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# Routing optimizationin wireless sensor network based on improved ant colony algorithm

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## Abstract

**When ant colony algorithm is applied to wireless sensor networks, the disadvantages of large amount of computation and slow convergence of ant colony algorithm will be enlarged due to the large number of network nodes. To solve this problem, an improved heterogeneous ant colony algorithm is proposed. By introducing the strategy of alternate search of area ant and common ant, the number of candidate nodes in each search of common ant is limited, the search computation is reduced, and the convergence of the algorithm is accelerated. Finally, the simulation results show that the improved algorithm can solve the shortcomings of ant colony algorithm applied to WSN network problems, shorten the path distance, reduce network energy consumption, and prolong the network life cycle.**

## Keywords

**Wireless sensor network; Heterogeneous ant colony; Energy consumption balance; Region partition; Routing protocol.**

## 1. Introduction

With the increasing application of wireless sensor networks, how to reduce the energy consumption of wireless sensor networks and extend the network life cycle has become the research focus of scholars at home and abroad. According to research, the energy consumed by data transmission accounts for 80% of the energy consumption of the entire sensor network [1]. Therefore, the improvement of routing protocols has become the top priority in reducing the energy consumption of wireless sensor networks. The ADCAPTEEN algorithm proposed by Jingyu Ma et al. Reduces the energy consumption of routing and improves the average life of the nodes through the dual cluster head strategy. By constructing a multi-objective function, Sun et al. Considered the residual energy and the path trust value during node transfer, achieved node energy balance, and improved the degree of path security. Wang Xiaoming et al. Defined the node's advancing area through the deflection angle, and introduced an energy factor to make the node have energy awareness. Li Hao et al. Proposed the concept of resistin and location band to reduce unnecessary energy consumption and improve the network life cycle. Although Wang Xiaoming and Li Hao etc. guided the ants forward by using angle or area restrictions, they did not formulate a mature strategy or system that could not really guide the ants to the optimal direction, making the algorithm easily fall into local Optimal, reducing the accuracy of the algorithm. Based on this, this paper first modeled the fan grid map based on polar coordinates for the coverage area of the WSN network, and then proposed the regional ant

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concept. By defining the regional ant state transition strategy and pheromone update method, while ensuring the accuracy of the algorithm, Speed up the convergence speed of the algorithm.

## 2. Related work

### 2.1 Network model

In this paper, the grid modeling method made by Tiancheng Li is improved to make it suitable for WSN networks.

The fan-shaped grid is modeled as shown in Fig. 1. The sink node is used as the pole and recorded as O (0,0). The horizontal coordinate OM is established as the polar axis. Among them, the Euclidean distance between the ordinary node and the sink node is polar rho, and the angle between the connection between the ordinary node and the sink node and the OM is the polar angle θ, so the ordinary node coordinate is (rho, θ).

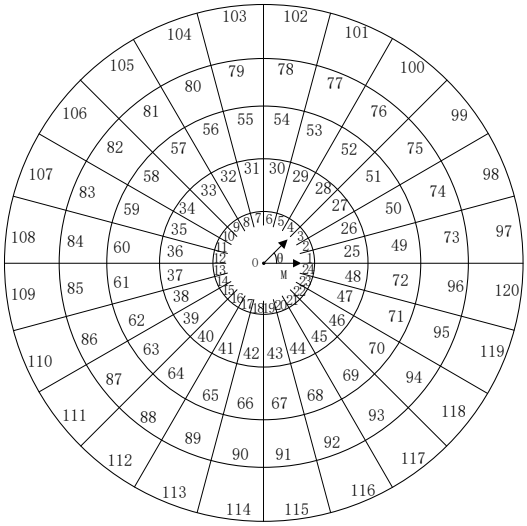

Figure 1. Fan grid number and polar coordinate system

In the figure, it is assumed that the communication radius of the wireless sensor is d, and the map is divided into several ring roads $R_i$ with a width of d. The ring road adjacent to the ring road $R_i$ and close to the sink node is called the parent ring road of Ri. The ring road is equally divided into several fan-shaped grids, called areas, denoted as Aj; the set of nodes in the Aj area is recorded as Nj; the parent ring of each area has two areas adjacent to its own, and recorded The region's parent and sibling regions. The sibling area is recorded as Ajb, the parent area is recorded as Ajf, and the sibling area of the parent area is recorded as Ajfb.

