# Wireless Charging Based Sensor Network Information Collection Through Unmanned Aerial Vehicles (UAVs)

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**Abstract.** In recent years, the proliferation of commercial unmanned aerial vehicles (UAVs) has led to the widespread adoption of wireless charging technology, fostering their increasing application in various domains. This trend has made UAVs increasingly suitable for replacing conventional information collection vehicles in wireless sensor networks, particularly in scenarios where sensors possess both sensing and communication capabilities. In this paper, we discuss the minimum information collection time for a large-scale wireless sensor network consisting of multiple mission UAVs and one charging UAV. The mission UAV is responsible for collecting data from each sensor, and the wireless charging pile is used to replenish power to the mission UAVs, in order to minimize the completion time of the mission UAVs. First, a modified *k-means++* clustering algorithm is utilized to assign sensor nodes with the number of clusters equal to the number of mission UAVs. The process of collecting sensor information within a certain range by the mission UAV is modeled as the traveling salesman problem (TSP). Then, we propose the concept of virtual center node which is found by using a gradient descent algorithm. We compare the performance of using a charging UAV to charge a mission UAV with three other methods, i.e., establishing a fixed charging pile to charge mission UAVs, and mission UAVs go back to original base station for charging, and combining both the charging UAV and a fixed charging pile. The experimental results show that the combination of a charging UAV and a charging pile outperforms the other three methods in reducing the completion time of mission UAV.

**Keywords:** UAV · Wireless Charging · Clustering · Data Collection

## 1 Introduction

### 1.1 Background

In recent years, wireless energy transmission technology has seen significant advancements. Due to the relatively limited power capacity of unmanned aerial vehicles (UAVs), the utilization of wireless charging technology to enhance UAV


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performance is becoming a prominent future trend. For example, magnetic resonance coupling technology works on the principle of resonant coupling, about 40% of non radiant power transmission efficiency can be achieved between two strongly coupled objects when the distance exceed 2 meters [1]. When applied to smaller devices, magnetic resonance coupling can achieve an impressive energy transfer efficiency of 60%, presenting a feasible avenue for using wireless charging technology to recharge UAVs [2]. Another approach to enable wireless charging over long distances involves using a laser beam from a ground station to charge the UAV while it is in flight [3,4].

Utilizing the aforementioned wireless charging technology to replenish the energy of UAVs offers numerous advantages, extending the UAVs' usability and enabling them to perform various tasks more effectively, such as information collection [5], serving as aerial bridging stations to support communications [6,7]. However, in scenarios where UAVs lack sufficient energy to complete their missions, the current mainstream approach involves returning to the base station for recharging, setting up fixed wireless charging piles which allows UAVs to recharge in-flight. Nonetheless, the issue of energy efficiency remains unsolved. The challenge arises because fixed base stations or charging piles are stationary, requiring UAVs to expend significant energy to travel to these fixed locations for recharging. This process not only adds to the mission time but also diminishes the energy efficiency of the UAV's overall operation. Consequently, this limitation hinders the UAV's ability to operate optimally and efficiently during critical missions. As a result, finding innovative solutions to address the energy efficiency problem is imperative to enhance the UAV's performance and extend its operational capabilities.

Recently, with the development of wireless charging technology, modules consisting of receiving antenna arrays, rectifiers and power management circuits have been implemented on UAVs, receiving microwave power and converting it to DC power to charge the UAVs [8]. Distributed laser charging can also be used as a wireless charging solution [9]. These new wireless charging methods make it possible to use one UAV to charge another [10]. UAVs that perform tasks such as data collection are known as mission UAVs, and the one that charges mission UAVs is known as charging UAV. The use of chargeable UAVs to charge mission UAVs eliminates the need for mission UAVs to travel to a base station or fixed base pile for recharging, and improves energy utilization without requiring the mission UAVs to travel to and from the base station. Instead, they can wait for the rechargeable UAVs to arrive at their current location to replenish their energy. The cost of constructing a fixed base station can also be reduced in the case of charging UAVs only.

In this paper, we discuss the UAV charging scenario in the context of wireless sensor networks collecting outdoor information. In this application scenario, the sensor nodes are distributed in a fixed area. We use multiple mission UAVs to collect the sensor network information, and the mission UAVs can either travel to a fixed charging pile to charge, or one charging UAV can charge the mission UAVs to minimize the time for the mission UAVs to complete the mission.

