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Article

Design of network self-organization-based energy-optimized routing algorithm for large-scale wireless sensor networks

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Abstract: Routing algorithms not only help the wireless sensor networks to accomplish their tasks but also help the nodes to select an optimal path among the many paths for the transmission of data packets. However, due to the limited energy and inadequate hardware conditions of wireless sensor networks, it is prone to data transmission delays and shortened life cycle due to insufficient energy of the nodes. For this reason, the article proposes the EAODV routing protocol based on energy optimization, based on the in-depth analysis of the existing routing protocols, establishes the mathematical model of network node characteristics, and proposes the energy-optimized routing algorithm E-EEABR with the improvement of the ant colony for solving. The next-hop route is precisely selected by considering three factors: distance band, search angle and distance factor, the transmission task of overloaded "hot" nodes is balanced by incentive strategy, and the probability transfer function is optimized by pseudo-random scaling rule to enhance the algorithm's optimization ability. Finally, the article verifies the effect of energy optimization of the routing algorithm through simulation experiments. From the results of simulation experiments, it can be seen that the average energy consumption of cluster head of E-EABR algorithm is lower than that of SEP algorithm, and its maximum energy consumption is about 2.35×10-3 J, while the maximum average energy consumption of cluster head of SEP algorithm is about 8.7×10-3 J. It can be concluded that the performance of cluster head energy consumption is better than that of the comparative algorithms, and the algorithm of this paper effectively reduces the average energy consumption of the cluster head and equalizes the energy consumption of the network.

Keywords: e-eeabr; ant colony algorithm; wireless sensor network; energy optimization; eaodv routing protocol

1. Introduction

With the advancement of wireless networks and data communications, the information industry is booming, the demand for data acquisition is increasing day by day, and collecting and analyzing data has become the key in the field of information technology research, which further contributes to the increasing maturity of sensor technology and the gradual reduction of sensor size and cost, which makes it technically and economically possible for a large number of wireless miniature sensors to be arranged in unattended and non-recyclable areas [1-3]. Wireless Sensor Networks (WSNs) connect and control sensor nodes in a random or predetermined way to sense, collect, process, and transmit physical data in the surrounding area, which greatly change the way people perceive the physical world and obtain data information [4-5]. WSNs connect the cyberspace and the real world, and people can obtain real and effective external data information such as temperature and humidity directly from the network. Wireless Sensor Networks are both practical and applicable, and have already shown outstanding contributions in military and civil fields, etc. The wide application prospects of WSNs make their development concerned by Chinese and foreign circles, and they are one of the most promising high-tech industries in the 21st century [6].

WSN consists of a large number of sensor nodes randomly distributed in a certain geographical area, and the nodes are usually powered by batteries [7]. The data measured by the nodes can be viewed as distributed data sources with a certain structure, which are transmitted to the Sink nodes through a communication interface in a wireless multi-hop manner [8-9]. The limitations of current hardware technology make the sensors have limited communication bandwidth, insufficient battery energy, and high failure rates. Therefore, thousands of sensors are usually deployed to form large-scale sensor networks with the intention of overcoming sensor hardware limitations through redundancy [10-13]. However, the limited energy and communication bandwidth are difficult to transmit a large amount of sensed data, and how to effectively fuse the sensed data to reduce the network communication has been an important topic in sensor network research.

For the energy optimization level of WSN routing protocols, in terms of topology, the research work of domestic and international researchers mainly focuses on two areas: hierarchical routing protocols and planar routing protocols. For early small-scale WSNs, the general choice is to use planar routing protocols, the more typical planar routing protocols, such as the Flooding protocol, the SPIN protocol and the DD protocol [14-17]. The Flooding Time Synchronization Protocol (FTSP) proposed by Yildirim, K et al [18] employs a clock speed consistency algorithm, which is able to reduce the undesirable effects of slow flooding on the synchronization accuracy without changing the flood propagation speed, and greatly improves the synchronization accuracy and scalability of slow flooding. Zhu, T et al [19] proposed an optimization algorithm called “Collective Flooding (CF)” based on the traditional flood propagation algorithm, which optimizes its scalability and complexity while reducing the total number of packet transmissions and propagation delay by 30% to 50% respectively.

Flooding protocol is data centric and uses broadcast form to send data to neighboring nodes which has the advantage of simple implementation but suffers from the problem of duplicate data reception [20]. For this reason, Pattani, K and Chauhan, P [21] proposed the SPIN protocol for wireless sensor networks with low power, low memory, and low energy consumption, however, the negotiation mechanism of the SPIN protocol, while solving the above mentioned drawbacks, in turn dramatically reduces the network performance. The DD protocol adopts the directional diffusion mechanism, which effectively solves the problem of redundancy of negotiation information, but it has the same defects as the Flooding protocol in selecting the optimal transmission path [22-23]. In conclusion, the planar routing protocol design scheme is simple and easy to implement, applicable to the network structure with a small number of nodes, but there are limitations in terms of network scalability, network delay and energy consumption equalization.

