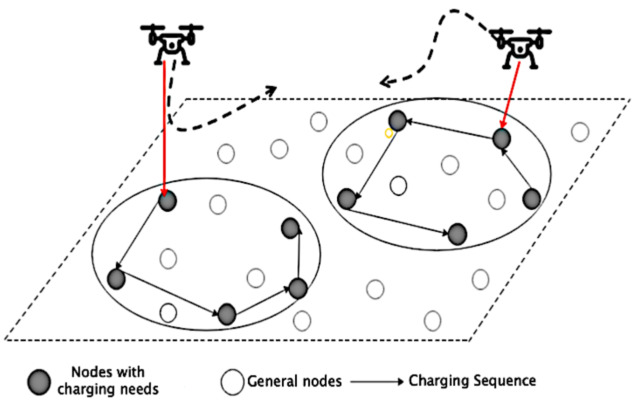

Fig. 3 Schematic Diagram of Multi-UAV Charging.

However, the traditional K-means algorithm directly based on geographic location has great limitations, especially when the distribution of charging requests in the network

 doi:10.20944/preprints202209.0402.v1

is not uniform. Figure 4 shows an extreme situation. Compared with other clusters, Cluster3 obviously allocates fewer points. If it is directly used as the basis for on-demand charging partition, it will cause no one unequal distribution of machine tasks.

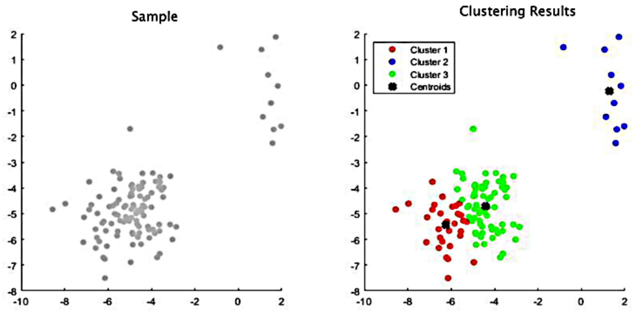

Fig. 4 K-means Non-uniform Clustering Diagram

In the non-deterministic WRSN charging scheduling based on the number of dynamic UAVs targeted in this paper, the unbalanced workload of UAV charging tasks will lead to uneven charging time, which will bring about scheduling problems: the probability of UAVs in the base station at the same time is lower, and it is more likely that fewer UAVs stay at the base station, that is, tasks are allocated by the waiting queue maintenance algorithm. Under the same energy demand, the number of UAVs is obviously smaller. A single UAV needs to cover a larger service area, and consumes more energy on the return journey of the node, resulting in a decrease in charging efficiency. Therefore, the clustering algorithm that can make the charging time of each UAV more equal can ensure that more UAVs participate in the task assignment in each task assignment, thereby bringing about a better charging scheduling effect.

In view of the traditional K-means algorithm that simply divides the samples according to the location, and does not take into account the problem of similar locations and equal charging time, this paper proposes an improved SPKM algorithm based on space-time partitioning, which comprehensively considers the node spatial location and the charging request execution time to divide charging tasks.

For each UAV, the execution time of its charging demand consists of two parts: the time on the journey and the charging time for the node. Considering that the former is much smaller than the latter, the charging time for the node is only related to the energy demand of the node. Therefore, the equal charging time of each UAV can be equivalent to the equal charging demand allocated to each UAV. Therefore, the optimization of the improved K-means algorithm proposed in this paper is that the energy metric and spatial metric are combined as the basis for the node to decide the partition division, so as to take into account the similarity in execution time between the partitions and the charging request within the same partition. The energy measurement is represented by the concept of energy offset, which is defined as the difference between the expected energy demand of the partition and the average energy demand after the node is inserted into a partition. The summation is used as the partition distance, which is the basis for the node partition in the algorithm iteration. The derivation process of the partition distance is as follows:

