Wireless Sensor Network Charging Strategy Based on Modified Ant Colony Algorithm

Chao Ma, Siguang An, Wei Wang, Dehui Lin, Mei Li, and Lihong Sun

***Abstract*—Using mobile charging devices to provide controllable and sustainable energy to Wireless Sensor Networks (WSN), has become an important topic of current research. A novel charging strategy based on the mobile device is proposed to add the net increase in network power. To improve the charging efficiency and avoid unnecessary charging, a charging threshold is evaluated and determined. A Modified Ant Colony Optimization (MACO) is introduced to minimize the travelling distance of the mobile charging device. A dynamic state transition rule, which considers the real-time power of the nodes is developed in MACO to guide the charging path of the mobile charging device. The sustainability of the WSN using the proposed charging strategy is also studied. A WSN model with 50 nodes and one mobile charging device is used to testify the effectiveness and the efficiency of the proposed method. The results demonstrate that the proposed charging strategy can maximize the net increase of the average power of the WSN with a shorter route in one or multiple charging tour and ensure the power supply of the WSN maintaining in a healthy state.**

***Index Terms*—Wireless sensor network, mobile charging, MACO, sustainability.**

I. Introduction

In recent years, with the advancement of wireless communication and hardware technology, WSN has developed rapidly [1].WSN-based applications have spread from the military to all aspects of life. The sensors in WSN are designed to collect a large amount of the data, which is energy consuming. However, due to the limited size of the sensor, the sensor using batteries only has a small capacity of power. Moreover, WSN is usually composed of a large number of sensor nodes, some may even be distributed in a dangerous, or toxic environments. Once deployed, it is difficult to maintain [2]. Therefore, the limited power of sensor nodes has become one of the key factors hindering the development of WSN. Breakthroughs in wireless energy transfer (WET) and rechargeable lithium battery make it possible to sustainably provide power to WSN, in which a carrier-powered wireless charging vehicle (WCV) or a robot acting as a mobile charger periodically transmits energy to sensor nodes.

WET is a promising way to supplement the energy of sensor nodes through a controlled charging power supply and WCV is mostly used as the charging power supply in the WET for providing energy to the rechargeable sensor nodes. The WCV is designated to move following a specific optimal route to charge one or more sensors [3]. However, the predefined charging path scheme is only applicable to static energy-consuming networks where the charging duration and charging sequence are always the same for each charging cycle. In fact, in one charging cycle, some of the sensors are in a relatively healthy condition and there is no need to charge them in this tour. In this regard, the charging strategy is essential to maintain the WSN in a healthy and sustainable situation. It is necessary to design a scheduling method that charges according to a set threshold. In this paper, we consider the dynamic energy consumption of sensor nodes, and propose a real-time charging scheduling strategy based on modified ant colony algorithm under a charging threshold.

II. Related Works

The current charging strategy shows that there are two types of node charging: overall charging and on-demand charging. Lyu and Wei *et al.* [4] proposed a charging scheme for overall charging. A charging trip of a wireless charging vehicle charges all nodes in the network to avoid the death of sensor nodes. Shi *et al.* [5] considered supplementing the sensor energy in the WSN by charging each sensor node using a wireless charging vehicle. Hu *et al.* [6] studied overall charging time scheduling and charging path planning, and proposed a charging path planning method. Jiang *et al.* [7] proposed a novel periodic mobile charging method for large-scale networks by jointly considering charging tour planning and depot positioning. Amar Kaswan *et al.* [8] proposed a charging scheme for on-demand charging. The sensor node that needs to be charged proposes a charging request, and the charging device charges the sensor in turn after setting the charging sequence. Khelladi *et al.* [9] proposed to group sensor nodes, the nodes that need to be charged to make a charging request, and the chargers respectively charge the nodes of each group. Zhong *et al.* [10] used the on-demand charging method to charge the sensor and proposed the next charging node selection algorithm. Ye

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et al. [11] proposed two methods of charging all nodes and charging on demand: 1. Overall charging (offline) strategy 2. To charge the request (online) sensor, a fast scalable heuristic algorithm is designed to respond to the dynamic energy consumption of sensors in the network so that as many sensors as possible do not run out of energy. According to existing research, overall charging can maintain the network power at a high level, but requires a longer charging time, and even requires multiple chargers, which increases the cost. On-demand charging can reduce the workload of the charger, but the charging route is more difficult to develop, and the sensor is at risk of power failure. In order to avoid the exhaustion of power in any sensor and improve the charging efficiency, this paper proposes to set a charging threshold. Multiple values of the charging threshold have been compared and analyzed to maximize the net increase in network power and improve the charging efficiency of the sensor.