For the convenience of description, it is assumed that the wireless sensor network in this algorithm has the following characteristics [2]:

(1) All nodes are known and have unique ID numbers across the network;

(2) The communication radius of the node is the same as the sensing radius;

(4) All nodes have the same structure and can receive and send information;

(4) Except for sink nodes, the other nodes have the same energy and cannot be supplemented;

(5) The node has a GPS system to obtain its geographic location more accurately;

(6) The wireless links in the network are symmetrical.

### 2.2 Energy consumption model

Since the energy consumption of WSN networks is mainly concentrated in the data transmission stage, this paper uses a combination of a two-time fading model and a multipath fading model [8,9]. The specific energy consumption formula of node i sending data to node j is as follows:

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$$E_{send(i,j)} = \begin{cases} l * E_{elec} + l * \varepsilon_{fs} * d_{ij}^2, d_{ij} < d_0 \\ l * E_{elec} + l * \varepsilon_{mp} * d_{ij}^4, d_{ij} > d_0 \end{cases} \quad (1)$$

Where l is the length of the data packet sent by the node, the unit is bit; $\varepsilon_{fs}$and$\varepsilon_{mp}$ Is the power amplification factor when the distance between nodes is different; $E_{elec}$ is the energy consumed when processing unit data; $d_{ij}$ Is the distance between nodes i and j; $d_0$ is the distance threshold for the energy consumption model to be transformed from a secondary fading model to a multipath fading model. The value is:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (2)$$

The energy consumption formula of node j receiving the information sent by node i is as follows:

$$E_{receive(j,i)} = l * E_{elec} \quad (3)$$

Where l is the length of the data packet sent by the node, the unit is bit; $E_{elec}$ is the energy consumed when processing unit data.

### 2.3 Ant Colony Algorithm.

The ant colony algorithm finds the shortest path between two points by imitating the foraging process of ants. In a WSN network, assuming the number of nodes is m and the number of ants is n, the steps of the ant colony algorithm are as follows:

The probability of the kth ant from node i to node j is

$$P_{ij}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha} * [\eta_{ij}(t)]^{\beta}}{\sum_{s \in allow_k} [\tau_{ij}(t)]^{\alpha} * [\eta_{ij}(t)]^{\beta}}, s \in allow_k \\ 0, \ s \notin allow_k \end{cases} \quad (4)$$

In equation (4), $allow_k$ represents the next hop node set that ant k can choose, that is,. $\tau_{ij}(t)$ represents the pheromone concentration at the t-th iteration between node i and node j (both initial pheromone concentrations are 1). $\eta_{ij}(t)$ is the heuristic function:

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \quad (5)$$

Among them, $d_{ij}$ represents the distance between nodes i and j, and $\eta_{ij}(t)$ represents the expected degree of ants to transfer from node i to node j. α and β represent the pheromone concentration and the weight of the heuristic factor.

After ant k completes a cycle from the departure place to the destination, it needs to update the pheromone concentration of the path it travels through, as follows:

$$\tau_{ij}(t+1) = \tau_{ij} * (1-\rho) + \Delta\tau_{ij}(t) \quad (6)$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}{}^{k}(t) \quad (7)$$

In formula (14), ρ represents the pheromone volatility coefficient, and ρ ∈ [0 ~ 1], (1-ρ) represents the pheromone concentration remaining on the path after volatilization.

The pheromone concentration update in the ant colony algorithm uses the ant week system, that is, the pheromone concentration is adjusted after the ants reach their destination.

$$\Delta\tau_{ij}(t) = \begin{cases} \frac{Q}{L_k}, \text{Ant k passes path ij} \\ 0 \end{cases} \quad (8)$$

Among them, Q is a constant, which indicates the total amount of pheromone released by the ant once; $L_k$ is the length of the path of the kth ant.