1. Define the calculation of average energy demand E_a of each partition based on energy demand of all nodes in the waiting queue, and the average number of requests N_a:

$$E_a = \frac{\sum_{i=1}^{|Qw|} E_{qi}}{K} \qquad (15)$$

$$N_a = \frac{|Qw|}{K} \qquad (16)$$

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2. Define the energy offset $S_{i,k}$, score the number of nodes n_k in the current partition of the partition C_k, and the total energy demand in the current area Eck, for the energy offset $S_{i,k}$ after the node oi is inserted into the partition C_k, its value is divided into two types Situation: when Eck + Eqi < Ea, take the average energy of nodes in the partition and multiply by the average number of requests, which is the expected energy demand of the partition C_k, and the absolute value of the difference between it and the average energy demand E_a is the energy offset; when Eck + Eqi ⩾ Ea, the actual energy offset can be obtained by direct subtraction. The formula for the value of $S_{i,k}$ is expressed as follows:

$$S_{i,k} = \begin{cases} \left| N_a \dfrac{E_{ck} + E_{qi}}{n_k + 1} - E_a \right|, E_{ck} + E_{qi} < E_a \\ E_{ck} + E_{qi} - E_a, E_{ck} + E_{qi} \geq E_a \end{cases} \quad (17)$$

3. Define the partition distance$D'_{i,j}$, which is the weighted summation of the energy offset $S_{i,k}$ and the Euclidean distance $D_{i,j}$, and score the partition C_k
The centroid of is $P_k(\bar{x},\bar{y})$. For the node $q_i(x_i, y_i)$, the energy offset $S_{i,k}$ is normalized with the Euclidean distance $D_{i,k}$ and the weighted summation is obtained to obtain the improved partition distance $D'_{i,k}$:

$$D_{i,k} = \sqrt{(x - x_i)2 + (x - y_i)2} \quad (18)$$

$$D'_{i,k} = \alpha D_{i,k} + (1 - \alpha) S_{i,k} \quad (19)$$

In formula(19), α is the distribution weight of Euclidean distance and energy offset. When 1 is taken, it is a common location-based K-means algorithm, and subsequent experiments will be carried out to determine the optimal distribution weight. The space-time partitioning K-means algorithm is described as follows:

Algorithm 2 space-time partitioning K-Means (SPKM)

Input: charging queue Q_w, UAV set S, node set, average energy demand avgNrg, average number of requests avgReqNum
Output: Partition result C

```
C[0…S]←null; clusterCenters←null; flag←true;
clusterEngs[0…S]←null; //store energy sum of each cluster
randomly select |S| clusterCenters
add clusterCenters into C
while flag do
    for o in O do:
        for center in clusterCenters do:
        /*calculate energe-distance according to formula(14) */
            calculate ergDis(o, cluster,ClusterEng)
            calculate uldDis(o, cluster)
            clusterDis←α·ergDis+(1-α)·uldDis
```

 doi:10.20944/preprints202209.0402.v1


```
            end for
        end for
        put o into nearest cluster s
        update clusterCenters, clusterEngs[s]
        flag = any center changed
    end while
```

3.3. Intra-Partition Online Path Planning Algorithm

After the partition is completed, the charging task of each partition is performed by the corresponding UAV, and the path planning within a single UAV partition, that is, how to properly determine the access order of nodes, is another major factor that affects the effect of on-demand scheduling. As mentioned in the previous section, the charging path needs to take into account the goals of maximizing energy utilization efficiency and maximizing charging success rate. Existing schemes such as multi-objective discrete fireworks algorithm [29] and multi-objective ant colony algorithm [30] can achieve excellent results. However, the calculation is complicated, and it needs to be recalculated when the charging queue is adjusted. Therefore, this paper proposes an online path planning algorithm based on a greedy strategy to obtain a better path plan with a lower computational delay.

The main process of the path planning algorithm is to determine the next charging node of the UAV based on the established strategy at each step, and then form the UAV path. In this algorithm, the selection of the next charging node is divided into three categories: 1) is the node closest to the current location, selecting such a node can bring lower path cost and make the overall energy efficiency higher; 2) it is the nodes that die without charging in time, in most networks, the long-term dead time of the node will significantly affect the quality of service, so such nodes should be charged first when conditions permit; 3) the charging request is relatively urgent, if not charged in time, there will be shortages Electrode-dead nodes, so such nodes should be given a higher charging priority. In this paper, the priority of node selection is set to 3>2>1, that is, when selecting the next charging node, the node with urgent charging request is selected first to avoid the situation of power shortage and death, followed by the dead node to avoid node death if the time is too long, when there is no dead node, select the node closest to the current position to keep the path cost as low as possible. Both categories 1 and 2 are clearly defined, and how to decide whether a charging request is urgent is a key issue. In this paper, if a node's power is insufficient to support its operation to the next charging selection, its charging request is regarded as an urgent charging request. Iteratively execute the above node selection process to obtain the charging path of the UAV. The set C of nodes to be charged in the score area is recorded, and the path planning algorithm is divided into 5 steps as follows:

