

## Research Article

# Minimization of Energy Consumption for Routing in High-Density Wireless Sensor Networks Based on Adaptive Elite Ant Colony Optimization

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High-density wireless sensor networks (HDWSNs) are usually deployed randomly, and each node of the network collects data from complex environments. Because the energy of sensor nodes is powered by batteries, it is basically impossible to replace batteries or charge in the complex surroundings. In this paper, a QoS routing energy consumption model is designed, and an improved adaptive elite ant colony optimization (AEACO) is proposed to reduce HDWSN routing energy consumption. This algorithm uses the adaptive operator and the elite operator to accelerate the convergence speed. So, as to validate the efficiency of AEACO, the AEACO is contrast with particle swarm optimization (PSO) and genetic algorithm (GA). The simulation outcomes show that the convergence speed of AEACO is sooner than PSO and GA. Moreover, the energy consumption of HDWSNs using AEACO is reduced by 30.7% compared with GA and 22.5% compared with PSO. Therefore, AEACO can successfully decrease energy consumption of the whole HDWSNs.

## 1. Introduction

Nowadays, emerging high-density wireless sensor network (HDWSNs) technologies have attracted a large number of scholars to study new QoS routing optimization algorithms in this field. With the further development and popularization of wireless communication technology, HDWSNs have been used in many application fields such as community monitoring, smart home, military, traffic control, environmental and detection [1]. HDWSNs combine computing technology with wireless mobile communication technology and sensor node technology to revolutionize the architecture and mode of traditional networks [2, 3]. However, due to the constraints of the sensing environment, in HDWSNs, a lot of nodes only provide restricted energy through batteries. Therefore, effectively cut down the energy consumption of nodes and realize energy-saving routing and data transmission have important research and application value for improving the performance and stability of HDWSNs [4, 5].

For multicondition restricted QoS routing optimization problems, the purpose is to find the best path from beginning to end for specific problems in HDWSNs, rather than the shortest path. And this path should meet multiple QoS constraint requirements such as delay jitter, delay, packet loss rate, and link bandwidth. These QoS routing conditions are used as the criteria for QoS routing considerations [6]. Due to energy limitations, how to maximize the reduction of routing energy consumption and extend the lifetime of sensor networks have become a bottleneck problem faced by HDWSNs.

Generally speaking, the volume and mass of sensors are very small. It is necessary to take into account the completion of specific communication tasks and to ensure that the internal energy utilization rate is increased [7]. The QoS routing optimization algorithm is an efficient way to cut down energy consumption within the network [8].

In this paper, a QoS routing optimization based upon AEACO is recommended to minimize the energy consumption

of HDWSNs. In order to assess the effectiveness of the AEACO, the model of QoS routing is first given. To improve the execution effectiveness of the algorithm, the routing fitness function is designed. Moreover, the adaptive and elite mechanisms are introduced into the ant colony optimization. We designed a new adaptive mechanism to improve the global search ability in the pheromone update phase and avoid falling into local optimum. A new elite mechanism is designed to retain the optimal ants and improve the optimization ability of the algorithm.

In the simulation, AEACO showed a good ability to find the best individual. It speeds up the convergence of the algorithm. The simulation results show that implementing AEACO in HDWSNs has higher performance than the particle swarm optimization (PSO) and genetic algorithm (GA). The consequence also shows that the adaptive and elite strategies proposed in this paper improve the global search capability of ant colony optimization.

The main contributions are as follows:

- (1) First, we propose an improved adaptive elite ant colony optimization (AEACO), which can effectively minimize the routing energy consumption in HDWSNs. After several iterations, the energy consumption of routing optimized by AEACO is reduced by 22.5% and 30.7%, respectively, compared with PSO and GA under the same experimental conditions. In addition, when the number of nodes increases, a similar conclusion can be drawn by comparing the experimental results with the other two algorithms. Therefore, the AEACO-based routing method can effectively improve energy utilization
- (2) Secondly, the AEACO that combines adaptive operators and elite operators has better performance in the absence of premature convergence. Increased global search capabilities. When the number of sensor nodes is 50 and 70, respectively, AEACO has a higher convergence speed than PSO and GA. Compared with the other two algorithms, the fitness after AEACO optimization converges to a small value after iteration
- (3) Finally, the total routing energy consumption of HDWSNs depends on the transmission and reception energy consumption of all nodes. Under the algorithm's adaptive mechanism, the overall energy consumption will be reduced. With the increase in the number of sensors in HDWSNs, the demand for data transmission increases, and the effect of AEACO in optimizing routing energy consumption also increases accordingly

The continuation of this paper is shown below. Section 2 discusses the author's related work for this article. Section 3 describes the QoS routing model. In Section 3, AEACO is used to optimize the QoS routing algorithm process. Section 5 presents the simulation results and comparison. The conclusion is given in Section 6.

## 2. Related Work

In HDWSNs, there is a direct relationship between lifetime and performance. Appropriate and efficient routing algorithms can decrease the energy consumption in the sensor networks, which is of excellent meaning to extend the HDWSN life span. Therefore, in [9], the author proposed a multimobile trajectory scheduling method based on coverage, using PSO and GA for optimal scheduling. The paper [10] combined the PEGASIS algorithm and Hamilton loop algorithm together, designed the best route, and effectively reduced energy consumption. The paper [11] proposed an enhanced high-performance aggregation algorithm, determine the best communication distance, set thresholds, and use mobile technology to reduce energy consumption between nodes. The paper [12] proposed a maximum data generation rate routing algorithm based on data flow control technology, which greatly reduced the time synchronization energy consumption. The paper [13] proposed a new coverage control algorithm based on PSO, by dividing the entire network into multiple A grid to increase coverage and reduce energy consumption.

Research on optimization of energy consumption in sensor networks has attracted scholars recently. The paper [14] proposed an energy-conscious green opponent model used in a green industrial environment, which can improve the hardware and software of the electronic physical system to reduce its energy consumption. The paper [15] uses the bat algorithm to select the best monitoring sensor node and the best path to reduce energy consumption. The paper [16] uses the whale optimization algorithm to solve the RA problem, achieves the best RA, and reduces the total communication cost. The paper [17] uses linear adaptive congestion control to improve the situation of greedy routing and data distribution.

HDWSNs has developed speedily in recent years, and it can well solve the problems of physical control and sensing. Based on the performance of the routing scenario used, computing and processing power is minimal considering the limited battery power [18]. For this reason, in paper [19], the author uses the genetic algorithm (GA) for simulation experiments in multihop QoS routing wireless networks, and the performance of the algorithm is analyzed from the aspects of scalability, energy consumption, and HDWSN life cycle. It can maximize the activity of the sensor by saving energy, thereby extending the service life of the network.