To find an optimal route for WCV, optimization algorithms are also researched. Yang *et al.* [12] proposed a network format charging algorithm. Liang *et al.* [13] proposed the problem is NP-hard, they devise an approximation algorithm with a provable performance guarantee for it. The charging scheduling problem in the WSN is similar to the Vehicle Routing Problem (VRP) and TSP. Ant colony algorithm (ACO) adopts distributed computing method, which has the characteristics of strong global search ability and positive information feedback. It is widely used in VRP and TSP [14]-[16], and the algorithm is introduced into the WSN charging problem. However, the WSN charging problem is essentially different from VRP and TSP. The arrival time of the WCV has effect on the energy demand of the sensor node. If the WCV cannot charge the node in time, the node may face the problem of energy exhaustion. In order to ensure that the power condition for all the sensor nodes is healthy, the next charging node is selected in real time according to the dynamic change of sensor power and combined with the position of the sensor relative to the charging device [17]. In this paper, the transition rule is modified in the ant colony algorithm based on the real time reminder of the power on each sensor.

In addition, the sustainability of the WSN using the charging strategy is also important. Most of the current researches are only for one charging cycle. Since the entire network is in a continuous state, it is meaningful for WCV to be able to implement the charging strategies continuously.

The main contributions of this paper are as follows.

1) A novel charging strategy is proposed to maximize the net increase of the power in WSN. A charging threshold is set and only the sensors below the threshold level are charged each time to improve the charging efficiency of the sensor.

2) Modified the ant colony algorithm is developed to find the optimal route for the WCV in real time. The current power of the sensor is added to the transition rule of the algorithm to ensure that each sensor node can survive while waiting for being charged, which can also optimize the route for the WCV and improve the success rate of the algorithm.

3) Quantitative analysis of the mean and variance of the power in the WSN after multiple charging is studied to demonstrate the charging sustainability of the proposed charging strategy.

III. Wireless Sensor Network Model

In this section, the model of WSN and the charging method are described in detail.

A. Network Model

The WSN is deployed on a two-dimensional area with n sensor nodes randomly distributed in the area. The position of each node is fixed and known. Base station B is the receiver of the data generated by all sensors, and also monitor the power status of all sensor nodes in real time, analyze the power status and set the charging path to send to WCV. WCV starts to charge the nodes one by one after receiving the charging task. The network model is shown in Fig. 1.

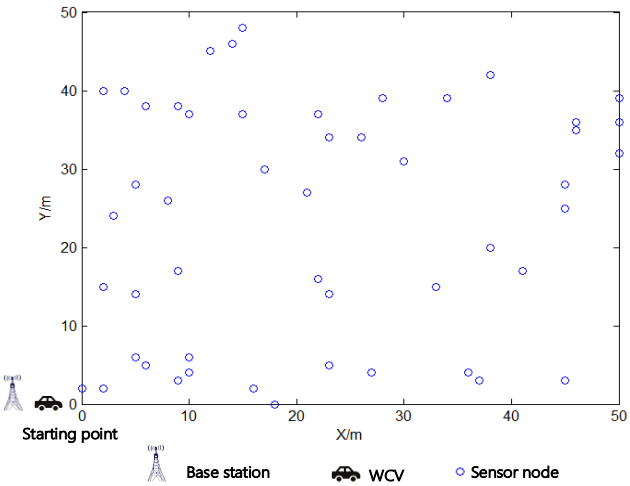

Fig. 1. Network model.

The base station also undertakes the task of charging the WCV. Each sensor node is equipped with a wireless rechargeable battery of the same capacity, with the same level of computing and communication. The maximum capacity of each battery is represented as E_{max}, the minimum power required to keep the sensor survival is E_{min}. The distance traveled by the WCV is represented by L. The sensor that need to be charged is set to G which contains m sensors, $0<m\leq n$. In order to implement the network model, simplifications and assumptions are made: the base station B has enough energy supply; WCV moves at a constant speed and has enough energy to complete a cycle of charging; during the charging process, WCV can only charge one sensor at a time with an uniform charging speed; the parking place of WCV is close enough to the sensor considering the efficiency of wireless charging.