Hierarchical routing protocols are relative to planar routing protocols and have become a mainstream research direction in routing protocols due to their advantages such as high energy utilization and easy network management. Hierarchical routing protocols are based on the idea of clustering, which distinguishes nodes into two different classes: ordinary nodes and cluster head nodes (CH) [24]. Domestic and foreign researchers have conducted in-depth studies on the directions about how to select cluster heads, set the cluster size, and find inter-cluster routes, etc. LEACH, as a classical distributed cluster routing protocol, adopts the mechanism of randomly campaigning for cluster heads in the form of a roulette wheel in order to balance the energy consumption of CHs [25]. However, the LEACH algorithm also has defects, in the selection of cluster heads, the algorithm relies solely on probability and does not take into account the real-time situation of the network [26]. Based on the LEACH algorithm, the cluster routing algorithm has been continuously improved and developed, and the cluster-based preference and data transmission-based cluster routing improvement algorithms have been proposed successively.

For example, in 2010, Tong, M and Tang, M [27] proposed LEACH-B algorithm in which the optimal number of cluster heads is calculated with reference to the nodes' residual energy during the second selection of cluster heads, and nodes are rotated to be elected as cluster heads in order to maintain the same number of cluster heads in each round.In 2016, Gambhir, S [28] proposed an optimized energy-efficient LEACH algorithm for WSNs (OE-LEACH), which is able to improve the performance of LEACH protocol by reducing the time delay and energy consumption, while the network lifetime and throughput of WSNs are also improved.In 2018, A Bendjeddou et al [29] proposed LEACH-S algorithm in which the remaining energy of the cluster head node is less than the current average residual energy of the cluster members a new cluster head will be selected. In the same year, Huang, W et al [30] proposed a new energy efficient routing algorithm (NF-LEACH) for the problem of inaccurate cluster centers, irrational clustering, and a single data transmission mode, which extends the life cycle of the network by considering the membership degree, residual energy, and the distance to the base station in order to make it more energy efficient.

In recent years, the emergence of more and more intelligent optimization algorithms has been successfully applied to improve the WSN cluster routing algorithm, which improves the reasonableness of clusters by finding the optimal cluster header groups and optimal cluster sizes to effectively extend the WSN life cycle [31-33]. With the goal of reducing unnecessary energy consumption for the improvement of redundant packet control, in 2010, Tuteja, A et al [34] who discussed in detail a clustering algorithm, which divides the nodes in the network into a number of clusters according to a certain rule, and the source of the communication in the cluster is the CH. after the nodes within a cluster have established a communication path to another cluster, other nodes in the same cluster share the communication path to the target path to other nodes within the node cluster, i.e., the nodes in the same cluster share the intra-cluster information, which reduces unnecessary grouping of route requests.In 2014, Kaur, A et al [35], on the other hand, proposed an improved mobile node localization algorithm based on the study of Monte Carlo mobile node localization algorithm based on the Particle Swarm Algorithm (PSO) and Least-Squares Fitting, which effectively overcomes the effect of signal fading on localization and fully takes into account the mobility of the nodes, thus reducing the localization error.In 2016, Shankar, T et al [36] et al. proposed a HAS-PSO algorithm by mixing the Harmonic Search Algorithm (HAS) and PSO, which utilizes the ratio of node-to-cluster-head distance and residual energy to construct the fitness function but does not consider the multi-hop inter-cluster routing scenario, which may lead to high cluster-head energy consumption in the far base station. In 2020, Guo, K and Lv, Y [37] used PSO algorithm to improve AODV protocol considering bandwidth, latency and cost factors of WSNs and conducted simulation experiments in NS2 simulation platform and found that the improvement of AODV protocol by Chaotic Particle Swarm Optimization (CACPSO) can transmit data faster and more stably.In 2021, Jacob, I and Darney, P [38] used bee agent behavior in artificial bee colony optimization algorithms to make synchronous and decentralized routing decisions while discovering and determining multipaths in the network with the help of breadth-first search variants, which improved the efficiency of the energy usage of the entire WSN routing protocol. In the same year, Lipare, A et al [39] proposed an SF-MPSO algorithm using a combination of particle swarm and fuzzy systems with reference to energy and distance factors, but no inter-cluster routing optimization was performed, and the direct communication between the cluster head and the base station increased the energy consumption, which is not applicable to large and dense networks.In 2023, Mekala, S et al [40] proposed an energy efficient routing protocol based on energy-efficient regression and fuzzy systems for Heterogeneous Wireless Sensor Networks (HWSN)) proposed an energy-efficient regression and fuzzy based intelligent routing algorithm which selects fine cluster heads from CHs through a fuzzy inference system, which has significant advantages in terms of energy efficiency, packet delivery rate, and throughput.In 2024, Yang, X et al [41] fused the Whale Optimization Algorithm (WOA) and deep reinforcement learning in group intelligence to propose an innovative intelligent routing algorithm (WOAD3QN-RP), which first determines the optimal cluster heads by WOA, and then uses a two-layer deep Q-network (D3QN) to determine the optimal multihop paths in terms of multihop path selection as a way to adapt to the dynamic changes in the network topology and to ensure the balance between energy consumption and multihop routing performance.