Step 1: Update the node status, calculate the power exhaustion time of each node according to the remaining power of the node and the power of the node, that is, the death time, record the death time of node i t_d^i, and calculate the estimated power exhaustion time of all nodes in the charging zone according to the latest far ordering is sequence Q_d;

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Step 2: Determine the preliminary candidate node. If there is a dead node in C, select the node closest to the current position from the dead node as the candidate node, otherwise directly select the closest node, and denote the candidate node as c, which can be calculated by formula (3) the time t_e^c when the UAV is expected to finish charging node c;

Step 3: Judging the urgency of charging, considering that the time for the UAV to charge the node is much longer than the time for the UAV on the path between nodes, the charging time is regarded as the total time that the UAV serves the node, and the candidate whether node c as the next charging node will cause the death of the first node in Q_d, that is, whether t_e^c is earlier than the earliest death time in Q_d:

$$\min\{Q_d\} < t_e^c \qquad (20)$$

If the above formula is true, no other nodes will die during the charging period for candidate node c, then node c is directly used as the next node. Select the node closest to the current position in the node set earlier than t_e^c as the next node n;

Step 4: Add node n to the charging path, update the remaining energy after UAV service n according to the distance from the current position to n and the energy consumption demand of node n, take node n as the current position, and return to step 1 until the collection all nodes in C are placed in the path, or the UAVs expected to have insufficient power to support more charging requests, and put the nodes in C that have not entered the path back into the waiting queue for rescheduling;

Step 5: The UAV charges the nodes according to the access sequence of the path, until the execution is completed, and returns to the base station. Go back to step 1 when waiting for an incoming emergency charging request from the queue maintenance algorithm. The algorithm is described as follows.

Algorithm 3 Online Path Planning

Input: set C to be charged, base station location BS, UAV battery capacity Eu, waiting queue Q_w
Output: Charge Path Path

curNode←BS; nrg←Eu; Path←null; Q_d←nul;
while (nrg > 0 and C not null) or urgentRequest added to C **do** //nrg is UAV's electricity
    if exist dead node in C **then**
        candidate←nearest dead node
    else
        candidate←nearest node
    end if
    $t_e^c \leftarrow ER_c/Pr$ //calculate when charge on candidate ends based on formula(3)
    update Q_d on starvation time
    if min(Q_d) < t_e^c **then**
        candidate←nearest node n in $\{n \mid Qdn < t_e^c, n \in C\}$
    end if
    /*consider schedule ability based on formula (9)*/

```
update nrg = nrg-nrgDemand(candidate)-nrgDis(curNode, candidate)
if nrg < 0 then
    break; //if not schedulable, stop Path calculating
end if
add candidate into Path;
remove candidate from C;
end while
if C not null then //put unserviceable node back into waiting queue Q_w
    put C into Q_w
end if
```

The overall process of the UOCS on-demand charging scheduling scheme proposed in this paper is shown in Figure 5, which consists of three parts: waiting queue maintenance (algorithm 1), space-time partitioning (algorithm 2), and path planning (algorithm 3). The number of nodes is recorded as n, and the main work of algorithm 1 is to dynamically maintain the minimum spanning tree. Here, the heap-optimized Prim algorithm is used to implement the time complexity of O(nlogn). It is executed once for each inserted node, so the overall time complexity is O(n^2logn). Algorithm 2 improves the distance calculation of the K-means algorithm, and the complexity is the same as that of the classical K-means. The number of UAVs is recorded as k, the number of iterations is t, and the complexity is O($n \cdot k \cdot t$). The main work of Algorithm 3 is the comparison of node death time based on insertion sorting, and the complexity is O(n^2). The overall time complexity of the algorithm is O(n^2logn). When the UAV charges a node, it is automatically recorded, and it will not be charged repeatedly, and for the flight trajectory in a large area, the flight height can be ignored for plane path planning.