In sensor networks where multiple UAVs collect information from sensor nodes, we assume that UAVs cannot reach all sensor nodes at once. We discuss the minimum mission time for the following three scenarios: the UAV returns to the initial base station in time to recharge, returns to the fixed base pile and uses both the fixed base pile and the recharging UAV at the same time.

The goal is to minimize the time taken by the mission UAVs to complete their tasks. As the time taken by the mission UAVs to collect information at the sensors is much less than the flight time, we ignore it in order to simplify the computation. In the paper, we first equalize the amount of tasks for each mission UAV. Since there is only one charging UAV, the mission UAV may wait long time for the charging UAVs' arrival. Therefore, the location of the fixed charging pile is crucial to enable the mission UAVs reach the fixed charging pile faster. The mission UAVs and charging UAV find suitable scheduling strategies to minimize the completion time of the last mission UAV to improve the efficiency of the whole system.

## 1.2 Main Contributions

In this paper, we consider the location of the fixed Charging piles, data collection from sensors by mission UAVs, and path planning for charging UAVs. The main contributions are as follows:

- *Rational categorization of the sensor nodes.* In previous work, the sensors are usually distributed equally according to their number, which does not take into account the location of the sensors from the origin base station, resulting in a larger load for UAVs that are far from the origin base station. In this paper, distance from the origin base station is used as one of the factors to categorize the sensors, and each mission UAV is responsible for collecting a class of sensor information.
- *Proposition of the concept of virtual center.* While performing information collection tasks, the mission UAVs can call the charging UAVs, especially when they do not have enough power to return to the base station. However, the charging UAVs may not be able to fly from one mission UAV to another in time if the distances between them are far apart. By gradually moving closer to the virtual center while performing the tasks, the charging UAV can reach the mission UAV in time. Additionally, establishing the charging pile at the virtual center node can reduce the travelling time for the mission UAV to charge.
- *Path optimization for the mission UAV.* In each cluster, the mission UAV need to reach every sensors in the cluster once. The path for the mission UAV is optimized to reduce the flight time between the charging UAV and the mission UAVs, as well as the time of mission UAVs flying to the charging pile.

### 1.3 Related Work

The energy of the UAV is an important limiting factor for the UAV to collect information [11]. For some large wireless sensor networks, a single UAV cannot accomplish the task of collecting information from all sensors in a short period of time. Yang et al. [12] use UAV to provide IoT communications and maximize network energy efficiency by optimizing the trajectory of the UAVs and other practical. Li et al. [13] present the main concern for information collection by UAVs in emergency situations is the time to complete the mission, and propose a method for UAVs to help information collection from ground users, optimizing the trajectory, altitude and speed of the UAVs. Zhan et al. [14] propose a wake-up scheduling approach using jointly optimized UAV flight trajectories and sensors to minimize the UAV information collection time and thus reduce the energy consumption of the UAV. Jie et al. [15] considered the problem of minimizing the time for a UAV to complete a information collection task in a network of sensors on a straight line.

Due to the energy constraint of UAVs, the use of wireless charging is an promising way to address the lack of capability in UAV missions. Wireless charging technology is developing rapidly and is being used in many areas. There are many kinds of wireless charging technologies, including non-directional RF energy transfer [16], electromagnetic induction [17]. Moreover, some new wireless charging technologies emerge in recent years, such as laser power transfer, distributed laser charging [9], simultaneous wireless information and power transfer [18]. Hua et al. [19] use a relay network with malicious amplification and forwarding to replenish the UAV and maximize network throughput. Zhang et al. [9] propose a multi-module distributed laser charging model and derived the maximum power transfer efficiency, which is shown to depend on the power supplied by the transmitter, the laser wavelength, the transmission distance et al. Zhu et al. [10] propose the concept of using one UAV to charge another UAV on a controlled mission by means of wireless charging technology, with the aim of minimizing the time it takes for the mission UAV to complete the mission. Mission UAVs can be used to perform functions such as collecting sensor information or communicating with sensors for data.