Although the above methods save a certain amount of system energy consumption, they still have problems such as network delay, high energy consumption, bring security risks and poor adaptive ability, especially when the scale of the WSN is very large, and the number of nodes may reach thousands, e.g., forest monitoring [42-43], and monitoring of active volcano activity conditions [44]. Even though the intermediate nodes adopt data fusion techniques, the sensor nodes at the end will still transmit a large amount of monitoring data into the network, which extremely consumes the valuable network resources in unattended areas.

The article firstly proposes EAODV routing protocol based on energy optimization on the basis of wireless self-organized network structure, and describes the design process of EAODV protocol. Then, a mathematical model of network node characteristics is established, and the EEABR algorithm is introduced, and the energy-optimized routing algorithm E-EEABR is proposed to improve the ant colony, considering three factors, namely, the distance band, the search angle, and the distance factor, and utilizing the incentive strategy to equalize the transmission tasks of overloaded hot nodes, and optimizing the probability transfer function through the pseudo-random scaling rule to enhance the optimization capability of the algorithm. Optimize the probability transfer function to enhance the algorithm's optimization ability. We analyze the impact of three important ACO parameters, namely, pheromone volatility coefficient ρ , pheromone weighting factor α , and weighting factor of residual energy and link congestion indicator β , on the performance of the protocol, and finally, we conduct a comparison experiment of energy optimization of the proposed algorithm with SEP algorithm in the simulation platform.

2. EAODV routing protocol based on energy optimization

2.1. Wireless Self-Organizing Network Architecture

The term Ad Hoc is derived from the Latin word for “unprepared, temporary”, and is a temporary multi-hop, uncentered network consisting of many nodes. These nodes are equipped with wireless receiving and transmitting devices, and the nodes are randomly distributed across different geographical areas and are mobile. Nodes and nodes have the same status, there is no central node, all of these irregular nodes can build a communication network at any time, anywhere, do not need to rely on a fixed physical infrastructure. The nodes of wireless self-organizing networks can be divided into four types from the physical structure: one host with multiple routers, one host with one router, multiple hosts with multiple routers, and multiple hosts with one router. The physical configuration of nodes in Mobile Ad Hoc network is shown in Fig. 1.

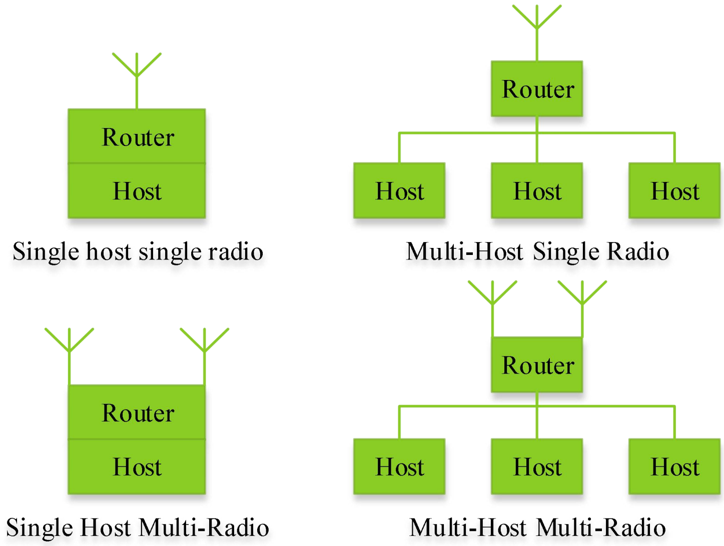


Figure 1. The physical structure of nodes in mobile Ad-Hoc networks.

The network topology of a Mobile Ad Hoc network can be generalized into two structures: hierarchical and planar. In the planar structure, every node in the network has equal status, there is no such thing as which node is the center node, so this kind of network can also be called a peer-to-peer network structure.

The topology of a planar network is relatively simple, and the status of each node in the network is completely equal, so there is no bottleneck node in common sense, so the robustness is better. The disadvantage of this structure is that it is not very scalable. Any node must maintain all the routing information to the other nodes, however, all these routing messages are constantly changing dynamically, so a lot of relevant control messages are needed. Another type of network topology is the hierarchical construction, in which the network is divided into many isolated subnets, and it can be said that any subnet in the middle is an independent autonomous system. Connectivity between subnets can be achieved by electing a node in the network to act as a wireless access point, or it can be handled by a distribution system consisting of specialized wireless access points. The network topology of the hierarchical structure is shown in Fig. 2.