B. Restrictions

To ensure the WCV complete an entire charging tour without power exhaustion of any sensor node, it must conform to (1).

$$E_i/s > L_i / v + \sum_{k=1}^{i-1} t_k \tag{1}$$

where, E_i is the instantaneous power of node i; s is the power consumption speed of the sensor node; v is the moving speed of the WCV; L_i is the moving distance when the node i is reached, $0<i\leqslant m$, and t_k is the charging time of the node k.

In addition, the residual power of each node can remain the sensor in a healthy state , that is $E_i \geqslant E_{min}$. Considering the relationship between the constraint and the objective function, the penalty function is used to transform the nonlinear programming problem into the unconstrained minimum problem.

C. Objective Function

The purpose of the charging strategy is to get an optimal charging path; the length of the charging route is used to evaluate the merits of different charging paths. The mathematical objective function is as follows:

$$\min\ L = dist(x_0, x_1) + \sum_{i=1}^{m-1} dist(x_i, x_{i+1}) + dist(x_m, x_0) \tag{2}$$

where, L is the travelling distance of the WCV in one tour. x_0 is the starting point of the WCV. x_i represents the location of the i-th node. *dist* is the travelling distance of the WCV between two sensor nodes.

Adding the penalty function P to the objective function due to the existence of the constraint. In this point of view, the objective function is finally determined as:

$$\begin{aligned} &\min\ L = dist(x_0, x_1) + \sum_{i=1}^{m-1} dist(x_i, x_{i+1}) + dist(x_m, x_0) + P \\ &P = cM \end{aligned} \tag{3}$$

If $E_i < E_{min}$, c=1; else c=0. M is a penalty factor.

The net increase in network power per minute ε is taken as the charging efficiency given in (4). ε can reflect the overall change of the power in WSN. The larger ε is, the faster the overall power of the network grows, and the higher the charging efficiency of the WCV. We use ε to evaluate the charging strategies in this paper.

$$\varepsilon = E_{av} / T \tag{4}$$

$$T = L / v + \sum_{k=1}^{m} t_k \tag{5}$$

where, T is the total time of a charge cycle, E_{av} is average power of the WSN. Charging time T is equal to WCV moving time plus charging time.

IV. Charging Strategy and Algorithm Analysis

A. Charging Strategy

In order to reduce the charging time of the network and add the net increase in network power, a novel charging scheme based on modified ant colony algorithm is proposed. A charging threshold is set for one charging cycle. Put the sensor into the set G when the sensor is below the threshold. WCV charges the sensor inside the G during a charge cycle.

The value of the charging threshold is crucial to the charging process. If the threshold is set too low, there may be no enough time for the WCV to charge all the sensor nodes in G. While if the threshold is designated too high, it may cause a frequent operation of the WCV, which is a waste of energy. In order to obtain an optimal charging threshold, the charging process is implemented in multiple times. Different charging thresholds were used to compare the charging condition of the WCV and the power increase of the network. The charging efficiency ε is calculated in each the charging process. The threshold with the highest ε is selected as an optimal charging threshold.

Response mechanism of WCV based on both the average power of the WSN and the bottleneck senor is presented to start the charging program. The base station B calculates the mean value of the overall power in the WSN. When the average power of WSN is lower than response power E_0, the WCV starts to charge. According to (1), E_0 cannot be smaller than 4.8kJ, otherwise the WCV has no enough time to finish the whole charging cycle before power exhaustion of some node. Moreover, sometimes there is bottleneck senor in the WSN whose remain power is extremely lower than the other sensors. To avoid the power exhaustion of bottleneck sensor and maintain the stability for the entire WSN, if the power of any sensor is lower than 1kJ, the WCV will perform the charging task regardless the average power.