Gui et al. [20] use a UAV-assisted approach to collect data from the machine. However, as the power of the UAV is limited, which machine to visit is constrained by the remaining battery power, the location of the machine, and the quality of the data. The problem of mission UAV flight path planning can be converted to a TSP problem in tasks where the goal is to minimize the time of collecting data by the mission UAV. A lot of previous work has discussed the problem of electricity shortage. Shen et al. [21] propose clustering-based service strategies and adynamic trajectory planning algorithms, which dynamically adjust the hovering position of the UAV providing the data collection task to maximize the data collection efficiency. Di et al. [22] propose an energy-aware path planning algorithm to maximize the reduction of energy consumption. Liu et al. [11] consider the flight speed of the UAV, the hovering position and access sequence, the information age, and the recorded energy of the UAV, and solve the UAV speed and path planning problem by using a continuous convex approximation method and a genetic algorithm. Chai et al. [23] propose a solution for joint path optimization and wireless communication network for multiple UAVs, and obtained a decentralized solution with reduced complexity by mean-field equilibrium analysis, and the simulation results show that the proposed solution is better than the existing methods. All these methods present good solutions for path planning of UAVs in specific scenarios. Different from previous works, this paper consider not only the paths of the mission UAVs, but also the paths of the charging UAV and the deployment of the fixed charging piles. Unreasonable deployment of fixed charging pile can lead to longer waiting time for the charging UAV to charge mission UAVs and longer time for mission UAVs to travel to charging pile, resulting in longer time for the last mission UAV to complete the mission.

The rest of this paper is organized as follows. In Sect. 2, we improve the *k-means++* algorithm by dividing the sensors into proper different clusters to balance the load of the mission UAVs, and use the gradient descent method to find the virtual node. In Sect. 3, we conduct experiments to evaluate the results. Finally the paper is concluded in Sect. 4.

## 2 System Model

The limited power capacity of UAVs necessitates the need for an efficient approach to collect information from a large sensor network. To achieve this, the sensor network is classified using the *k-means++* algorithm, providing an initial segmentation of the sensors. If the sensors are farther away from the origin base station, the UAV will consume more energy in the process of traveling to the long-distance sensors to collect information. Thus, we assign fewer sensors to the UAV responsible for long-distance sensor data collection than the UAV responsible for the closer sensor data collection to balance the load of the UAVs as much as possible. After the allocation is completed, each UAV uses a greedy strategy to select a suitable path for the sensors in the responsible area to perform the information collection task. The network configuration is illustrated in Fig. 1.

The overall idea of the whole paper from sensor classification, the concept of minimum point, reclassification of individual sensors, the concept of the virtual center node, mission UAVs path planning approach, and mission UAVs charging method is as follows:

- *Step 1.* The sensors are classified using the *k-means++* algorithm, which reduces the negative impact of randomly selecting the initial clustering centers compared to the *k-means* algorithm.
- *Step 2.* The coordinate point in each category with the smallest distance from all sensor locations, called the minimum point, is found by gradient descent, and the mission time required to collect sensor information for each cluster is calculated using the greedy algorithm.

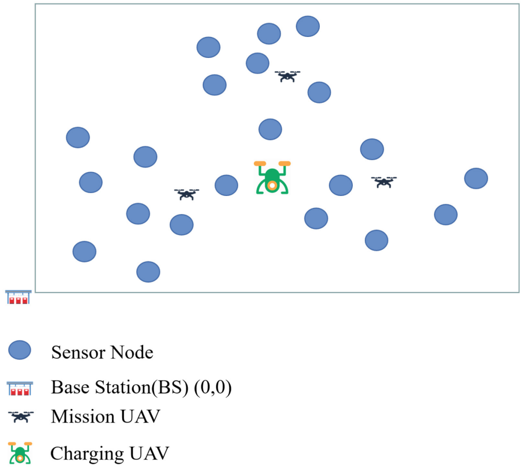


**Fig. 1.** Illustration of network components.

- *Step 3.* Calculating the variance of the mission time for each cluster and setting a threshold, if the variance is larger than the threshold, assigning a sensor from the cluster with the largest mission time to each of the other clusters, which is the one with the smallest distance from the minimum point of the other clusters' center, and re-calculating the variance until it is smaller than the threshold or after $n$ rounds of loops.
- *Step 4.* The point with the smallest distance from the minimum point in all categories is found and is called the virtual center node.
- *Step 5.* Path planning is performed for the order in which the UAVs in a specified cluster collect sensor information, and the UAVs in each cluster start from the sensor closest to the origin base station and use a greedy strategy to select the next sensor, and if two sensors with the same distance are encountered, the sensor closer to the origin base station is prioritized.
- *Step 6.* The charging UAV flies to the virtual center node and arrives at the location of the mission UAV in time when the mission UAV is low on power, or the mission UAV goes to the fixed charging pile to replenish the power using wireless charging technology.