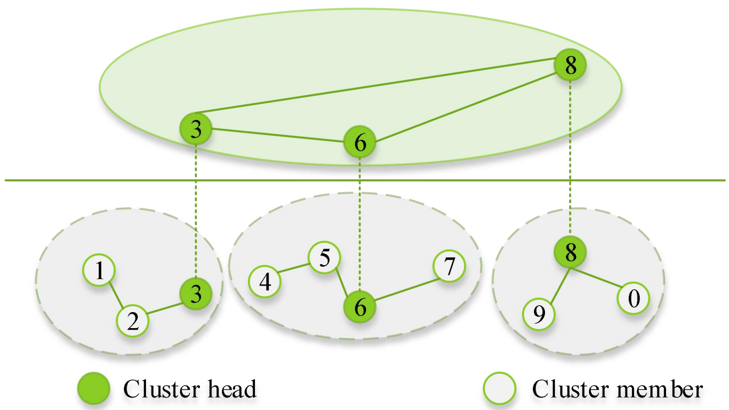


Figure 2. Hierarchical network topology.

In a hierarchically structured network, cluster head nodes can be realized either by some predefined method or can be generated by a specific algorithmic calculation. The sending of information and data between groups is accomplished by the head node. In contrast, the function of non-cluster head nodes is relatively simple, only need to maintain some simple routing information, the number of control information in the network can be reduced a lot, so this network scalability is very good. Hierarchical structure is not only applicable to the relevant connection between isomorphic networks, but also applicable to most of the heterogeneous networks, along with the continuous expansion of the scope of application, different types of wireless networks can also be utilized in the form of hierarchical structure to form an Ad Hoc network. In conclusion, we should use different network structures according to different network scales, when the scope of the network is relatively large, we usually use hierarchical structure, while when the scope of the network is not very large, we use relatively simple planar structure.

2.2. AODV Routing Protocol

AODV routing protocol is widely used on-demand routing algorithm in wireless self-organizing networks.Only after the routing path is created between source and destination nodes, the routing path is created according to the need of the source node and then the transmission of the packet starts.The AODV protocol combines on-demand functionality of DSR protocol with hop-by-hop routing, sequence numbering etc. of DSDV protocol. It creates routes on demand and reduces the acquisition time and uses bi-directional links to establish links between sources and destinations. In AODV protocol the routing information is not updated periodically and the source node establishes the route to the destination node only at the moment of forwarding the data to the desired node. The source node first finds the shortest path to reach the destination node and then all the data is delivered through the same path. In this process, the protocol prevents the formation of loops in the network and identifies the freshness of routes in the network by using sequence numbers.The AODV protocol defines three types of packets i.e., Route Request (RREQ), Route Reply (RREP) and Route Error (RERR). Route discovery cycle can be used to find the routing path between source and destination nodes.AODV routing protocol mainly uses routing table to store the routing information.Each node is kept in routing table with destination address, next hop address, destination sequence number and survival period. If the route is not used within the specified survival period of the routing table, it is immediately discarded. When the source node wants to send data to the destination node, it checks the routing table to determine if the path to the destination node is available. If the path is available, the packet is forwarded to the next hop node in the routing table, otherwise the route discovery process is initiated to the target node.The process of processing control messages by AODV is shown in Figure 3.

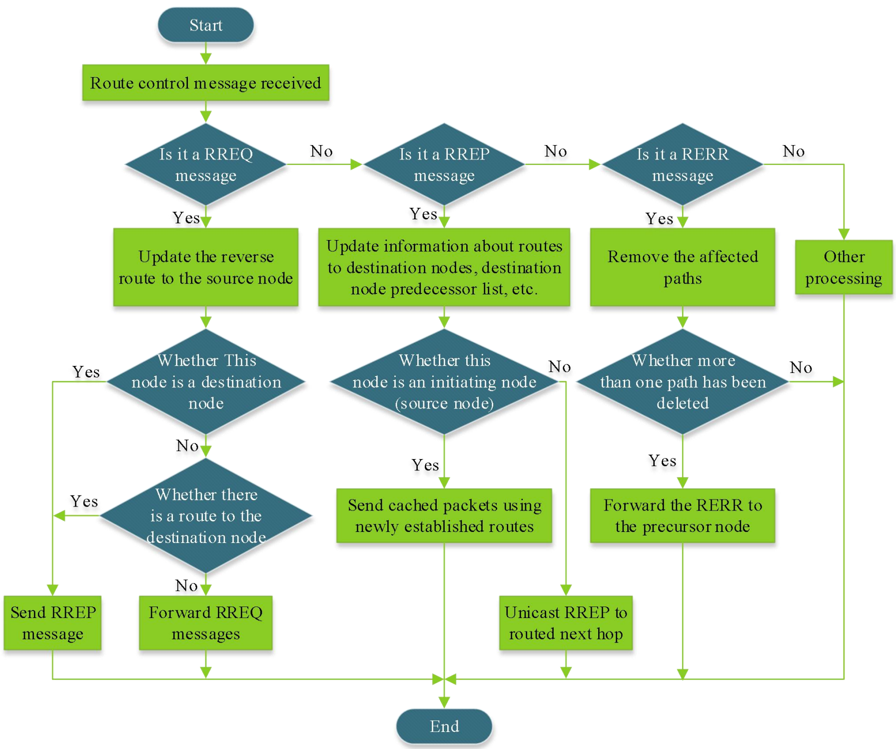


Figure 3. The processing procedure of AODV receiving control messages.