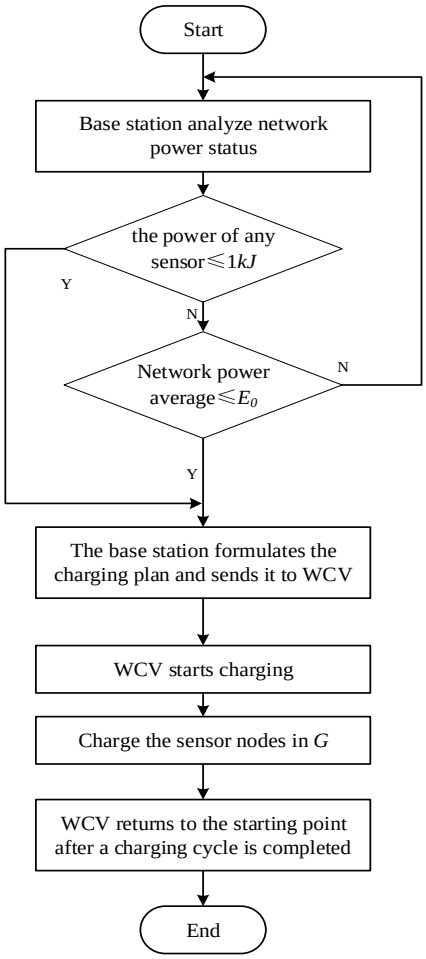

Fig. 2. Flow chart of the charging process.

The charging process of the WCV in one tour is demonstrated. Once receiving the charging request, the

WCV starts from base station B to charge the sensors in G one by one according to the charging plan made by the base station. After completing the current charging cycle, the WCV returns to base station B to prepare for the next charging cycle. The charging flow chart is shown in Fig. 2.

B. MACO

To meet the energy requirements of sensor nodes and improve the success rate of the algorithm, some modifications have been discussed based on ant colony optimization.

1) Dynamic transition rule

The transition rule is a critical mechanism in the ant colony optimization to determine the future searching direction [18]. In order to guarantee all the sensor nodes are in a healthy situation and avoid energy exhaustion of any node, the power state of the sensor E is introduced in the state transition rule of the ant colony algorithm. The state transition probability $pk\ ij$ that the ant k moves from the node i to the node j is shown as:

$$p_{ij}^{k}=\begin{cases}\dfrac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}(c/E_j)^{\gamma}}{\sum\limits_{S\in allowed_k}\tau_{iS}^{\alpha}\eta_{iS}^{\beta}} & j\in allowed_k\\ 0 & j\notin allowed_k\end{cases} \tag{6}$$

where, τ_{ij} is the pheromone concentration; $\eta_{ij}=1/d_{ij}$ is a priori available heuristic information; d_{ij} is the distance between nodes i and j; E_j is the remaining power of sensor j; $allowed_k$ indicates the sensor node that is allowed to be accessed by the aunt k. α, β, γ, c is the weight coefficient.

According (6), the transition probability is determined by the remaining power of the node, the distance between two nodes, and the pheromone concentration. To avoid the ant falling into the local optimal solution, the pheromone is evaporating as time goes by, which is update by (7).

$$\begin{cases}\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t)+\Delta\tau_{ij}\\ \Delta\tau_{ij}=\sum\limits_{k=1}^{n}\Delta\tau_{ij}^{k}\end{cases},0<\rho<1 \tag{7}$$

$\Delta\tau k\ ij$ represents the concentration of pheromone released by the k-th ant on the connection path of node i and node j. $\Delta\tau_{ij}$ represents the sum of pheromone concentrations released by all ants on the connection path between node i and node j. ρ represents the volatility of pheromone.

2) The optimal solution

An ant starts from the starting point and select the next charging node based on the state transition probability. If all nodes in G have been visited, the ant returns a charging path. Until all the ants complete the process and record the shortest charging path as the current global optimal path L^*. The population of ants is updated to complete another round of searching. When a current best path is obtained by one generation of ants, it is compared with the current global optimal path L^*. If the current best path is better than L^*, replace L^* with the current best path.