## 3. Ant colony algorithm for heterogeneous dual population optimization

In order to solve the problems of ant colony algorithm applied to the WSN network due to too many nodes, the algorithm has slow convergence speed and is easy to fall into a local optimum, etc. This paper proposes a heterogeneous dual population optimization ant colony algorithm. By defining a new type of artificial ant: regional ant, it guides the common ant's forward direction, so that the

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common ant can find the optimal path faster. While maintaining the accuracy of the algorithm, the convergence speed of the algorithm is improved. The following describes the regional search strategy, heuristic factor, and pheromone update strategy for regional ants.

For the convenience of description, the following definitions and explanations are made.

Definition 1: The number of regional ants is the same as that of common ants, and there is one-to-one correspondence.

Definition 2: When the common ant k is located at the node a, its regional ant is located at the region $\{A_j | a \in N_j\}$;

The optimal paths mentioned in the following descriptions are all common ant optimal paths.

### 3.1 Regional search strategy

The regional search strategy of regional ants is as follows:

Definition 1: Regional ants and ordinary ants search alternately. The regional ants give priority to completing the area search, and the ordinary ants then perform node search in the target area of the regional ants.

The mathematical model is:

$$allow_k \in \{N_j | target_{kk} = A_j\} \tag{9}$$

In the formula, $target_{kk}$ is the target area of the area ant kk.

Definition 2: Area ants can only search within their own area, their sibling area, parent area, and parent area's sibling area.

The mathematical model is:

$$allow_{kk} = \left\{A_j, A_{jb}, A_{jf}, A_{jfb}\right\} \tag{10}$$

### 3.2 Regional ant heuristic

When the traditional ant colony algorithm is applied to WSN network routing protocol, the heuristic function usually takes the inverse of the distance between nodes. Therefore, problems such as precocity of the algorithm and overload of individual links are easy to occur. In order to solve the above problems, this algorithm introduces the node concentration factor and regional energy value into the regional ant heuristic function. A dynamic weighted regional center is also proposed. By increasing the weight of the optimal path node in calculating the center of the area, the regional center is shifted to the optimal path node, the probability of being selected that includes the optimal path node is improved, and the algorithm convergence is accelerated. The node concentration factors, residual energy factors, and weighted region centers are described in detail below.

3.2.1 Node density factor

In order to ensure that the ant colony algorithm has a large search range in the early stage and prevent the algorithm from premature, a regional ant heuristic function is introduced to the number of regional node weights. The formula for calculating the weight of regional nodes is as follows:

$$C_{A_j} = \frac{\text{number}(A_j)}{number(allow_{kk})} * \delta \tag{11}$$

In formula (11), $\text{number}(A_j)$ represents the number of nodes in the area $A_j$, and $number(allow_{kk})$ represents the sum of the number of nodes in the area that the ants kk can choose to advance. The ratio of the two represents the weight of the number of nodes of the region$A_j$ in all candidate regions. The higher the number of nodes, the greater the number of nodes in the candidate area, the larger the ant search range, and the higher the quality of the solution.

In formula (11), δ is a compensation coefficient for the number of nodes. By changing this coefficient, the degree of influence of the number of nodes on the region selection probability can be influenced. In order to reduce the impact of the number of nodes on the ant in the later stage of the algorithm, so that the ant can focus on the path with a higher pheromone concentration, set the value of δ as:

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$$\delta = \frac{Iter - iter_{kk}}{Iter} \tag{12}$$

Where $Iter$ is the total number of iterations of the algorithm, and $iter_{kk}$ represents the current number of iterations of the regional ant kk.