The AODV route discovery process is shown in Fig. 4.The AODV routing protocol consists of two main parts, the route discovery process and the route maintenance process. In the route discovery phase, when a source node wishes to send information to a destination node and it does not know a suitable route to that destination node, it initiates the route discovery process to locate another node. Route request (RREQ) packets are broadcast to nearby neighbors who then forward the route request to other neighbors and this process continues until it reaches the destination node or identifies the transponder node with the latest route to the destination as shown in figure (a). AODV uses destination sequence numbers to avoid acyclic topology and contains up-to-date routing information. Each node in the network maintains its own sequence number of broadcast IDs. The broadcast ID is incremented whenever a new RREQ is issued by the source. A broadcast ID with the node's IP address can be used to identify the RREQ separately. The destination, in combination with its own sequence number and broadcast ID, can recognize the latest sequence number from the RREQ of the source node. The intermediate node responds to the RREQ only when it learns the destination's route and its corresponding destination sequence number is greater than or equal to the sequence number already available in the RREQ.

During RREQ forwarding, intermediate nodes in the network store the addresses of their neighbors in their routing tables, from which they receive the first copy of the broadcast packet, thus establishing a reverse path. If other copies of the same RREQ are received later, it drops those packets. If the destination or intermediate node receives a new RREQ message, it will respond with a single-path Route Response Answer (RREP) packet message via the reverse path as in Figure (b). According to RREP, the reverse path will be converted from source to destination to forward routing table. Forward routing information indicates the active forward route. The route should be used for a specific period of time or the route entry will be deleted.The AODV protocol can use the following process to accomplish route maintenance. If the source node leaves its location, the route discovery process will be restarted. If the intermediate node moves from its path, the neighboring nodes will recognize its movement and send a link failure notification message to either end system, which is RREP with infinite metric. Thus, the source node receives the link failure message and restarts the route discovery process for the corresponding destination.

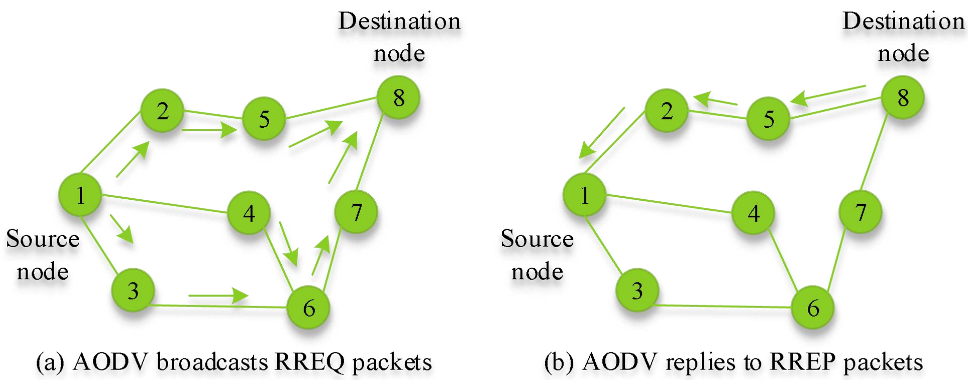


Figure 4. The AODV route discovery process.

2.3. EAODV routing protocols

2.3.1. Energy levels

In the network, each node has a different energy level. As far as residual energy is concerned, it is important to select intermediate nodes with high residual energy to participate in routing. If the energy of a node is exhausted during data transmission, a new route discovery process will be carried out which will interrupt the data transmission. The cost of route discovery becomes high in terms of transmission delay and energy consumption. In order to avoid retransmission of data and to prevent wastage of energy on the network, EAODV protocol achieves energy awareness of the nodes by grading the node energy and trying to involve the nodes with high energy in the routing for prolonging the survival time of the network. Define the energy threshold μ and classify the node energy into two energy classes $Normal$ and $Danger$ as shown in (1).

$$level\left(node\right)\begin{cases} Normal & E_{res} \geq \mu \\ Danger & E_{res} < \mu \end{cases} \tag{1}$$

Where E_{res} is the residual energy of the node, if the residual energy of the node is more than the inter-energy value then the node is in the normal class, then the node can participate in the routing as a forwarding node. If the residual energy of the node is less than the energy threshold value then the node is in dangerous class and the node in this case is not used as a forwarding node.

Since the energy of the nodes generally decreases with the operation of the network, it is required that the energy threshold μ also dynamically adapts to the energy changes of the nodes in the network. Therefore, the dynamic energy threshold μ is defined as shown in equation (2).

$$\mu = \frac{\delta}{f(x)}\sqrt{E_{res}} \tag{2}$$

Where δ is the coefficient that controls how fast or slow the energy threshold changes, and is experimentally set to 2 for best results. $f(x)$ is a specific function about the total number of nodes and the number of threshold updates, and E_{res} is the residual energy of nodes.