The algorithm is as follows:

Algorithm: MACO

Input: n: number of ants, k: number of iterations, sensor set G to be charged, v: WCV moving speed, s: sensor's power consumption rate, t: charging time at one node;
Output: L^*: the best moving path of WCV; T: the charging time of all sensor node; E_{av}: average power of the network node;

```
Initialize the parameters;
n ants are placed at the starting point;
Calculate the distance between nodes;
for i=1: k
  for j=1: n
  Select the next visited node according
  to (1) and (6);
  if all nodes are accessed
  Record L_j;
  Calculate the path distance of each ant;
L_i=Min{L_j};
End
Compare the minimum path distances of each
generation;
L*=Min{L_i};
End
Output L*;
Time T is obtained according to (5);
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$$E_{av}=\sum_{i=1}^{n}E(x_i)/n;$$

End Algorithm

C. Sustainability

The current researches on the WSN charging are mostly considering one charging cycle. However, in the actual environment, it is necessary to ensure that the WSN is stable and smooth. The charging strategy should keep the power of the WSN in a healthy and steady state. In order to ensure the stability of WSN, the power status of the WSN is analyzed with continuous implementation of the proposed charging strategy. After one charging cycle is completed, the WCV returns to the base station B for charging and maintaining. When the charge request is received, the WCV begins to charge for another cycle. The power situation of the WSN is analyzed quantitatively after multiple charging.

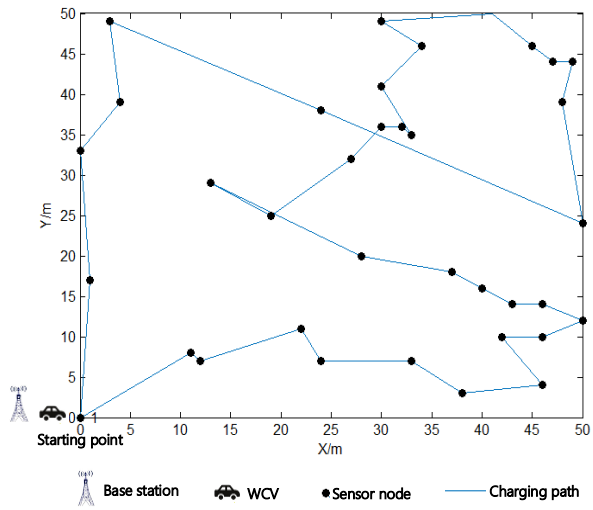


Fig. 3. An example of a charging path.

V. Simulation Results and Analysis

In the area of 50 × 50 meters, 10-50 sensor nodes are distributed, as shown in Fig. 3. The battery capacity of one

sensor is 10.8kJ [19]. The initial power of each sensor node is given in a normal distribution with average power is 4.8kJ, and the variance is 20kJ^2. The given simulation result is the average of 30 randomly running. The parameters of the WSN are given in Table I.

TABLE I: NETWORK ENVIRONMENT PARAMETERS

Parameter	Numerical value	Meaning
area	50m×50m	Simulation area
N	10-50	Number of sensor nodes
s	50J/min	sensor's power consumption rate
v	2m/s	WCV moving speed
t_c	5min	Charging time

A. Charging Scheme Analysis

To explicate the effectiveness of the charging threshold, the proposed charging strategies with threshold and the overall charging mode are compared. In the experiment, we use 7kJ and 8kJ as two typical charging thresholds and compare the charging efficiency ε based on the proposed threshold and overall charging policy with different size of the WSN. Table II and Fig. 4 show the comparison of ε between threshold and overall charging. It can be seen from the Fig.4 that the threshold charging strategy improves ε compared with overall charging. Table II demonstrates that when the charging threshold is 7kJ, ε is higher than the all node charging by 1.3%, 5.4%, 11.0%, 25.1% and 32.3%with the WSN size of 10, 20, 30, 40 and 50; when the charging threshold is 8kJ, ε is increased by 0.9%, 4.2%, 5.8%, 14.0% and 19.2%, respectively. And also, as the increasing size of the WSN, the growth of the ε is greater. In a conclusion, the threshold charging strategy can increase ε compared to overall charging, and the advantage becomes more obvious with the increase of the WSN scale.