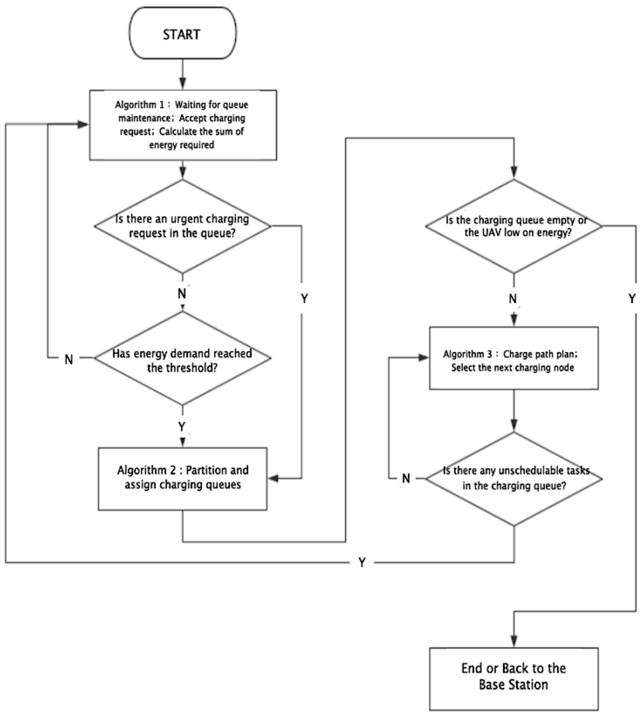

Fig. 5 Flow Chart of On-demand Scheduling Scheme.

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4. Experiment and result analysis

This section tests the performance of the UOCS scheme in terms of the number of starved nodes, charging success rate and charging time, and compares it with other related schemes. The number of starved nodes represents the number of nodes that fail due to insufficient energy in a charging cycle; the charging efficiency represents the percentage of the total energy that the UAV supplements for nodes in the network to its own total energy consumption in one charging schedule; the charging time refers to the UAV from the time for starting from the base station and returning to the base station after completing a round of charging.

4.1. Parameter Settings

The parameters required for experiment are shown in Table 2:

TABLE II : Parameter Settings

Parameter	Description	Value
A	Wireless rechargeable sensor network area	1000m*1000m
n	Total number of sensor nodes	[100，500]
Eu	UAV carries total energy	15000J
Ei	Energy when the sensor is fully charged	30J
v	UVA flight speed	5m/s
Cv	UAV flight energy consumption	125J/s
Cx	UAV hovering energy consumption	3J/s
Ci	UAV charging energy consumption	5J/s
a	Charging parameters	100
S_v	Sensor energy consumption	[0.2-0.3] J/s
S_x	UAV energy consumption per take-off and landing	300 J

4.2. Algorithms to Compare

This paper uses K-means, mTS[36], and Pushwait[38] schemes for comparative experiments.

4.3. Experimental Results and Analysis

The experimental scene is a 1000*1000m WRSN, and sensor nodes with different residual energy are randomly distributed among them. In view of the fact that the traditional K-means algorithm cannot take into account the equalization of all UAV tasks when it is applied to charging distribution, an improved SPKM partition algorithm is proposed. Figure 6 compares the uneven distribution of 50 charging requests in the monitoring area.

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The node energy is 30%, and the charging task is allocated to three UAVs. The partition results of the K-means algorithm and SPKM, where the partition distance distribution weight α of SPKM is 0.5. It can be seen that in the results of the K-means algorithm, the distribution of nodes in the three partitions is quite different, partition 1 is assigned more charging tasks, while partition 2 and partition 3 have relatively few tasks, while in the SPKM algorithm in the result, partitions 2 and 3 are assigned more tasks, and the nodes whose partitions are changed are marked with arrows, and the three partitions are more balanced than K-means.