Define the specific function $f(x)$ as shown in equation (3).

$$f(x) = \frac{N \times x}{N - x}(1 \leq x < N) \tag{3}$$

N is the total number of nodes in the network and x is the number of updates to the threshold. In the interval $1 \leq x < N$, $f(x)$ is an increasing function of x . Combining Eq. (2) yields that μ is inversely proportional to $f(x)$ and that μ is a decreasing function on x . When μ decreases to a certain level, certain nodes located in the danger zone can be reused. Avoiding the situation that nodes cannot join the network when their energy is generally very low in the late stage of network operation, it equalizes the network energy and prolongs the survival time of the network.

2.3.2. Routing Metrics

1) Energy factor

In this paper, node energy factor is introduced as an evaluation parameter of link quality to select the nodes with higher residual energy so as to extend the effective time of the routing path [45].

Define the energy state of node i as shown in equation (4).

$$E_i = \frac{E_{res}}{E_{init}} \tag{4}$$

Where E_{res} is the residual energy of the node and E_{init} is the initial energy of the node. In order to maintain the principle of "smaller value means better path" of the protocol, E_i is replaced by the node energy factor in the way of equation (5).

$$E_f = 1 - E_i \tag{5}$$

The above equation indicates that the smaller the residual energy of the node, the higher the node energy factor. The lower the probability of being selected in the subsequent routing criterion.

2) Stability factor

In order to reduce the impact of node mobility on routing stability, the stability factor of a node with respect to its neighboring nodes is proposed, which is achieved by building a stability model to compute the relative speed of the node and its neighboring nodes as well as the normalized distance.

Based on the position coordinates in two consecutive HELLO messages from a neighbor, using the Euclidean distance equation, the receiving node can compute its own relative velocity and distance with respect to the HELLO message source. For example, when node A receives a HELLO message from node B containing $\left(x_b, y_b\right)$ at moment t_1, node A uses the Euclidean distance equation to compute its distance d_1 and computes it when it receives the next HELLO message at moment t_2 , d_2 . Subsequently, the relative velocity V_r of node A with respect to node B is shown in equation (6).

$$V_r = \Delta d_B / \Delta t \tag{6}$$

Among them:

$$\Delta d_B = |d_2 - d_1| \tag{7}$$

$$\Delta t = t_2 - t_1 \tag{8}$$

The relative velocity factor V_{rf} and the normalized distance D_n are shown in Eqs. (9) and (10).

$$V_{rf} = V_r / V_{\max} \tag{9}$$

$$D_n = d_2 / R_{\max} \tag{10}$$

where $V_{\max}$ is the maximum speed of node A, and $R_{\max}$ is the maximum transmission range of node B. Therefore, the stability factor S_f of node A with respect to node B is shown in Equation (11).

$$S_f = V_{rf} + D_n \tag{11}$$

In order to maintain a long connection lifetime between any two neighboring nodes, the stability factor S_f should be as small as possible.

2.3.3. Routing criteria

In the traditional AODV routing protocol, the routing mainly considers the path with the smallest number of hops, the EAODV protocol considers both the energy of the nodes, the relative speed and the relative distance between the nodes to achieve energy awareness and link stability. The energy factor and stability factor are combined by means of weights into a metric for assessing the quality of each link segment, which is called link efficiency factor λ, as shown in equation (12).

$$\lambda = \alpha E_f + \beta S_f \tag{12}$$

Where λ corresponds to the cost function between the nodes, α, β are the weighting factors of the energy factor and the stability factor all the time, respectively, and satisfy $\alpha + \beta = 1$. By changing the size of the weight factor, the weight of each parameter in the routing criterion can be adjusted. In this paper, we mainly consider the energy optimization problem, and the energy factor is considered a little more in routing. Therefore, $\alpha = 0.6; \beta = 0.4$ is set in the simulation.

The metric for evaluating the quality of the whole path is obtained by accumulating the link efficiency factor for each segment of the path, called the routing efficiency factor λ_R, as shown in equation (13).

$$\lambda_R = \sum_{i=1}^{n} \lambda_i \tag{13}$$

Where λ_R is equivalent to the routing cost function of the whole path and n denotes the number of nodes on the path. After receiving the RREQ message, the nodes firstly calculate the link efficiency factor between the nodes, secondly, the routing efficiency factor of the whole path is obtained by accumulating the link efficiency factor of each section of the path, and finally, the route with the smallest routing efficiency factor is selected as the primary route for data transmission, and the one with the second-smallest value is used as a backup route, and the route with the smallest number of hops is selected as the best route when the values are the same.