TABLE II: ε UNDER DIFFERENT CHARGING STRATEGIES

Network size	Threshold: 7kJ	Threshold:8kJ	All nodes
10	221.1	220.3	218.3
20	132.3	130.8	125.5
30	82.5	78.6	74.3
40	65.2	59.4	52.1
50	55.7	50.2	42.1

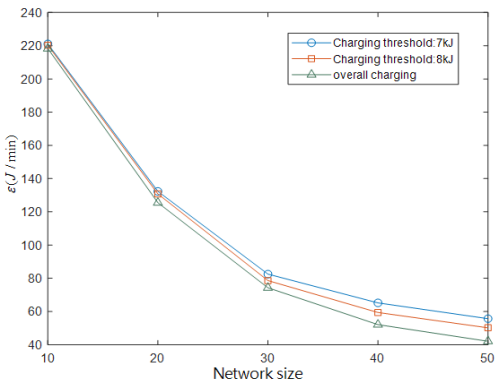


Fig. 4. Under different charging strategies ε.

To maximize ε and determine an optimal charging threshold for the WSN model, different thresholds are tested with the WSN size 50. Fig. 5 and Table III give the change of ε under different charging thresholds. From Fig. 5, it is shown that when the charging threshold is 7kJ, the value of ε is the largest, that is, the net increase of network power per minute is the largest, and the charging efficiency of WCV is the highest. According to Table III, when the threshold is set to 6.5kJ, E_{av} after charging is 4.78kJ, which is approximately to initial average power. So the charging threshold cannot be lower than 6.5kJ. Therefore, the optimal charging threshold is selected as 7kJ, about 65% of the maximum capacity, to utilize the WCV efficiently.

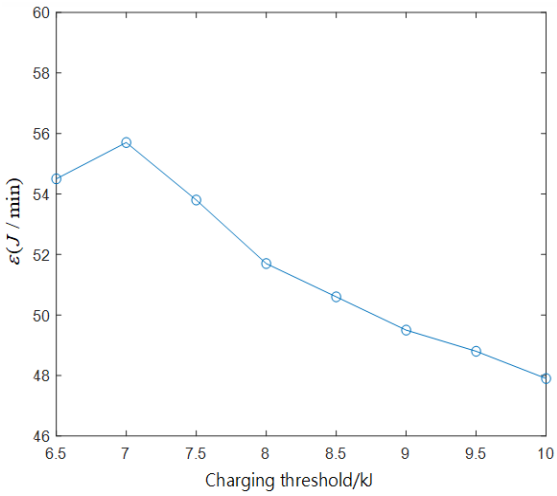


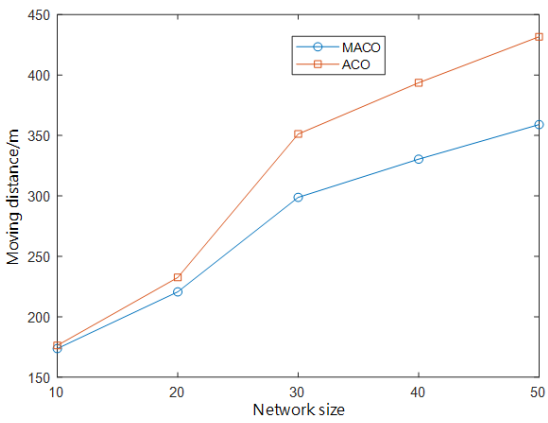
Fig. 5. Network size: 50 nodes, ε under different charging thresholds.

TABLE III: COMPARISON OF DIFFERENT CHARGING THRESHOLDS

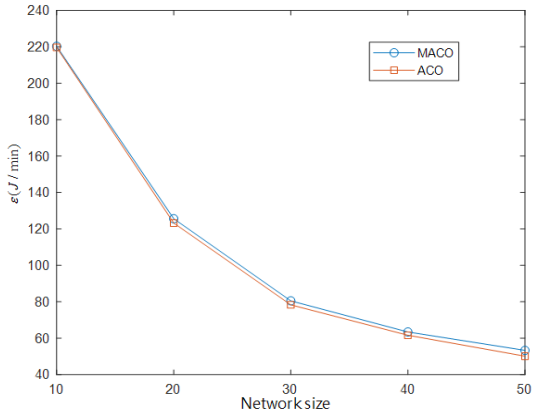
Charging threshold/kJ	Corresponding percentage of sensor power/%	ε(J/min)	E_{av} after charging/kJ
6.5	60.2	54.5	4.78
7.0	64.8	55.7	5.61
7.5	69.4	53.8	6.17
8.0	74.1	51.7	6.36
8.5	78.7	50.6	6.57
9.0	83.3	49.5	6.73
9.5	88.0	48.8	6.82
10.0	92.6	47.9	6.86

B. Comparative Analysis of Algorithms

A WSN model with the scale varied from 10 to 50 is solved by the proposed MACO and the original ACO to compare the charging distance of WCV and ε with the charging threshold 7kJ and response power E_0 4.8kJ.



(a) charging distance



(b) charging efficiency ε

Fig. 6. Comparison of two algorithms on charging distance and ε.

TABLE IV: CHARGING DISTANCE(M) OF THE TWO ALGORITHMS

Network size	ACO	MACO
10	176.3	173.7
20	232.5	220.6
30	351.2	298.8
40	393.6	330.4
50	431.7	359.0

TABLE V: ε(J/MIN) OF THE TWO ALGORITHMS

Network size	ACO	MACO
10	219.7	220.3
20	123.2	125.6
30	78.3	80.5
40	61.6	63.4
50	50.1	53.3

The simulation results are given in Fig. 6, Table IV and Table V. From Fig. 6, it is shown that the charging route of the WCV obtained by MACO is less than ACO, and the charging efficiency ε is also promoted using the proposed method. Table IV demonstrates the moving distance of WCV is reduced by 1.5%, 5.1%, 14.9%, 16.1% and 16.8% and ε is increased by 0.3%, 1.9%, 2.8%, 2.9%, 4.4% using the MACO with the WSN size of 10, 20, 30, 40 and 50. Through the above analysis, the superiority of the MACO is verified. Compared to ACO, MACO can get a shorter charging path and a higher charging efficiency ε.