For QoS problems in high-quality wireless sensor networks, the simulated annealing algorithm is first found in [20], and the performance of SA is evaluated through routing energy consumption. Routing optimization for wireless sensor networks is with limited resources and computing power. The results show that the computational complexity increases with the rise of the quantity of network nodes in the case of limited computing capacity.

Paper [21] analyses a wireless powered sensor network, where the energy efficiency maximization problem is developed as a nonlinear fractional problem, which is hard to address for global best due to the absence of convexity. To prolong the life span of the network and reduce energy loss,

TABLE 1: The key parameter of AEACO.

Algorithm	Number of generations	Population size	Pheromone volatilization factor	Information heuristic factor	Pheromone weight
AEACO	100	50	0.98	1	3

TABLE 2: The key parameter of PSO.

Algorithm	Number of generations	Population size	Maximum speed	Social factor	Individual factor
PSO	100	50	10	2	2

a PSO routing strategy is proposed. With the PSO method, routing and forwarding can be performed quickly and directly. In this way, the algorithm searched for the optimal solution to the energy optimization problem. Results show the stability and fast convergence of the suggested algorithm. However, the algorithm is very easy to fall under premature convergence.

In [22], an SFLA sensor network routing scheme is put forward to cut down the total energy consumption of the network system. The SFLA is applied to resolve QoS routing issues of wireless sensor networks with mobile receivers. The authors describe the above problem as an optimization problem. To solve the NP-hard problem, the authors propose an improved shuffled frog-leap algorithm with delay constraints. The algorithm uses chaos technology to obtain a diverse group of frogs and gives an adaptive operator to speed up the algorithm. Operating speed: the author also proposes a new task scheduling algorithm which takes surplus energy into account to balance the network load. Finally, a large number of simulation experiments validate the efficiency of the algorithm. By this means, the best route delivery path can be selected to reduce network delay and energy consumption. However, the execution speed of the SFLA is still slow and cannot satisfy the requirements of QoS routing.

In [23], the QoS routing algorithm determines the lowest energy consumption path for information transmission from the start point to the endpoint. Because wireless sensor network nodes lack sufficient energy, energy efficiency utilization is an essential sign of wireless sensor network data transmission. The basic significance of HDWSNs in the current scene is to decrease the energy consumption of nodes in the network, improve data transmission effectiveness and availability, and extend entire network lifetime. In this regard, author demands to find the best route for data transmission in HDWSNs. To resolve this problem, authors put forward to an energy-saving routing algorithm for HDWSNs based on ant colony optimization (ACO). The improved low-energy routing method selects the cluster head by considering the energy and the distance between nodes. In order to decrease the energy consumption between nodes, the remaining energy is taken as a factor to extend the network life and improve the efficiency of routing data transmission. However, due to the high complexity of the algorithm, the efficiency of the program is not ideal.

In [24], in the design of HDWSNs, the energy consumption of HDWSNs has become a serious problem due to the limited battery energy. Therefore, a fast and robust algorithm is needed to optimize QoS routing in HDWSNs. Battery

TABLE 3: The key parameter of GA.

Algorithm	Number of generations	Population size	Crossover probability	Mutation probability
GA	100	50	0.75	0.06

power is needed to run the network. In order to extend the life cycle of the network, it is necessary to optimize the energy consumption. Energy consumption and QoS are two important factors. In HDWSNs based on low-energy consumption standard, energy consumption lies in activities such as data collection, data forwarding, and exchange with the gateway. Therefore, improving the routing efficiency of HDWSNs is an important task to extend the network life cycle. In the process of solving the problem, the author improved the hybrid leap-frog algorithm and modified the number of leap-frog and the population size appropriately. The author carried out extensive simulations on the proposed routing algorithm according to various performance parameters. However, the algorithm has poor robustness and cannot meet the requirements of HDWSN's QoS routing algorithm.

In this research, the key parameters of AEACO, PSO, and GA are listed in Tables 1–3.

### 3. System Model

This section introduces the QoS routing optimization model with multiple constraints. The mathematical model of HDWSNs can be expressed as the path set between each node in the sensor network, which is represented by  $G(V, E)$ . Graph theory is used to represent the source, destination, and multiple relay nodes and links. The node set includes the source node  $v_1$ , terminal node  $v_n$ , and numerous intermediate nodes  $v_2 \rightarrow \dots \rightarrow v_{n-1}$ . The source node is the  $No.1$  node, the intermediate nodes are  $No.2$  to  $No.(n-1)$  nodes, and the terminal node is the  $No.n$  node. Therefore, the route from the starting node to the terminal node can be expressed as  $r(v_1, v_n) = \{v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_{n-1} \rightarrow v_n\}$ .

Two nodes form a link. In this way, the sequence numbers of the adjacent 2 nodes are  $a$  and  $b$ , which can be expressed as  $e = \{v_a \rightarrow v_b\} (a \neq b)$ . Transmission performance over links is restricted by 4 parameters of link bandwidth, packet loss rate, delay jitter, and delay. The energy consumption in every path may be expressed as  $LS(e)$ , the jitter may be expressed as  $D(e)$ , the link bandwidth may be expressed as  $BW(e)$ , the packet loss rate may be expressed as  $PL(e)$ , and the delay jitter may be expressed as  $DJ(e)$ .

**3.1. Radio Energy Model.** Before the algorithm starts, we assume that constraints such as jitter, delay jitter, bandwidth, and packet loss rate in QoS routing already exist, and sensor nodes are randomly distributed in a two-dimensional coordinate.

On a link consisting of two conjoining nodes  $a$  and  $b$ , the energy consumption is consisting of data transmission and data reception energy consumption, and the total energy consumption  $LS(e)$  between the two adjacent nodes can be expressed as

$$LS(e) = LS_s + LS_r, \quad (1)$$

where  $LS_s$  can denote energy consumption of data transmission between neighboring nodes, and  $LS_r$  can denote the energy consumption of data receiving between neighboring nodes.