3.2.2 Regional energy value

In order to solve the problem that the optimal path is likely to be overloaded and cause the optimal path to die prematurely at the later stage of the algorithm, this algorithm proposes a regional energy value function to evaluate the regional residual energy, the formula is as follows:

$$W_{A_j} = \frac{E_{avg}^{A_j}}{\sum E_{avg}^{A_j}} \tag{13}$$

In the formula, W represents the energy value of the region $A_j$. $E_{avg}^{A_j}$ is the average remaining energy of nodes in area$A_j$, and $\sum E_{avg}^{A_j}$ is the sum of the average remaining energy of nodes in all candidate areas

In summary, the regional ant heuristic function is:

$$\eta_{ij}(t) = \begin{cases} \mu C_{A_j} + \nu W_{A_j} + \gamma D_{(A_j, A_i)}, & i \neq j \\ \mu C_{A_j} + \nu W_{A_j} + \gamma D_{(a, A_j)}, & i = j \end{cases} \tag{14}$$

Among them, when the target area and the area where the ants are located are the same area, that is, i = j, the area center distance $D_{(a,A_j)}$ of the nodes a and $A_j$ is used as the distance; when the target area and the area where the ants are located are different areas, use The center distance $D_{(A_j,A_i)}$ of the areas of $A_j$ and $A_i$ is taken as the distance between them. μ, ν, γ are the weighting factors of the number of regional nodes, the value of regional energy, and the distance between regions. μ, ν, and γ are all greater than 0, and μ + ν + γ = 1.

Therefore, the regional ant regional transition probability formula is:

$$P_{(A_j,\ A_i)}(t) = \begin{cases} \dfrac{\left[\tau_{(A_j,\ A_i)}(t)\right]^{\alpha} * \left[\eta_{(A_j,\ A_i)}(t)\right]^{\beta}}{\sum_{A_i \in allow_{kk}} \left[\tau_{(A_j,\ A_i)}(t)\right]^{\alpha} * \left[\eta_{(A_j,\ A_i)}(t)\right]^{\beta}}, & A_i \in allow_{kk} \\ 0, & A_i \notin allow_{kk} \end{cases} \tag{15}$$

3.2.3 Dynamic Weighted Area Center

Because the distribution of nodes in the region is random and chaotic, simply averaging the coordinates of each node in the region cannot accurately represent the true position of the center of the region, which is not conducive to the regional ants to quickly and accurately find the optimal forward region. In order to solve this problem, this algorithm proposes the concept of dynamic weighted regional center. By assigning weight to each node in the region, and referring to the idea of pheromone update, the node weight is updated to increase the weight of the node that the optimal path passes in the region. , Reduce the weight of unselected nodes. Move the center of the area closer to the node that the optimal path passes through, and accelerate the convergence speed of the algorithm. The regional center is calculated as follows:

$$rho_{A_c} = \sum_{i=1}^{number(A_j)} rho_i * \varphi_i \tag{16}$$

$$\theta_{A_c} = \sum_{i=1}^{number(A_j)} \theta_i * \varphi_i \tag{17}$$

In formula (16), $rho_{A_c}$ is the polar meridian length at the center of area A, and $rho_i$ is the polar meridian length at node i. In formula (17), $\theta_{A_c}$ is the polar angle at the central location of area A; $\theta_i$ is the polar angle at node i ; $\varphi_i$is the weight of node i, and the sum of the weights of each node is 1.

$$\sum_{i=1}^{number(A_j)} \varphi_i = 1 \tag{18}$$

After all the ants complete one iteration, the node weights in each region are updated. At each update, the node weight update rules are divided into three types according to whether the node has passed through the path, and if there is a path passed but not the current optimal path. The first is a node that

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has not been passed by any path. This type of node will be reduced by ω% of the weight to reward other nodes that have passed the path, and at the same time, the weight of ω / 2% will be used to reward the optimal path. The second type is the node that has passed the path but has not passed the current optimal path. This type of node increases the ω% weight of the first type of node that is reduced first according to the number of times it is selected. At the same time, it reduces the weight before the increase. ω / 2% is used to reward the nodes that the optimal path passes; the third type is the nodes that the optimal path passes. This type of node not only has a way to increase the weight of the second type of node, but also divides the optimal path reward equally (the optimal path has only one, and all nodes can only be selected once by the same path). , which is

$$\varphi(t+1)_a = \begin{cases} \varphi(t)_a * (1-\omega\% - \frac{\omega}{2}\%) & \text{,No path through i} \\ \varphi(t)_a * (1-\frac{\omega}{2}\%) + \frac{num_{(p,a)}}{\sum_{j=1}^{n} num_{(p,j)}} * \sum_{k=1}^{m}[\varphi(t)_k * \omega\%] & \text{,There are paths through i.But non-optimal paths} \\ \varphi(t)_a + \frac{num_{(p,a)}}{\sum_{j=1}^{n} num_{(p,j)}} * \sum_{k=1}^{m}[\varphi(t)_k * \omega\%] + \frac{\sum_{l=1}^{l}(\varphi(t)_l \frac{\omega}{2}\%)}{number_{A_j} - l} & \text{,Has a path through i and contains the optimal path} \end{cases} \quad (19)$$