3. Improved energy-optimized routing algorithm for ant colonies

3.1. Mathematical modeling of network node characteristics

MANET nodes communicate with each other by radio, the first order energy consumption model of network nodes can be established, the first order energy consumption model of MANET network nodes is shown in Fig. 5. The energy consumption of sending data includes the energy consumption of the transmitting circuit and the amplifying circuit, and only the receiving circuit consumes energy for receiving data. The mathematical model of first order energy consumption model can be expressed as follows:

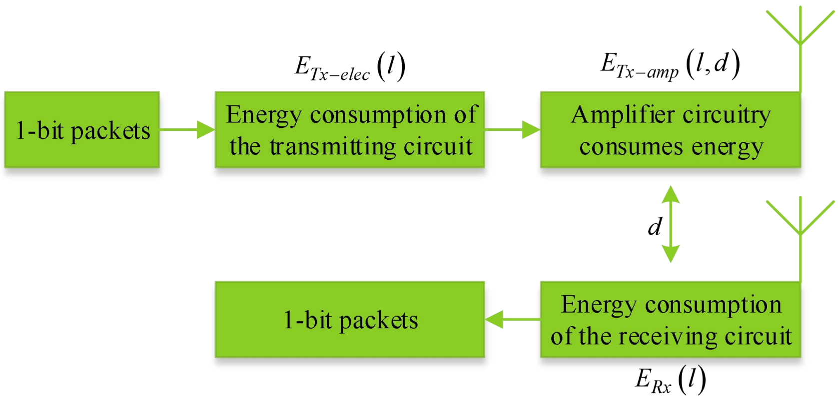


Figure 5. First-order energy consumption model of MANET network nodes.

$$\begin{cases} E_{Tx} = lE_{elec} + l\varepsilon_{fs}d^2 \\ E_{Rx}(l) = E_{elec} \times l \end{cases} \tag{14}$$

where E_{Tx} denotes the sender energy consumption, E_{Rx} denotes the receiver energy consumption, E_{elec} denotes the energy consumed by the transmitter and receiver circuits, l denotes the number of bits contained in the sent packet, d denotes the transmission distance, and ε_{fs} is a constant. Typical values of the above parameters are $E_{elec} = 50nJ / bit, \varepsilon_{fs} = 10pJ / (bit \cdot m^2)$.

All nodes in the network are in a dynamic movement state, and this section describes the movement state of the network nodes as well as the connectivity status between the nodes. The position, rate and direction of motion of node i at moment t can be expressed sequentially as $(x_i(t), y_i(t)), v_i(t), \theta_i(t)$. Therefore, the node motion characteristics can be described by the following equation:

$$\begin{cases} x_i(t+\Delta t) = x_i(t) + v_i(t) \times \cos(\theta_i(t)) \times \Delta t \\ y_i(t+\Delta t) = y_i(t) + v_i(t) \times \sin(\theta_i(t)) \times \Delta t \end{cases} \tag{15}$$

At moment t, the distance between node i and node j can be expressed as equation (16):

$$d_{ij}(t) = \sqrt{(x_j(t) - x_i(t))^2 + (y_j(t) - y_i(t))^2} \tag{16}$$

In MANET, the direct communication distance between two nodes is R. If the distance between two points is less than R, then two nodes can communicate directly. Otherwise two nodes need to be forwarded through an intermediate node for communication between them. Define the node connectivity matrix $D(t) = (d_{ij}(t))_{N \times N}$. If the element is "1", it means that two points can communicate directly with each other, and if the element is "0", it means that two nodes cannot communicate directly with each other. Therefore, the elements in the matrix should satisfy the following conditions:

$$d_{ij}(t) = \begin{cases} 1 & l_{ij}(t) \leqslant R \\ 0 & l_{ij}(t) > R \end{cases} \tag{17}$$

At the moment t, the node degree $Degree_i(t)$ of node i denotes the number of nodes connected to this, which can be expressed as follows:

$$Degree_i(t) = \sum_{j=1}^{N} d_{ij}(t) \tag{18}$$

3.2. E-EEABR algorithm

3.2.1. Network Distance Bands and Search Angles

In order to make full use of the limited node energy and current pheromone concentration, the concept of distance band is introduced into the ant colony routing optimization algorithm to optimize the way ants search for the next-hop node and avoid blind forwarding of nodes. Assuming that node i in layer n is the source node, it is limited to select only nodes within the current layer n or neighboring layers $n-1$ and $n+1$ when choosing the next hop node, then its neighboring nodes are only node $A\sim$ node F and node j. According to the above rule, the next hop node of node i can only choose the neighboring layer nodes, i.e., node $A\sim$ node F and node j, but not node G, which means that nodes far away from the source node i are excluded [46]. At the same time, this method reduces the number of hops and energy consumption of ants transferring to Sink nodes. Since node A is far away from the Sink node, the focus of the next hop selection of node i is concentrated on node B, node C, node D, node E, node F and node j. However, relying on the distance band can only determine the selection region of the next-hop node, not the direction of the best path. Therefore, the concept of search angle is introduced on the basis of distance band.

In this paper, we determine the optimal path direction by calculating the angle between the line from the source node i to the Sink node and the line from the source node i to the next hopping node, combining the angle factor and the distance factor. The search angle is generally limited to $0°\sim 90°,\theta$ the smaller indicates that the ants from the source node i to the Sink node of the distance closer to a straight line, in the path-finding process, the node closer to the source node i to the Sink node of the straight line between the node, the energy consumption is less, then the greater is the probability that it will be the next-hop node. $0° < \theta_1 < \theta_2 < \theta_3 < \theta_4 < 90°$, where θ_1 is the smallest indicating that the node j has the highest probability of being the next hop node.