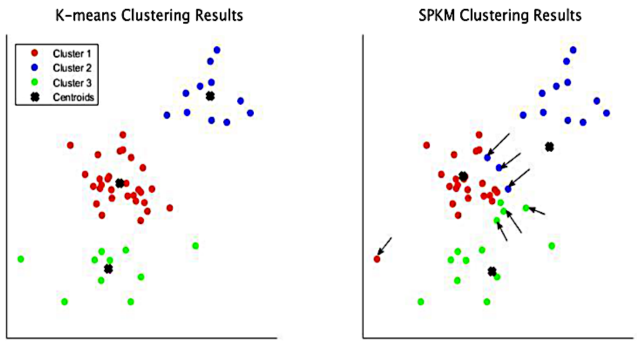

Fig. 6 Comparison of Partition Results Between K-means and SPKM.

In addition, before carrying out the comparison experiment, it is necessary to determine the value of the Euclidean distance and the energy offset distribution weight α in the SPKM algorithm, as shown in Figure 7. The charging success rate and energy efficiency under 0.9 determine the trade-off between the two goals. Within a certain range, with the increase of the α value, the partition will pay more attention to the task allocation among multiple UAVs. Balance degree, and make the UAV charge the nodes farther away to eliminate the uneven distribution of tasks, and sacrifice energy efficiency to bring a higher charging success rate. At the same time, it is noted that when α is set to 0.9, the energy efficiency and the charging success rate are both lower, because at this time, the partition algorithm focuses too much on the equal division of tasks and ignores the similarity of the geographical location of nodes in the partition, resulting in the partition being too scattered and making the UAV unmanned. More energy is consumed on the charging path, resulting in a shortage of charging resources and the inability to respond to charging requests in time. When α is set to 0.1, the charging success rate is too low, because the charging task division is not well balanced at this time, and the total idle time is prolonged when each UAV partition is unbalanced, and it is also unable to respond to charging requests in time. Therefore, the value of α should not be too large or too small, in order to take into account the goals of energy efficiency and charging success rate, and α is set to 0.5 in the subsequent experiments.

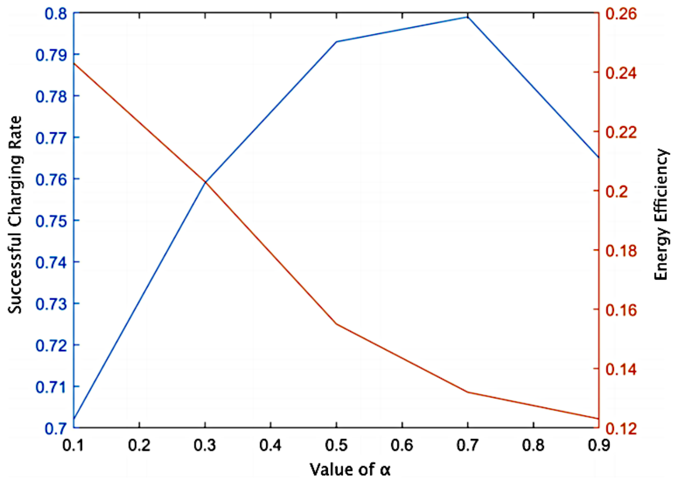

Fig. 7 Successful Charging Rate and Energy efficiency Under Different Values of α.

Figures 8 and 9 respectively show the charging success rate under different network scales, compared with the total idle time of the UAV. When the number of nodes is small, the charging success rate of the three algorithms is higher, and as the number of sensor nodes gradually increases , the increase in charging requests, the mTS algorithm and the Pushwait algorithm always need to wait for all UAVs to return to the base station and then perform scheduling, resulting in a large number of nodes not charging in time and dying, while the UOCS algorithm in this paper has always maintained a low waiting time, making full use of the charging resource ensures a higher charging success rate when the charging request increases.