Among them, $\varphi(t)_a$ is the current node weight, $\varphi(t+1)_a$ is the updated node weight, $num_{(p,a)}$ is the number of times that node a has been passed, n is the number of nodes with a path, m is the number of nodes without a path, and $n + m = number_{A_j}$ is not Number of nodes that the optimal path passes; ω is the attenuation factor, which is constant, and ω> 0.

### 3.3 Pheromone Update Strategy

Due to the positive feedback characteristics of the ant colony algorithm, the pheromone concentration on the optimal path gradually increases with time, so that more ants choose this path to search, resulting in the rapid death of nodes on the optimal path, causing The network topology changes, and the change of the topology results in the continuous change of the route query, which wastes the energy of the nodes and reduces the network life [3]. In order to improve the global activity of the network and avoid overloading individual lines in the later period, an update strategy using a combination of local and global pheromones is proposed to solve the problem of too wide disparities in pheromone concentrations, balance network energy consumption, and improve the network life cycle . Among them, the local update strategy represents the pheromone update rule on the optimal path, and the global represents the pheromone update rule on the ordinary path.

Regional ant local pheromone update strategy In order to avoid the premature death of the optimal path node due to the high pheromone concentration of individual routes in the later stage of the algorithm, when it is updated, it is multiplied by $1/iter_{kk}$ to slow down the optimal path pheromone The growth rate balances the global pheromone concentration and maintains the competitiveness of other nodes in the later stage of the algorithm. At the same time, this coefficient has a very small impact in the early stage of the algorithm and does not affect the convergence speed of the algorithm. The updated formula can be expressed as Equation (20).

$$\tau_{(A_j,\ A_i)}(t+1) = \tau_{(A_j,\ A_i)}(t) * (1-\rho) + \frac{\Delta\tau_{(A_j,\ A_i)}(t)}{iter_{kk}},\ (A_j,\ A_i)\text{is the optimal path} \quad (20)$$

$$\tau_{(A_j,\ A_i)}(t+1) = \tau_{(A_j,\ A_i)}(t) * (1-\rho) + \frac{E_R^{A_j} + E_R^{A_i}}{\sum E_R^{A_j}},\ (A_j,\ A_i)\ \text{is a non-optimal path} \quad (21)$$

In the regional ant global pheromone update, the natural update of the non-optimal path pheromone is canceled, that is, the ant does not leave a new pheromone on it. At the same time, in order to prevent the nodes on the non-optimal path from losing competitiveness in the later stage of the algorithm, causing uneven energy distribution, an energy pheromone increment is added for the non-optimal path. That is $\frac{E_R^{A_j} + E_R^{A_i}}{\sum E_R^{A_j}}$. $E_R^{A_j} + E_R^{A_i}$ is the sum of the remaining energy of regions $A_j$ and $A_i$, and $\sum E_R^{A_j}$ is the remaining energy of the entire network. The ratio of the two is the non-optimal path energy pheromone increment. The regional ant global pheromone update formula is expressed as Equation (21).

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The above is the regional ant regional search strategy, heuristic factor and pheromone update strategy. The implementation process of the heterogeneous dual population ant colony algorithm will be described in detail below.

## 4. Improved ant colony algorithm implementation process

The implementation process of the heterogeneous dual population ant colony algorithm designed in this paper is as follows:

Step1: Initialize each parameter

Setp2: number of iterations N = N + 1

Step3: kk = kk + 1, k = k + 1.