Suppose the distance between two conjoining nodes is  $l$  and the bits of transmitted data can denote  $q$ , and the energy cost of data transmission over a link can be expressed as

$$LS_s(q, l) = E_e \cdot q + \eta_{amp} \cdot q \cdot l^3, \quad (2)$$

where  $E_e$  is the electronics energy parameter.  $LS_s$  is the transmitter dissipated energy. The power amplification parameter for multipath fading  $\eta_{amp}$  determine the energy of the amplifier. The distance between two nodes is  $l$ , and the length of bits is  $q$ . The receiving energy consumption can be shown as

$$LS_r(q) = E_e \cdot q. \quad (3)$$

We can assume some parameters under constraints. For example, suppose when two sensor nodes are  $0.5m$  apart and  $q = 1 Mbit$ . We can set  $\eta_{amp} = 10pJ/bit/m^3$ . According to Equation (3),  $LS_r(q) = E_e \cdot q = 50nJ/bit \cdot 10^6 bit = 0.05J$  can be obtained.

### 3.2. Route Functions

**3.2.1. Energy Consumption Functions.** Assume that the data is from  $v_1$  to  $v_n$ , the energy consumption of link  $r(v_1, v_n)$  can be calculated by formula (4).

$$LS(r(v_1, v_n)) = \sum_{e \in r(v_1, v_n)} LS(e). \quad (4)$$

**3.2.2. Delay Functions.** The whole delay of data from node  $v_1$  to node  $v_n$  can be calculated by formula (5):

$$D(r(v_1, v_n)) = \sum_{e \in r(v_1, v_n)} D(e), \quad (5)$$

where  $D(r(v_1, v_n))$  is the total delay time of routing,  $r(v_1, v_n)$  is a routing from  $v_1$  to  $v_n$ , and  $e$  is a link on the route  $r(v_1, v_n)$ . The delay of link  $e$  can be expressed as  $D(e)$ .

**3.2.3. Bandwidth Functions.** The whole link bandwidth from node  $v_1$  to  $v_n$  can be expressed as formula (6)

$$BW(r(v_1, v_n)) = \min \{BW(e)\}, \quad (6)$$

where  $BW(r(v_1, v_n))$  is the bottleneck bandwidth of routing  $r(v_1, v_n)$ , and  $e$  is a link on routing  $r(v_1, v_n)$ . The bandwidth on the routing  $e$  can be represented as  $BW(e)$ .

**3.2.4. Delay Jitter Functions.** The whole delay jitter of data from node  $v_1$  to  $v_n$  can be expressed by formula (7).

$$DJ(r(v_1, v_n)) = \sum_{e \in r(v_1, v_n)} DJ(e). \quad (7)$$

**3.2.5. Packet Loss Rate Functions.** The whole packet loss rate of data from node  $v_1$  to  $v_n$  can be expressed by formula (8).

$$PL(r(v_1, v_n)) = 1 - \prod_{e \in r(v_1, v_n)} (1 - PL(e)), \quad (8)$$

where  $PL(r(v_1, v_n))$  is the whole packet loss rate of routing  $r(v_1, v_n)$ ,  $e$  is a link on routing  $r(v_1, v_n)$ , and  $PL(e)$  is the packet loss rate of link  $e$ .

**3.3. Objective Function.** In HDWSNs, many restrictions of the QoS routing model can be formed by the graph model. According to the delay energy loss model based on the conditions, the goal of QoS routing of is to find a route from the start node to the end node with the lowest energy consumption.

Fitness (fitness) is a parameter of all individuals based on the degree of adaptation of organisms to the natural environment. The fitness function refers to the one-to-one correspondence between all basic units in the actual problem and their own fitness. Normally, it is a constant function. In this paper, fitness is used to represent the energy consumption of HDWSNs QoS routing, and the fitness function can be shown by equation (9).

$$\text{fitness} = \min \{LS(p(v_1, v_n))\}. \quad (9)$$

**3.4. Restrictions.** Finding the best route with minimum energy consumption is the main goal of QoS routing model. Data transmission begins at source node  $v_1$  and ends at terminal node  $v_n$ . Links between adjacent nodes on this route need to meet the following restrictions ((10), (11), (12), (13)).

$$D(r(v_1, v_n)) \leq D_{\max}, \quad (10)$$

$$BW(r(v_1, v_n)) \geq BW_{\min}, \quad (11)$$

$$DJ(r(v_1, v_n)) \leq DJ_{\max}, \quad (12)$$

$$PL(r(v_1, v_n)) \leq PL_{\max}, \quad (13)$$

where  $D_{\max}$  represents the maximum delay acceptable on the route,  $BW_{\min}$  represents the minimum link bandwidth,  $PL_{\max}$  represents the maximum packet loss rate, and  $DJ_{\max}$  represents the maximum delay jitter.

#### 4. AEACO-Based Routing Minimizes Energy Consumption in HDWSNs

Aiming at QoS routing problem in HDWSNs, an optimization algorithm based on AEACO is put forward. The idea comes from the ant creature [25, 26]. In our AEACO strategy, a significant improvement is to add adaptive strategy and elite strategy on the basis of traditional ant colony optimization. These strategies enable AEACO to route well and direct search to the best solution.

Ant is a kind of social insect with the characteristics of social life, which has strict social structure and division of labor. In addition to harmonious division of labor, the highly complex “ant colony” system also has a mechanism of information transmission among ants, which makes the system operate orderly and efficiently. According to research, ants in nature are able to self-organize and choose the best route from nest to food source and can spontaneously find new good choices based on their surroundings [27, 28]. Ants can use pheromone as a medium to interact with each other.

The original ant colony optimization is an intelligent algorithm proposed by Italian Dorigo M. in 1992 and was successfully applied to solve TSP and QAP [29, 30] and then gradually developed by many scholars. At present, ACO has been applied to various fields, such as coloring problem, vehicle scheduling problem, and job scheduling problem [31, 32].

AEACO is a group intelligence approximate optimization technology. The process of evolution can be divided into two stages: adaptation stage and cooperation stage. In the initial stage of search route adaptation, pheromones accumulate with the increase of evolution time, and the more times ants pass, the higher the pheromone content in the route is, and the route is more likely to be selected by other ants. Therefore, the number of ants choosing this route is increasing. Finally, all ants will concentrate on the best route with positive feedback. At this time, the corresponding route is the optimal route of the routing problem.

This paper discusses several parts of AEACO from the aspects of parameters and population initialization, fitness calculation, path selection, operator optimization, pheromone change, and condition termination.