### 2.1 Sensor Clustering

The *k-means* algorithm is a simple and practical classification algorithm, but the results are easily influenced by the selection of the initial points. A poorly chosen initial clustering center chosen at random may have a relatively large impact on the results. Therefore, we utilize the *k-means++* algorithm to cluster the sensors. The clustering sensors is as follows:

- *Step 1.* Randomly selecting a sensor from the sensor network as the first cluster center.

- *Step 2*. Calculating the shortest distance between each sample and the currently existing clustering center, denoted as $D(x)$, and calculate the probability $\frac{D(x)^2}{\sum_{x\in X} D(x)^2}$ of each sample being selected as the next clustering center, and select the next clustering center according to the roulette wheel method.
- *Step 3*. Repeating the second step until $k$ clustering centers are found.
- *Step 4*. Assigning each sensor to a cluster, calculating the Euclidean distance between each sensor and clustering center, and assigning it to the cluster corresponding to the closest clustering center.
- *Step 5*. Updating the clustering center of each cluster to the average of all points in that cluster.
- *Step 6*. Iterating *step 4* and *step 5* repeatedly, if the distance between the new clustering center and the previous clustering center is less than a certain threshold, the clustering algorithm is considered to have achieved the desired result and the algorithm stops, otherwise continue iterating.

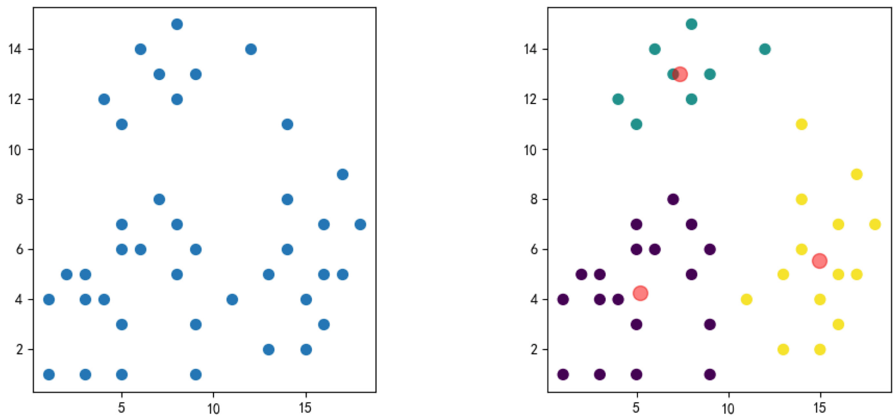


**Fig. 2.** Sensor classification effect with $k$-means++.

The use of the *k-means++* algorithm enables the selection of more appropriate initial clustering centers and reduces the influence of the clustering centers on the results due to randomly taken values.

Figure 2 shows the result of *k-means++* classification algorithm. Different from the *k-means* algorithm, by selecting the initial points, *k-means++* significantly improves the classification results. However, in the sensors network, it may lead to a more uneven allocation of nodes to each cluster. The procedure of the improved classification method is summarized as follows:

- *Step 1*. Starting from the base station, traversing the sensors of each cluster and returning the base station. The point closest to the starting point of each cluster is the first sensor to be accessed, and a greedy strategy is used to

determine the next sensor to be accessed. When equal distance sensors are encountered, the sensor closer to the base station is selected.
- *Step 2*. Calculating the center point of each cluster that has the smallest distance from the points in current cluster.
- *Step 3*. Calculating the standard deviation of the traversal length of each cluster. If the standard deviation is greater than the threshold, the cluster with the maximum traversal length will allocate one sensor to each other cluster, and the allocated sensor is the one closest to the other clusters.
- *Step 4*. Repeating *step 1*, *step 2* and *step 3*, until the standard deviation is less than the threshold or after updating $k$-1 times.

As shown in Fig. 3, there are two sensors assigned to a new cluster i.e., transferring from Cluster 3 to Cluster 1 and Cluster 3 to Cluster 2, respectively, trying to balance the workload of each mission UAV.