Step4: The area ants perform area search first: each area ant performs area transfer in $allow_{kk}$ according to the area transfer probability formula (17).

Step5: After the regional ant completes the regional transfer, the common ant finds the next hop node range in the area except its own node, according to the next hop node probability formula (4), prioritizes the nodes in the transfer range and forwards the probability The higher the priority, the lower the priority. And the priority of each node is added to the sending message.

Setp6: The node broadcasts the data. After receiving the data, all candidate nodes start their own timers according to the node priority. The lower the priority, the shorter the timer time. After the timer expires, reply ACK to node i [4].

Setp7: After receiving the ACK command from node j, node i broadcasts and stops forwarding the command. After receiving the command, all nodes except node j stop forwarding the data packet. At the same time, node j is added to the taboo table $\mathrm{tabu}_k$.

Setp8: Whether the transfer node j is a sink node,

If yes, return Setp3; otherwise, return Setp4.

Step9: Perform pheromone update on regional ant and common ant path.

Step10: If the number of iterations N <N_max, then clear $\mathrm{tabu}_k$ and return Setp3, otherwise end the loop.

## 5. Experimental simulation and result analysis

In order to verify the superiority of the algorithm in a network environment with a large number of nodes, in the simulation environment of matlab2018, a circular static WSN network environment with a radius of 200m was established, and 201 sensor nodes were randomly distributed inside it. Heterogeneous two-population ant colony algorithm (HACA) and traditional ant colony algorithm were applied to this WSN network to build a routing protocol. By comparing its path distance, network energy consumption, path success rate and first The death time of each node is compared and analyzed. Table 1 shows the experimental environment settings and parameter settings.

Table 1: Simulation experiment parameter settings

| Experimental parameters | Parameter value | Experimental parameters | Parameter value |
|---|---|---|---|
| Node initial energy E0 | 1J | Processing unit data loss Eelec | $50 * \frac{10^{-9} j}{bit}$ |
| Packet size l | 1000bit | Pheromone heuristicsα | 1 |
| Power amplification factor $\varepsilon_{fs}$ | $10 * \frac{10^{-12} j}{bit} / m^2$ | Heuristic functionβ | 5 |

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| | | | |
|---|---|---|---|
| Power amplification factor $\varepsilon_{mp}$ | $1.3 * \frac{10^{-15} j}{bit} / m^4$ | Regional node number weighting factorμ | 0.3 |
| Number of ants m | 30 | Regional energy value weighting factor $\nu$ | 0.4 |
| Pheromone volatility coefficient $p$ | 0.1 | Regional distance weighting factorγ | 0.3 |
| Regional node weight volatility factor ω% | 0.1 | Q | 1 |
| Maximum node communication radius R | 40 | Number of iterations n | 100 |

## 5.1 Experimental path distance comparison

Figure 2 is a comparison of the optimal path distance between the source node a and the sink node after each iteration of 100 iterations. The asterisk polyline in the figure is the path and path distance after HACA optimization, and the circle polyline is the path and path distance after ACA optimization. It can be seen that because HACA introduces regional ants, the direction of common ants is planned, and the probability of ordinary ants making invalid transfers is reduced. The initial path distance of HACA is significantly smaller than the ACA path. At the same time, the final result and convergence speed of the HACA path are obvious due to the number of regional nodes, regional weight centers, and "local" + "global" pheromone update methods introduced by HACA in defining the regional ant heuristic function and pheromone update method Better than ACA path. Therefore, when applied to WSN, the quality of HACA's solution is higher and the solution speed is faster.