**4.1. Coding Scheme.** The first task of AEACO to solve routing problem is program coding. In the implementation of AEACO, coding will greatly affect the routing, fitness evaluation, and pheromone change. There are many coding methods, including real number and binary number. In order to increase the search space, real numbers are used to encode. Suppose there are  $K$  ants and  $s$  nodes. Each ant generates a route after it reaches the destination. In the restriction QoS routing optimization problem, the route of data transmission is expressed as  $p(v_1, v_n)$ . The whole number of nodes on the route can be expressed as  $n$ , which satisfies the formula (14)

$$n \leq s. \quad (14)$$

The population can be described formula (15),  $x_{K,s}$  represents the single node passed by the  $No.k$  ant, and  $(x_{k,1}, x_{k,2}, x_{k,3} \dots x_{k,s})$  represents the route of the  $No.k$  ant.

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \dots & x_{1,s} \\ x_{2,1} & x_{2,2} & x_{2,3} & \dots & x_{2,s} \\ \dots & \dots & \dots & \dots & \dots \\ x_{k,1} & x_{k,2} & x_{k,3} & \dots & x_{k,s} \\ \dots & \dots & \dots & \dots & \dots \\ x_{K,1} & x_{K,1} & x_{K,3} & \dots & x_{K,s} \end{bmatrix} \quad (x_{K,s} \in [0, s], k \in [1, K]). \quad (15)$$

**4.2. Ant Colony Initialization.** Ant colony is based on routing model coding. Its purpose is to establish a link between routing issues and AEACO. So, before stimulation,  $K$  ants were randomly generated as the initial ant colony. The initial ant colony holds  $K$  ants can be described as  $X = \{X_1, X_2, \dots, X_K\}$ . The  $No.i$  ant can be expressed as  $X_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,s}\}$ .

**4.3. Fitness Evaluation.** Each ant has its own fitness value and has a path selection solution. Therefore, the fitness function will greatly affect the performance of the algorithm. In the multicondition constrained QoS routing optimization issue, when the delay, link bandwidth, packet loss rate and jitter delay conditions are met, the fitness value can be calculated by formula (9); thus, the routing energy consumption of every one ant in the population in the process of data transmission is got. The lesser the energy consumption is, the better the route is.

Therefore, the criterion of evaluating each ant's path is the value of energy consumption. The less energy consumption of a route, the better the route.

**4.4. Select Path.** The  $K$  ants in the colony have the following characteristics: the energy consumption and pheromone content on the route determine which node the ant will choose.  $\tau_{ij}$  is the summation number of pheromones in the adjacency link between the 2 nodes. Moreover, the search rules of ants are as follows: each ant need complete a walk from the source to the destination, but it does not necessarily traverse all nodes and cannot access the nodes that have been traversed. Each ant will leave a certain amount of pheromone on its routing after completing the journey. In the initial stage of the algorithm, the pheromone content in the path between adjacent points is the same. At this moment, the  $No.k$  ant chooses the next node, and the number of pheromones and the energy consumption value determines which node the ant will choose.  $P_{d,e}^{j,j+1}$  represents the probability that ants choose the next node link  $No.j$  to  $No.(j+1)$ .  $d$  and  $e$  are adjacent to each other.

The amount of pheromone on the path and the energy consumption benefit can be calculated to select the probability of other nodes, so as to select the next routing node. Assuming conditions are met, ants can choose routing nodes. The chance  $p$  of the  $No.t$  generation ant accessing node  $d$

from node  $e$  is calculated by formula (16). In formula (16), the Roulette method can be routed nodes on the route that ants have not passed.

$$P_{d,e}^{i,j+1}(t) = \frac{\tau_{de}^\alpha(t) u_e^\beta(t)}{\sum_{l=1}^s \tau_{dl}^\alpha(t) u_{l,j+1}^\beta(t)} \quad (d \in [1, s], e \in [1, s], u_e \in u_{ij}, u_{l,j+1} \in u_{ij}), \quad (16)$$

$$C_{ij} = \begin{bmatrix} c_{11} & c_{12} & c_{13} & \cdots & c_{1(s-1)} \\ c_{21} & c_{22} & c_{23} & \cdots & c_{2(s-1)} \\ c_{31} & c_{32} & c_{33} & \cdots & c_{3(s-1)} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ c_{K1} & c_{K2} & c_{K3} & \cdots & c_{K(s-1)} \end{bmatrix} \quad (i \in [1, K], j \in [1, s-1]), \quad (17)$$

$$u_{ij} = \frac{1}{C_{ij}}. \quad (18)$$

In formula (16),  $t$  is the iteration time.  $\tau_{de}(t)$  is the pheromone content of the  $No.t$  generation link  $(d, e)$ .  $u_{ij}$  represents the reciprocal of the energy consumption value from the  $No.j$  node to the  $No.(j+1)$  node, which is called energy consumption benefit, which is calculated by formula (18).  $\alpha$  and  $\beta$  on behalf of the weighted value of pheromone and energy consumption correspondingly, which affects pheromone concentration and energy consumption. With the value of  $\alpha$  increases, the probability of ant selecting nodes increases. With the value of  $\beta$  increases, ants will also increase the chance to select other nodes according to  $j$  nodes.

In formula (16), With the increase pheromone concentration and energy efficiency, the probability of ant selecting routing node increases.

$C_{ij}$  represents the energy consumption value of the ant's route, and it is made up of  $K$  the same matrixes, which can be expressed as  $[c_1 \ c_1 \ c_1 \ \cdots \ c_{s-1}]$ .  $u_{ij}$  is a matrix of fitness of energy consumption, which can be calculated by formulas ((17) and (18)).

**4.5. Pheromone Update.** In search of the best route, the pheromone needs to be calculated and updated. When ants visit each routing node, they leave pheromone from the  $No.d$  node to the  $No.e$  node. With the continuous evolution of the algorithm, the content of pheromone will volatilize in the process of evolution. In AEACO, after each ant completes a walk from the origin node to the end node, the pheromone on the route is updated. The pheromone content on the link  $(d, e)$  during  $(g, g+1)$  round is modified in

$$\tau_{de}(g, g+1) = \rho \cdot \tau_{de}(g) + \Delta\tau_{de}(g, g+1), \quad (19)$$

$$\Delta\tau_{de}(g, g+1) = \sum_{k=1}^m \Delta\tau_{de}^k(g, g+1). \quad (20)$$

In equation (19),  $\Delta\tau_{de}(g, g+1)$  represents the pheromone content that the ant remaining on the link  $(d, e)$  during

$(g, g+1)$  round.  $\rho$  represents the volatility factor of pheromone, which is used to reduce the accumulated pheromone on the link. According to formula (20),  $\Delta\tau_{de}^k(g, g+1)$  means the content of pheromone that the  $No.k$  ant remaining on the link  $(d, e)$  during  $(g, g+1)$  round.