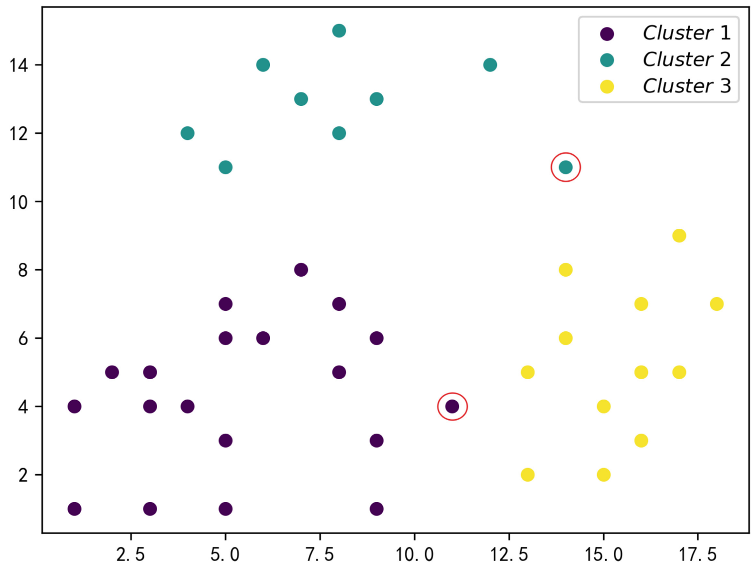


**Fig. 3.** Improved classification sensors.

The comparison between Fig. 2 and Fig. 3 shows that further classification enables the classes closer to the base station to be assigned more sensors, reducing the load on the mission UAVs responsible for long distance cluster. It also benefits the path planning for charging UAVs, which will be discussed in Sect. 3.

### 2.2 Virtual Center Node Selection

In order to find the virtual center node, note that it is the point with the smallest sum of distances from all clustering centers, which can be treated as an optimization problem. Define the objective function as the sum of the distances from the current position to all clustering centers. Suppose that there is a set $S$ and the coordinates of the clustering center point are $(x_i, y_i)$, and the objective is to find the point $(x, y)$ such that the objective function $F(x, y)$ is minimized, which is given as follows:

$$F(x,y) = \sum_{i=1}^{n} \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{1}$$

Assume that there are $n$ clustering centers, Eq. (1) represents the sum of the distances to all clustering centers. The gradient descent algorithm is used to solve this problem by computing the derivative of the objective function with respect to the variables and updating the values of the variables in the opposite direction of the gradient, gradually approaching the optimal solution. The specific steps are as follows:

$$x = x - \alpha \frac{\partial F}{\partial x} \tag{2}$$

$$y = y - \alpha \frac{\partial F}{\partial y} \tag{3}$$

- *Step 1.* Initializing the coordinates to be optimized $(x, y)$.
- *Step 2.* Calculating the gradient of the objective function with respect to $x$ and $y$, calculating the partial derivative of $F(x, y)$ with respect to $x$ and $y$.
- *Step 3.* Updating the values of the variables according to the direction of the gradient and the learning rate $\partial$. Equation (2) and Eq. (3) represent the updated values of $x$ and $y$ along the direction, respectively.
- *Step 4.* Repeating *step 2* and *step 3* until a predetermined number of iterations is reached or certain termination conditions are qualified.

The gradient descent algorithm gradually approaches the minimum point of the objective function by updating the values of the variables and finds the position of the point with the smallest distance from all the prime points. The location is defined as the virtual center node, the fixed charging pile location is set at the virtual center node, and the charging UAV is set at the virtual center node at the beginning, thus the charging UAV can reach the mission UAV faster, and the mission UAV can reach the fixed charging pile for charging faster.

### 2.3 Virtual Center Node Optimization

In previous work, it has been discussed how to classify the sensor network in a rational way and a virtual center node has been proposed as a fixed charging pile and the node is found using the gradient descent method. However, even the mission UAV is fully charged when it departs from the origin base station, the mission UAV often needs to be recharged at a later stage. Therefore, taking all points into account when finding the virtual center node may result in the fixed charging pile being farther away from the mission UAV that needs to be charged, as well as the charging UAV taking longer to reach the mission UAV, which leads to a longer time to complete the mission.

In the following, we will take the last, penultimate, and penultimate third of each cluster–until the number of sensors in a given cluster is all considered as an influencing factor for the virtual center node. As a comparison with the virtual center node formed by the entire sensor network together, the location of the fixed charging pile with the minimum time to complete the information gathering task is found out, as shown in Fig. 4. Note that even though Cluster 2 has only 9 sensors, the number of sensors is equal to 10 in Fig. 4, including all sensors to compute the virtual center node.