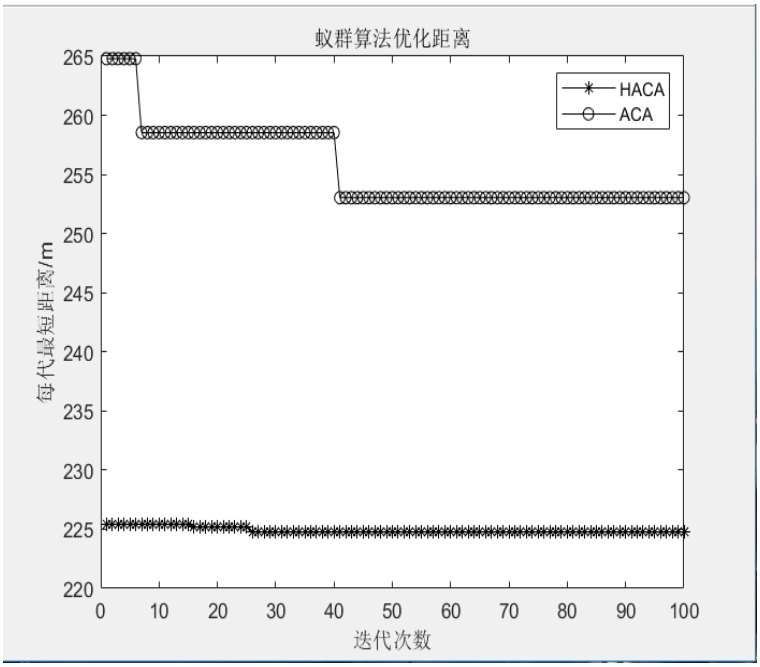


Figure 2. Optimal path distance between HACA and ACA

## 5.2 Network energy consumption

Figure 3 is a comparison diagram of the overall energy consumption of three algorithms, HACA, AEEABR, and ACA, with 100 iterations. As shown in the figure, the energy consumption of the HACA algorithm is lower than the other two algorithms, which solves the energy consumption problem of the WSN network.

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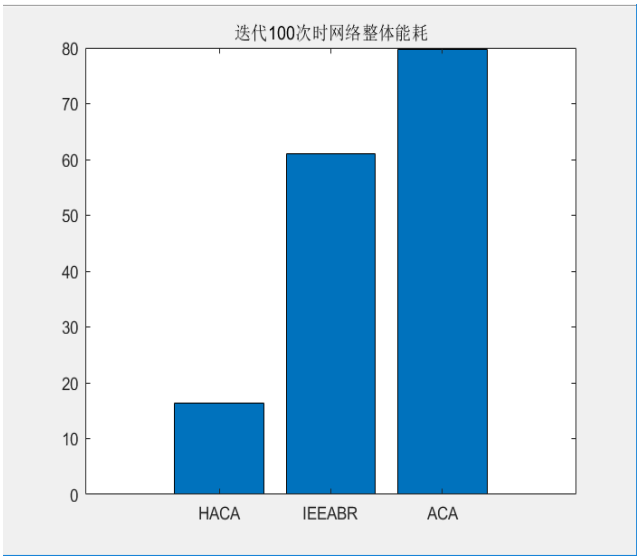


Figure 3. Comparison of overall network energy consumption

### 5.3 Path construction success rate

Table 2 shows the success rates of the three routing algorithms from the initial node to the sink node. Among them, the HACA algorithm has the advantages of regional ant guidance and less energy consumption in the process of path construction. The success rate is much higher than the Flooding algorithm and IEEABR algorithm. Can significantly improve the data collection rate of WSN networks.

Table 2. Relationship between path construction success rate and number of iterations

| Number of iterations | Flooding | IEEABR | HCAC |
|---|---|---|---|
| 100 | 77 | 41 | 97 |
| 200 | 60 | 45 | 98 |
| 300 | 0 | 50 | 96 |
| 400 | 0 | 70 | 95 |
| 500 | 0 | 81 | 94 |
| 600 | 0 | 83 | 94 |
| 700 | 0 | 82 | 94 |
| 800 | 0 | 65 | 76 |

### 5.4 First node death time

When the network's first node death occurs, its topology will change, and all nodes will frequently communicate that the routing table has been rebuilt, consuming a lot of energy and accelerating node death [5]. So this paper uses the time of the first dead node to measure the network lifetime. Table 3 shows the number of rounds of the first dead node, the total number of current dead nodes, and the average energy consumption when the three algorithms construct the path. As can be seen from the table, this algorithm only appeared in the death bound in the 87th round. Compared with the IEEABR and ACA algorithms, the nodes of the algorithm have a longer network life cycle. At the same time, the total number of dead nodes and the average energy consumption are smaller than the IEEABR and ACA algorithms. Comparing these three indicators, this algorithm does balance the energy consumption of the network and prolongs the life cycle of the nodes. Figure 4 shows the trend of the number of iterations of the remaining nodes.