The ant colony pheromone value update calculation of AEACO is represented by equation (21).

$$\tau_{de}^k = u_e Q. \quad (21)$$

In equation (21),  $Q$  represents a constant and represents the pheromone unit concentration left by ants on the path to complete the search.  $u_e$  is the energy consumption revenue value between two nodes. In this model, when the ant finds the optimal route, the ant releases pheromone. Therefore, the ant colony uses the overall pheromone environment.

**4.6. Termination Condition.** During the execution of the AEACO, When the algorithm runs to the stop condition statement, it will automatically judge whether it meets the condition. If it meets the upper limit value, it will end the algorithm and output the result.

**4.7. Adaptive Operator.** In the process of AEACO, the algorithm adopts an adaptive operator, which reduces the speed of the algorithm in the iterative evolution process. The main function of the positive feedback mechanism is to accelerate the algorithm convergence and make the algorithm have good performance, but it is very easy to lead the algorithm to be too premature. Therefore, in the selection operator, an adaptive method can be used. The purpose of the adaptive operator is to flexibly adjust the probability of choosing other paths during the search process. Through multiple loop iterations, the evolution direction of the ant colony can be basically determined, and the pheromone on the path completed by the ants can be dynamically adjusted.

Adaptive strategy is a new information update strategy. When the problem is more complicated, if the pheromone volatilization factor exists, then the pheromone content on the path that ants choose less or has not chosen will be exhausted. Therefore, it will reduce AEACO's global search capabilities. However, if the pheromone content in other paths is very high, then the amount of information in these paths will increase again, so the chance of finding these high-content paths again increases. The path traversed by the previous generation of ants is likely to be selected again by the next generation of ants, which will lead to local optimal search and reduce global search performance. Therefore, AEACO's global search capability can be increased by changing the pheromone volatilization factor. The adaptive strategy proposes an adaptive method to change the pheromone, and the pheromone update formula (22) is expressed as

$$\begin{cases} \tau_{de}(g, g+1) = (1 - \rho)^{1+\varphi(w)} \cdot \tau_{de}(g) + \Delta\tau_{de}(g, g+1) & \tau \geq \tau_{\max} \\ \tau_{de}(g, g+1) = (1 - \rho)^{1-\varphi(w)} \cdot \tau_{de}(g) + \Delta\tau_{de}(g, g+1) & \tau < \tau_{\max} \end{cases}, \quad (22)$$

$$\varphi(w) = w/c. \quad (23)$$

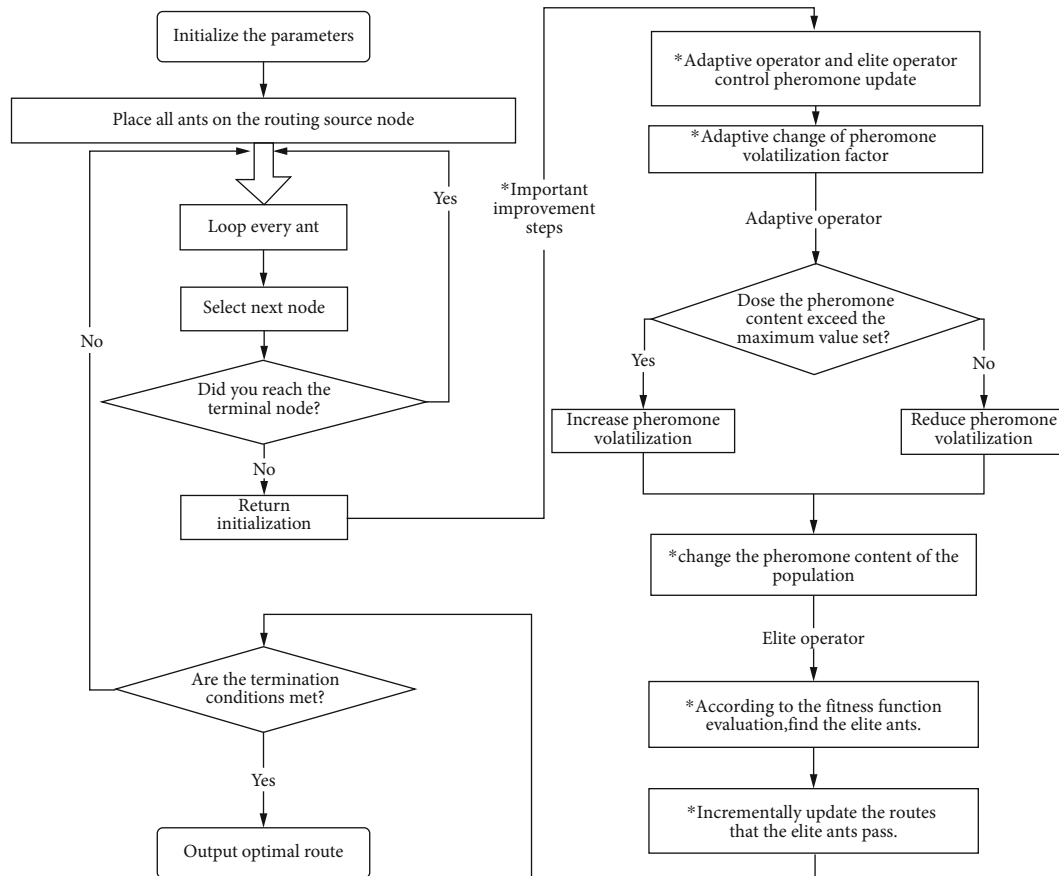


FIGURE 1: The flow chart of AEACO.

## Improved adaptive elite ant colony optimization based on routing energy consumption

Begin

*Step 1.* Set the parameters and QoS constraints of each node and each edge in the model, and the relevant parameters in the algorithm are set. Set the pheromone volatilization coefficient, initialize pheromone value, and energy consumption revenue value. The upper limit of iterations is  $N_{g\_max}$ . The primary value is  $N_g = 0$ . The colony size is  $K$ .

Set pheromone initial value of  $\tau_{de}$  on the link  $(d, e)$ ,  $\tau_{de}(0) = 1$ .

While the algorithm has not reached the maximum number of iterations.

*Step 2.* Increase iteration times,  $N_g = N_g + 1$ .

*Step 3.* Increase the number of ants,  $k = k + 1$ .

*Step 4.* Calculate the selection probability of the next node  $j$ , according to Equation (16).

*Step 5.* If  $j \neq s$ , continue *step 4*; otherwise, perform *step 6*.

*Step 6.* If  $k \geq K$ , go to *step 7*; otherwise, go to *step 3*.