TABLE VI: THE PROPORTION OF OBTAINING THE GLOBAL OPTIMAL SOLUTION OF THE TWO ALGORITHMS

Charging threshold/kJ	the proportion of obtaining the global optimal solution /%	
	ACO	MACO
6.48	80.0	100.0
7.0	73.3	100.0
7.56	66.7	100.0
8.64	46.7	95.0
10.0	33.3	92.5

The path problem belongs to np-hard problem. Sometimes the solution obtained by the algorithm is not the optimal solution, that is, the solution from more than one ant does not converge. Through multiple simulation experiments, the proportion of obtaining the global optimal solution using MACO and ACO is compared. The results are tabulated in Table VI.

From Table VI, MACO can find the global optimal solution in a higher probability compared to ACO. When ACO is applied to the charging model, the algorithm may not always converge to the global best solution. The proposed MACO can improve the convergence ratio by using the dynamic state transition rule.

C. Sustainability Analysis

In order to verify the charging sustainability of the WSN, five charging cycles are performed after the first charging process is completed. The average power E_{av} and variance of WSN after each charging are recorded in Table VII. In Table VII, the results show that E_{av} is almost the same and the variance is relatively stable within the five following charging cycles, which indicated that the proposed charging strategy can ensure the power of the WSN stable and sustainable.

TABLE VII: E_{av} AND VARIANCE OF WSN AFTER MULTIPLE CHARGES

Charging times	E_{av} /kJ	Variance /kJ^2
0	4.80	20.0
1	5.62	22.4
2	5.60	22.3
3	5.62	22.2
4	5.63	22.3
5	5.61	22.1

VI. CONCLUSION

This paper propose a real-time charging scheduling strategy based on modified ant colony algorithm under the charging threshold, which can improve the charging efficiency compared with the overall charging. Through the analysis and comparison of different schemes, the optimal charging threshold based on threshold value is found. The simulation results show that for the charging model in this paper, when the charging threshold is set at 65% of the current average power, the net power growth per minute of WSN is the highest. And the dynamic transition rule can ensure that no sensor nodes death during the charging process, the moving distance is reduced compared to the ant colony algorithm and the proportion of finding the optimal solution by the ant colony algorithm is increased. In addition, after five charges, the mean and variance of WSN's power still maintain a healthy and stable level, which proves that the charging strategy in this paper can make WSN sustainable.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Chao Ma and Siguang An concuted the research; Siguang An and Wei Wang revised the paper. Dehui Lin, Mei Li and Lihong Sun put forward valuable Suggestions to the paper; Chao Ma wrote the paper; All authors had approved the final version.

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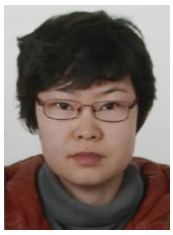

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