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Table 3. Death of the first node

| Algorithm name | First node death time | Total dead nodes | Node average energy consumption |
|---|---|---|---|
| HACA | 56 | 1 | 0.064 |
| IEEABR | 38 | 4 | 0.2852 |
| ACA | 7 | 3 | 0.2414 |

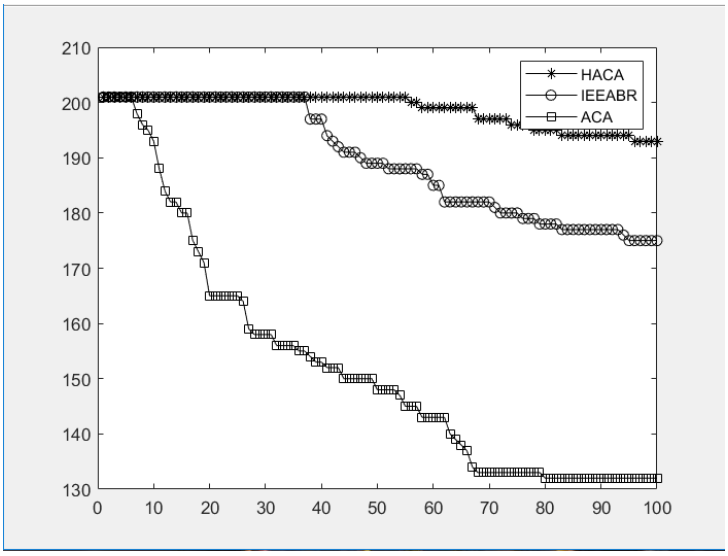


Figure 4. Comparison of the number of surviving nodes

## 6. Conclusion

Compared with IEEABR and ACA, the HACA algorithm proposed in this paper has achieved good results in reducing the energy consumption of sensor networks and extending the life cycle of sensor networks. The algorithm of this paper plans the area of the WSN network and classifies the sensor nodes, and then proposes the concept of regional ants to guide common ants forward, and the search of regional ants and common ants alternately to avoid the invalid transfer of common ants. At the same time, heuristic functions and pheromone update rules of regional ants are defined. Simulation experiments show that the improved ant colony algorithm has improved in path distance, overall network energy consumption, path construction success rate, and network life. It solves the local premature and energy consumption problems that occur when the ant colony algorithm is applied to WSN network problems. Issues such as uniformity extend the life cycle of the WSN network.

## References

[1] Anil Carie,Mingchu Li,Bhaskar Marapelli,Prakasha Reddy,Hayat Dino,Moneeb Gohar. Cognitive radio assisted WSN with interference aware AODV routing protocol[J]. Journal of Ambient Intelligence and Humanized Computing,2019,10(10).

[2] Zhong-xun Wang,Min Zhang,Xinglong Gao,Wenqi Wang,Xiaolin Li. A clustering WSN routing protocol based on node energy and multipath[J]. Cluster Computing,2019,22(3).

[3] Seyed Ali Fatemi Aghda,Mahdi Mirfakhraei. An Improved Cluster Routing Protocol to Increase the Lifetime of Wireless Sensor Network (WSN)[J]. Wireless Personal Communications,2019,109(3).

[4] A. Vinitha,M.S.S. Rukmini,Dhirajsunehra. Secure and Energy Aware Multi-hop Routing protocol in WSN using Taylor-based Hybrid Optimization Algorithm[J]. Journal of King Saud University - Computer and Information Sciences,2019.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202002_6(2).0001

[5] . Technology - Ambient Intelligence and Humanized Computing; Researchers from Dalian University of Technology Report Details of New Studies and Findings in the Area of Ambient Intelligence and Humanized Computing (Cognitive Radio Assisted Wsn With Interference Aware Aodv Routing Protocol)[J]. Computers, Networks & Communications,2019.