*Step 7.* Update pheromone adaptive adjustment, according to equation ((16), (22)).

*Step 8.* Find elite ants and update pheromone incrementally, according to Equation (9).

*Step 9.* When the condition meets the number of cycles  $N_g > N_{g\_max}$ , then output the result; otherwise, go to *step 2*.

End while

End

ALGORITHM 1: Algorithm flow.

In formula (23),  $\varphi(w)$  represents a functional formula proportional to the convergence factor  $w$ . The more the times  $w$ , the greater the value of  $\varphi(w)$ , and  $c$  represents a constant. According to the evolution of the algorithm, adaptive update pheromone, thereby dynamically adjusting the intensity of the amount of information on each path, so that the ants are neither

too concentrated nor too scattered, thereby avoiding premature and local convergence and improving the global search ability.

**4.8. Elite Operator.** The elite ant operator is an improvement of the basic ACO. Its design idea is to give the optimal path extra pheromone after each cycle. The ant that finds the best

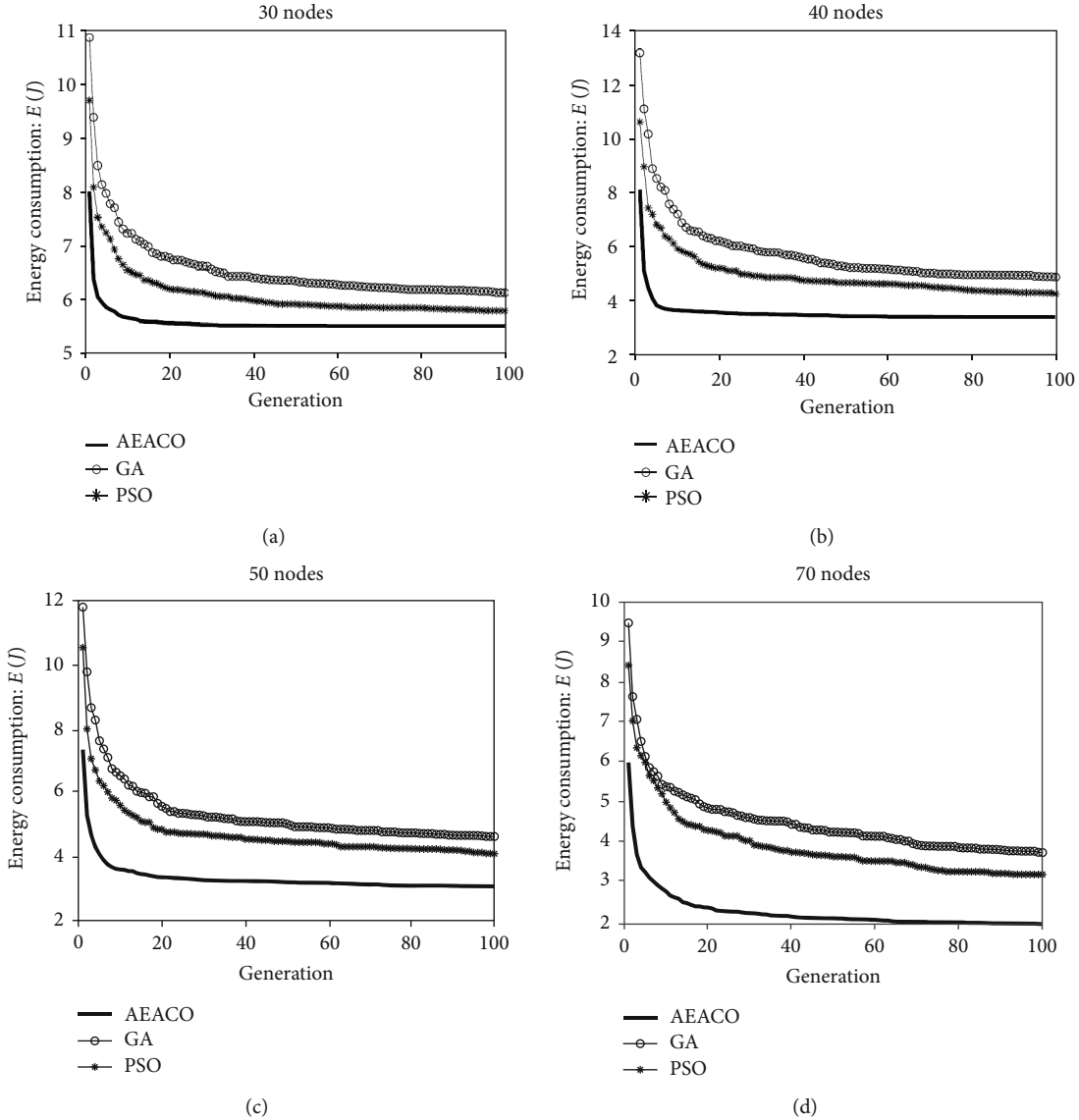


FIGURE 2: Comparison of energy consumption of three algorithms. (a) The energy consumption comparison of three algorithms after 100 generations of 30 nodes. (b) The energy consumption comparison of three algorithms after 100 generations of 40 nodes. (c) The energy consumption comparison of three algorithms after 100 generations of 50 nodes. (d) The energy consumption comparison of three algorithms after 100 generations of 30 nodes.

route is called the elite ant. Denote this optimal route as  $R_{\text{best}}$ . The additional enhancement for route  $R_{\text{best}}$  is obtained by adding pheromone to each edge in  $R_{\text{best}}$ . The update formula of pheromone can be expressed as ((24), (25))

$$\tau_{de}(g, g+1) = \rho \cdot \tau_{de}(g) + \Delta\tau_{de}(g, g+1) + \Delta\tau_{de}^*, \quad (24)$$

$$\Delta\tau_{de}^* = \partial \cdot Q \cdot u_e^*, \quad (25)$$

where  $\partial$  is a parameter that defines the weight given to route  $R_{\text{best}}$ , and  $\Delta\tau_{de}^*$  shows the change of pheromone on the link  $(d, e)$  according to the ant that completes the best path.  $u_e^*$  shows the benefit value of energy consumption.

**4.9. AEACO Steps.** As shown in Figure 1, the whole execution process of the AEACO algorithm is visually displayed.

In Figure 1, we can see the overall flow chart. The first is to initialize the parameters, place the ants at the source point of the route, and loop each ant to search. Each ant selects the next node in turn during its own search. After the entire population cycle is over, the next most important process is pheromone update. We propose an adaptive mechanism to determine whether the pheromone content on the current path exceeds the set maximum value, so as to adjust the volatilization factor to control pheromone update. When the entire population is updated, we evaluate the population according to the fitness function and find the elite ants with the least energy consumption for routing. Pheromone is incrementally updated on this path of elite ants. When the predetermined termination condition is reached, the algorithm ends, and the best route is output.