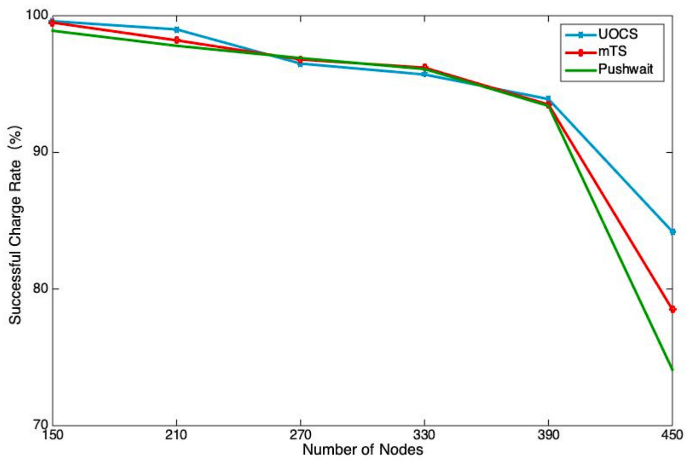

Fig. 8 Successful Charge Rates Under Different Network Scales.

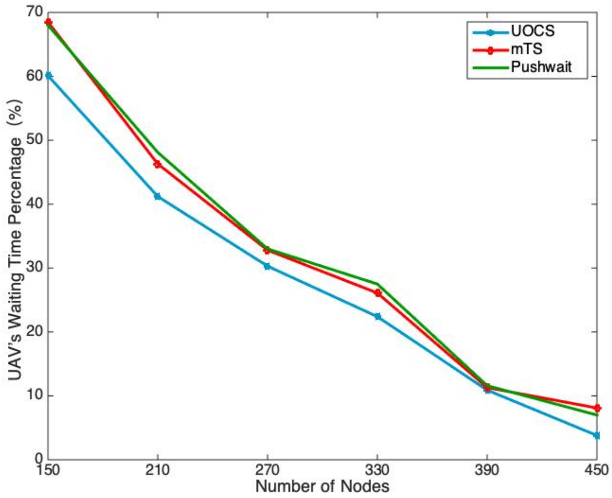

Fig. 9 UAV's Waiting Time Under Different Network Scales.

Figure 10 compares the energy efficiency of different network scales. Overall, the energy efficiency of the mTS algorithm is higher than that of Pushwait, while the UOCS algorithm is not much different from the two when the number of sensors is less than 330, and then is relatively low. When charging requests are frequent, the UOCS algorithm based on the number of dynamic UAVs sacrifices the effect of partition to ensure timely response, so that nodes with farther distances are assigned to the same partition, resulting in an increase in mobile energy consumption. Achieving a more efficient charging schedule when requests are intensive is an improvement direction in future.

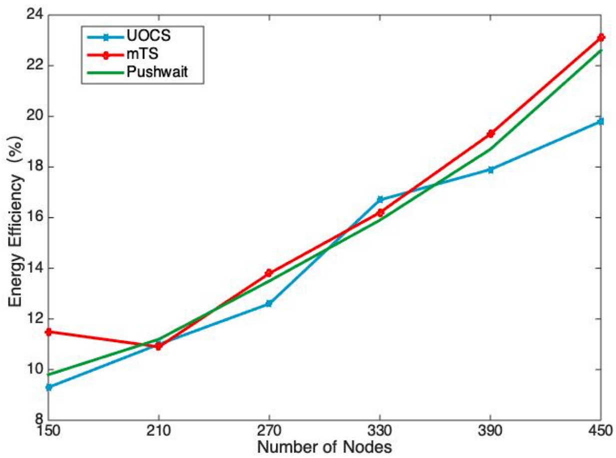

Fig. 10 Comparison of Energy Efficiency Under Different Network Scales.

5.CONCLUSION

Aiming at the limited energy of sensor nodes in small and medium-range wireless rechargeable sensor networks, this paper proposes a spatiotemporal coordinated on-demand charging scheduling algorithm UOCS based on the number of dynamic UAVs. The scheme combines the waiting queue and the number of UAVs to select the allocation timing, and the improved K-means partitioning based on space-time coordination, which simplifies the problem of multi-UAV cooperative charging. Compared with the existing schemes, UOCS achieves the optimal node survival rate with lower algorithm complexity and minimum charging cost.

At the same time, UOCS has room for improvement in energy efficiency. First, there is room for optimization in intra-cluster path planning. For example, meta-heuristic algorithms, reinforcement learning, etc. can be used to plan better paths. Second, how to better coordinate tasks when charging requests are dense. Distribution to achieve better energy efficiency is the focus of future work.

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