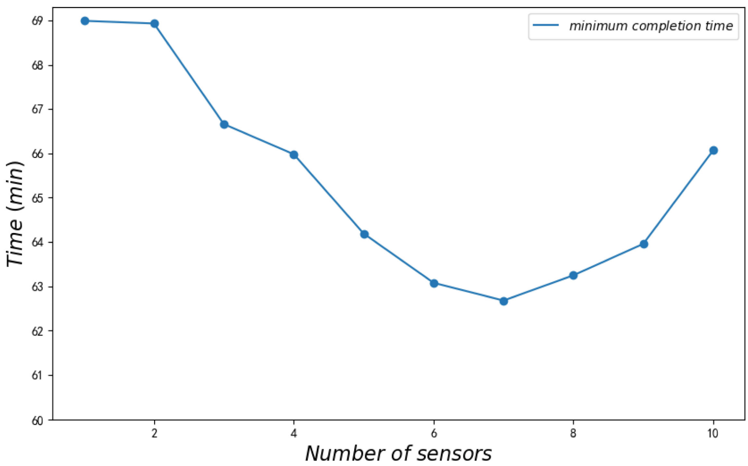


**Fig. 4.** Relationship between minimum completion time and number of sensors.

## 3 Experimental Results

In this section, we conduct experiments to verify whether the virtual central node can help reduce the energy consumption of charging UAVs, support more mission UAVs, and ultimately reduce the overall information collection time.

Algorithm 1 illustrates how to perform path planning for mission UAVs within a cluster in a better classified sensor network and select the appropriate charging method, i.e., using a charging UAV or a mission UAV going to a fixed charging pile to charge, to minimize the maximum mission. Before starting the information gathering task, the mission UAV departs from the origin base station and travels to the closest sensor in the cluster to perform the information gathering task, setting the distance to the current sensor to infinity if a sensor has already been visited, and placing the sensors that have already gathered information in the visited set. If the mission UAV's energy is below a certain

**Algorithm 1.** Path Planning

**Input:** position of charging pile at node $p$, sensors position set $S$, sensors distance matrix, mission UAV leftover lifetime $T$, UAV start point;
**Output:** Path $P$.

Initialize minDist $= \infty$, $i = 0$, total cost $R_t = 0$;
**function** FINDER$(p, T, S)$
    **while** $S \neq \emptyset$ **do**
        compute cost $c_{ij}$
        **if** $j \in visited$ **then**, $c_{ij} = \infty$
        **end if**
        find $j \leftarrow \arg\min\ c_{ij}$
        **if** $t_{i0} + t_{ij} > T_i$ **then**
            fly to charge or wait charging UAV flying to position $i$
            **continue**
        **else**
            $R_t \leftarrow R_t + c_{ij}, S \leftarrow S - j$, $visited \leftarrow j$, update $T$
        **end if**
    **end while**
    compute total cost $(R_t)$
    **if** cost$(R_t)$ $<$minDist **then**
        minDist $\leftarrow$ cost$(R_t)$
    **end if**
**end function**

value, the mission UAV can call a charging UAV to replenish its energy, or travel to the fixed charging pile to recharge.

In the experiment, we utilize the parameters of the latest UAV from DJI, and its energy consumption index is shown in Table 1. Short charging distances are more suited for laser transmissions that can fully charge mission UAV in a short period of time. All groups, in all ways, have shorter time than BASELINE in all cases, except for group 1, which ended up with a slightly higher completion time when charging with the charging UAV alone than the completion time of the mission UAV returning to the base station for charging. This shows that the use of wireless charging technology is able to reduce the mission completion time of the last mission UAV.

The sensor network is divided into three groups, using the improved *k-means++* algorithm from earlier to compare the four methods. *Baseline* mode means the time used by the mission UAV to return to the base station with insufficient power before proceeding to the next sensor and completing the mission. *CUAV* mode means the time used by the mission UAV to wait for the charging UAV from the selected fixed base station to arrive at the mission UAV's location to charge it and finally complete the mission when it is low on power. *Ground* mode means the time of the mission UAV taking to the selected fixed pile to recharge the mission UAV when its battery is low, then continue the task and return to the origin base station. *Ground + CUAV* mode means using both *Ground* and *CUAV* to reduce the mission time. Note that the virtual center

**Table 1.** Parameters of DJI UAV in experiments

| UAV | MAVIC 3 Pro |
|---|---|
| Weight/$kg$ | 0.958 |
| Flying time/$min$ | 43 |
| Battery capacity voltage/$mAh$ | 5000 |
| Maximum charging power/$W$ | 100 |
| Battery max voltage/$V$ | 17.6 |

node is calculated by using the coordinates of all the sensors. The result of the experiment is shown in the Fig. 5.