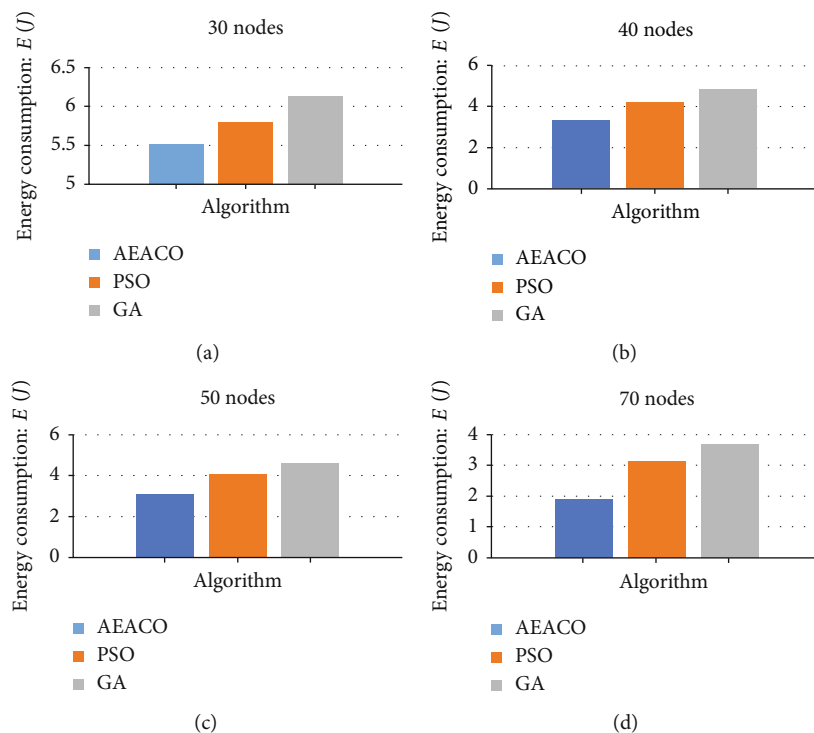


FIGURE 3: Compare the energy consumption of the three algorithms in the form of a histogram. (a) Comparison of energy consumption of three algorithms with 30 nodes. (b) Comparison of energy consumption of three algorithms with 40 nodes. (c) Comparison of energy consumption of three algorithms with 50 nodes. (d) Comparison of energy consumption of three algorithms with 70 nodes.

Through the detailed explanation of the above flowchart, we give the specific algorithm pseudo code of the specific AEACO as shown in Algorithm 1.

## 5. Discussion on Simulation Results

In the simulation part, we will test the algorithm performance of AEACO in HDWSN routing optimization and compare the results with the simulation results of GA and PSO for HDWSN routing optimization. Under the condition that other conditions are the same, HDWSNs of different numbers of nodes are used for comparison. The software and hardware environment are uniformly equipped with Intel (R) Core (TM) i5 2.40GHz CPU computers and the same version of Windows 10, and the programming language is MATLAB. On this basis, to prove AEACO's superior performance in optimizing QoS routing.

In the simulation, the performance of AEACO is compared with PSO and GA. The three of AEACO, PSO, and GA output results after 100 iterations of the loop and sets the population size to 50 individuals. In AEACO, set the pheromone volatilization factor to 0.98, the energy consumption gain coefficient to 2, the information heuristic factor to 1, the expected heuristic factor to be 4, and the pheromone intensity to 3. The crossover probability of genetic algorithm is 0.75, and the mutation probability is 0.06. In PSO, the value of the social learning factor is defined as 2, the value of the individual learning factor is defined as 2, and the absolute value of the upper and lower speed limits is defined as 10. These parameter settings are given in Tables 1–3.

Figures 2(a)–2(d) shows the simulation results of AEACO, PSO, and GA at four different node scales. It can be clearly seen from Figures 2(a)–2(d) that AEACO has superior performance than PSO and GA under four different node scales. Especially when the number of nodes is 70, AEACO's performance is more obvious. In the first 20 iterations, the energy consumption of AEACO has changed greatly, and the convergence speed has increased significantly after 20 generations. From 20 iterations to 100 iterations, the energy consumption of AEACO is close to 1.8986 J. At this time, PSO and GA are 3.1489 J and 3.7012 J, respectively, using adaptive operators and elite operators to improve AEACO's global search capability and convergence speed. In 100 iterations, the energy consumption of PSO is lower than that of the GA algorithm, while the convergence speed of the AEACO algorithm is faster and the energy consumption is the lowest. In Figures 2(a)–2(c), when the number of nodes is 30, 40, and 50, AEACO performs better than PSO and GA in solving routing energy consumption problems, and the convergence speed of PSO and GA algorithms is slower and easier to fall into a local optimal solution. In general, under the same algebra, AEACO has a faster convergence rate, better effect, and better performance than PSO and GA in terms of routing optimization.

Compare the performance of AEACO, PSO, and GA with the histogram in Figure 3. In Figure 3(d), when the number of nodes is 70 and when iterates 100 times, the energy consumption cost of AEACO is significantly lower than that of PSO and GA. At this time, the energy consumption cost of GA is greater than that of PSO, while the energy

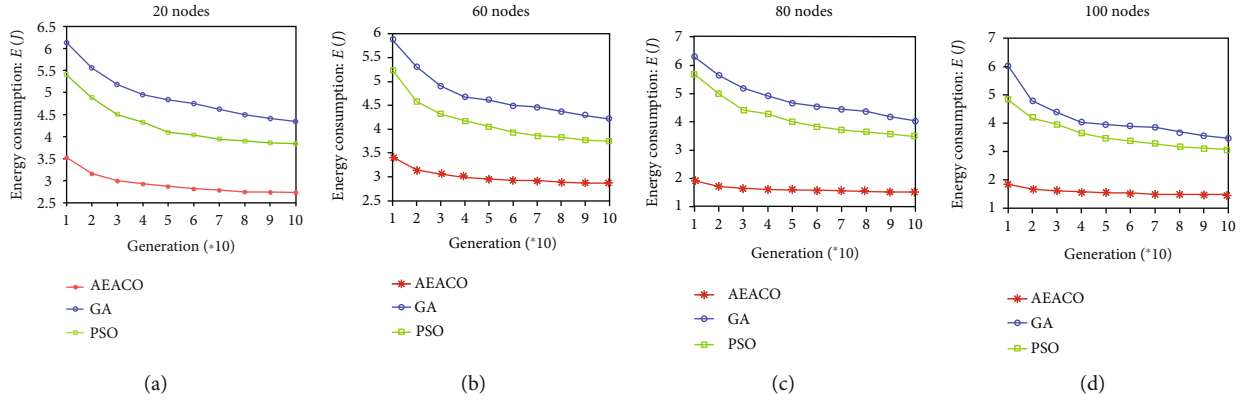


FIGURE 4: The energy consumption of the three algorithms is compared every ten generations. (a) Comparison of 20 nodes every 10 generations. (b) Comparison of 60 nodes every 10 generations. (c) Comparison of 80 nodes every 10 generations. (d) Comparison of 100 nodes every 10 generations.

TABLE 4: Energy consumption values of different node sizes.

Algorithm	30 nodes	40 nodes	50 nodes	70 nodes
AEACO	5.5195	3.3449	3.0690	1.8986
PSO	5.7957	4.2094	4.0883	3.1489
GA	6.1329	4.8302	4.6283	3.7012

consumption cost of AEACO is relatively the lowest and the performance is the best. In Figures 3(a)–3(c), when the number of nodes is 30, 40, and 50, respectively, the same conclusion can be drawn as in Figure 3(d). The performance of AEACO is always better than PSO and GA.

In Figure 4, 20 nodes, 60 nodes, 80 nodes and 100 nodes are set up, respectively. Data comparison is performed every 10 generations. In Figures 4(a)–4(d), it can be seen that in the 10th iteration, the energy consumption of AEACO is much lower than that of PSO and GA, and it quickly converges and stabilizes in the next 90 iterations. At this time, the convergence speed of PSO and GA is slower, PSO performance is better than GA, and AEACO performance is the best. In Figures 4(c) and 4(d), AEACO is basically close to the optimal solution at the 10th generation, while PSO and GA dissociate to the optimal solution, and the difference is great. The results show that AEACO is more effective than PSO and GA, and its performance is always better than PSO and GA.

Aiming at the QoS routing problem with different numbers of sensors, the same number of iterations is adopted. Table 4, respectively, lists the correlation between the energy consumption and node scale of AEACO, PSO, and GA.

The data in Table 5 shows the percentage improvement in energy consumption of AEACO compared with the other two algorithms. When the number of nodes is 30, AEACO's improvement in reducing routing energy consumption is 4.76% and 10.00% higher than that of PSO and GA. Especially when the number of nodes is 70, AEACO's improvement in reducing routing energy consumption is 39.71% and 48.70% higher than that of PSO and GA. It can be seen from Tables 4 and 5 that as the scale of nodes increases, the degree of optimization of the algorithm proposed in this paper is more obvious, which is suitable for dense networks

TABLE 5: Compared with the other 2 algorithms, the percentage of improvement in energy consumption is optimized by AEACO.

Number of nodes	PSO	GA
30	4.76%	10.00%
40	20.54%	30.75%
50	24.93%	33.69%
70	39.71%	48.70%

TABLE 6: Convergence time comparison of three algorithms.

Number of nodes	AEACO	PSO	GA
30	9.63 s	14.26 s	18.95 s
40	15.64 s	20.53 s	25.12 s
50	19.37 s	24.47 s	28.96 s
70	35.49 s	48.37 s	55.83 s

such as HDWSNs. The data shows that this method can effectively reduce routing energy consumption.

The data in Table 6 shows the calculated convergence time of the three algorithms under the conditions of 30, 40, 50, and 70 nodes, respectively. It can be seen from the data that the convergence time of AEACO's algorithm is shorter than that of PSO and GA. Especially as the number of nodes increases, the performance of AEACO's algorithm is more obvious than that of PSO and GA. Therefore, it is proved that the method has better performance.

Based on the above result data analysis, the AEACO we proposed has superior performance in reducing energy consumption and algorithm convergence. This is due to the strategy of combining adaptive and elite design we designed to control the volatilization of pheromone in the algorithm flow to increase the algorithm's global search capability. Add extra pheromone to the elite ants to increase the ability of the algorithm to quickly find the best. Simulation results show that this method can effectively reduce routing energy consumption.

In this research, for the energy consumption optimization method of high-density wireless sensor network under multiple constraints, this paper proposes an optimization method for the network model under the constraints of delay, jitter, bandwidth, and packet loss rate and only considers two nonmovable situations in the dimensional coordinates. We did not consider more complex situations, such as three-dimensional space, movable sensors, and other factors. In the future, it will be further studied under the combined effect of environmental interference, movable deployment conditions, and other influencing factors and expanded into three-dimensional space to optimize network energy consumption. Therefore, these issues are the content of this article that needs further research.

## 6. Conclusion

In order to optimize routing selection, an improved adaptive elite ant colony optimization (AEACO) is proposed, which combines the advantages of traditional ant colony optimization and adaptive strategy and elite strategy. The process of AEACO evolution, population coding, and population initialization calculates fitness, selects path, and updates pheromone. By adding an elite operator, additional pheromone will be added to the path taken by the individual ant with lower energy consumption to accelerate the algorithm convergence. AEACO after adding adaptive operator evolution has a more comprehensive global search capability. We compared this algorithm with PSO and GA in simulation. The outcomes show that the proposed AEACO has a quicker convergence speed and can be more effective find a data transmission path with minimum energy consumption.

## Data Availability

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

## Disclosure

The funders had no role in the design of the study in the collection, analyses, or interpretation of data in the writing of the manuscript, or in the decision to publish the results.

## Conflicts of Interest

The authors declare no conflict of interest.

## Authors' Contributions

Jie Zhou and Jing Xiao performed the conceptualization. Jie Zhou performed the methodology. Chaoqun Li performed the software. Jie Zhou, Jing Xiao, and Chaoqun Li contributed to the validation. Jing Xiao and Chaoqun Li contributed to the formal analysis. Jie Zhou contributed to the investigation. Jie Zhou performed the resources. Chaoqun Li performed the data curation. Jing Xiao and Chaoqun Li performed the writing—original draft preparation. Jie Zhou contributed to the writing—review and editing. Chaoqun Li

performed the visualization. Jie Zhou and Jing Xiao performed the supervision. Jie Zhou contributed to the project administration. Jie Zhou performed the funding acquisition. All authors have read and agreed to the published version of the manuscript.

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