The result shows that the mission completion time of all groups of the three methods is less than the *Baseline* except *Group* 1 of the *CUAV* mode. The mission completion time in the *Ground+CUAV* mode is shorter than the rest methods, which indicates that the use of the combination of the charging UAV and the ground pile is very effective and in line with our preliminary discussion.

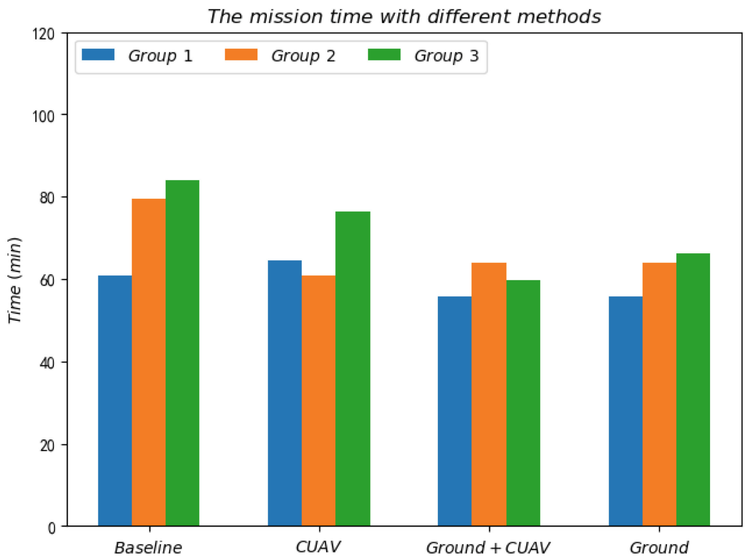


**Fig. 5.** Improved classification sensors.

Figure 6 shows the maximum and minimum completion time for the different groups under each mode, and the variance of the completion time in the groups under each mode is calculated. Using a combination of charging UAVs and fixed pile is able to minimize the standard deviation of the completion time for each

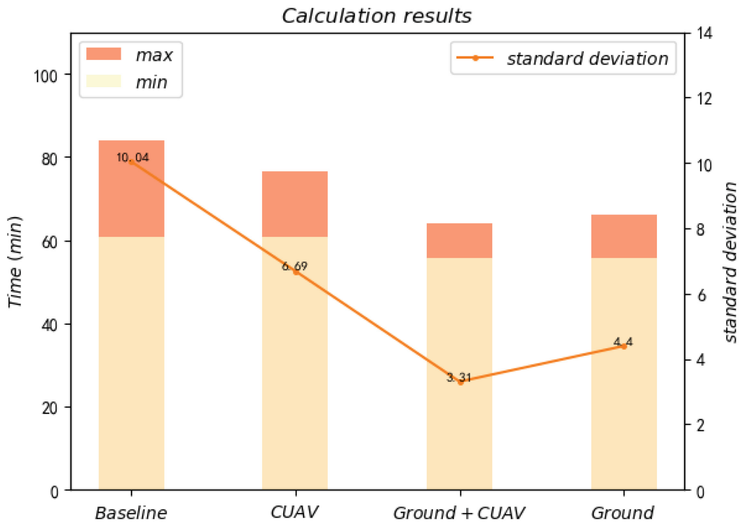


**Fig. 6.** Data under different modes.

mission UAV, indicating that the loads of each the mission UAV are close to each other. In addition, both the maximum mission completion time and the minimum mission completion time are smaller than other approaches.

## 4 Conclusion

This paper discusses the problem of minimizing the mission UAV information collection time for a sensor network consisting of mission UAVs, a charging UAV and a fixed charging pile, and sensors. For a known fixed sensor network, the sensors are first classified in an initial way using the *k-means++* clustering algorithm. Then, in order to balance the load of each mission UAV, the approximate time required by each cluster is calculated, and an algorithm is proposed to reduce the difference in the mission time required by each cluster. Path planning is performed within each cluster using a greedy algorithm, and the minimum mission completion time and the standard deviation of the mission completion time are compared under four different approaches. The results show that using charging UAVs combined with the fixed charging pile can minimize the maximum mission UAV completion time.

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