3.2.2. Improved path heuristic function

Although the above scheme can accurately guide the ants to find the next hop node, when the angle and distance of multiple candidate nodes do not differ much, the problems of pirouette hopping and uneven energy consumption among nodes will occur. Especially, the "hot" nodes near the Sink node are more likely to be overloaded than other nodes, resulting in energy "hot zones". In order to effectively solve the failure problem of the "hot" nodes near the sink node, this paper adopts an incentive strategy to screen out the "hot" nodes with lower energy and farther distance, and prohibit them from joining the transmission path. At the same time, the remaining nodes with sufficient energy and closer to the sink node are added to the transmission path to equalize the average residual energy of the "hot" nodes and prolong the survival time of the network.

The pathfinding ants filter out the "hot" node with the lowest energy level based on the overall energy level around the Sink node as it approaches the Sink node. Then, the pathfinding ants get the number of hops from the source node to the "hot" node from T_k^{tabu}, and use the ratio of the two numbers to get the defined incentive value as follows:

$$D_k^{drive} = P_{\min} / L_k \tag{19}$$

where D_k^{drive} denotes the incentive value of the path-finding ant k in converging to the Sink node as defined in this paper, $P_{\min}$ denotes the minimum energy value of the "hot" node in the filtered optimal path, and L_k denotes the number of hops of the ant k to the "hot" node with minimum energy.

Assuming that nodes D, E, and Sink are in the "hot zone" where the network nodes are overloaded with energy transfer, and node D and node E are the nearest "hot" nodes to the Sink node filtered by using the distance band, the search angle, and the distance factor, the problems of uneven energy consumption and round-tripping will exist when node D, When node 6 and node E are close to the sink node, there are problems such as uneven energy consumption and round-tripping.

During the visit, the next-hop node records the current maximum incentive value in T_k^{tabu} in addition to the position of the previous-hop node. If a better D_k^{drive} is encountered, the node updates D_k^{drive} and its corresponding previous-hop node. Suppose the 2 paths $\text{Source} \to A \to M \to E \to \text{Sink}$, and

$\mathrm{Source} \rightarrow M \rightarrow E \rightarrow \mathrm{Sink}$ are the exploratory paths of ant 1, $\mathrm{Source} \rightarrow A \rightarrow M \rightarrow B \rightarrow C \rightarrow D \rightarrow \mathrm{Sink}$, $\mathrm{Source} \rightarrow M \rightarrow B \rightarrow C \rightarrow D \rightarrow \mathrm{Sink}$ these 2 paths are the exploration paths of ant 2. When ant 1 and ant 2 arrive at node M at the same time, the minimum value of the energy of the node that the ant has traveled will be filtered based on the values of T_k^{tabu} and D_k^{drive} values of the path records the ant has traveled through, comparing the magnitude of the length of the paths and the energy values.

Suppose that ant 1 is selected as the optimal ant by computational comparison. The fallback ant generated by ant 1 is utilized to backtrack and update the pheromone and update the routing table information of each node. When the ant reaches node M , it filters out nodes with less energy and routes with longer length based on the information of visited nodes recorded in T_k^{tabu} and the value of D_k^{drive} , and filters out routes where nodes have sufficient energy and less number of hops. It can be concluded that node D and node E participate in ant pathfinding as "hot" nodes in the "hot zone" of the network. If $D_k^{driveE} > D_k^{driveD}$, then node E is more likely to be a candidate node, so the ants will choose $\mathrm{Source} \rightarrow M \rightarrow E \rightarrow \mathrm{Sink}$ as the optimal path.

From the above analysis, it can be concluded that the incentive value strategy proposed in this paper, compared with the original ACO algorithm that communicates through the pheromone concentration and the size of the heuristic function, the ants are more inclined to update the information on the short path [47]. At the same time, this strategy makes the communication between ants refer to the information of visited nodes in addition to relying on pheromone, which can balance the overall energy level around the Sink node, promote the communication between ants, and accelerate the convergence speed of the algorithm.

In order to make better use of the incentive value, avoid the network hole phenomenon due to the failure of the "hot" nodes, and guide the ants to be more inclined to the Sink node, the optimized pheromone-inspired formula proposed in this paper is as follows:

$$\Omega_{i,\mathrm{Sink}} = d_{i,j} + d_{j,\mathrm{Sink}} \tag{20}$$

$$\eta_{ij} = \frac{E_j(t)}{\sum_{k \in N_i(k)} E_j(k) / N_i(k)} \cdot \frac{1}{(1+\cos\theta)^{\gamma}} \cdot \frac{1}{\Omega_{i,\mathrm{Sink}}} \tag{21}$$

where $E_j(t)$ is the residual energy from the source node i to the next hop node j in the n layer, $\sum_{k \in N_i(k)} E_j(k)$ is the sum of residual energies of neighboring nodes of node i converging to the Sink node, and $N_i(k)$ is the number of the algorithm's current iterations , $\Omega_{i,Sink}$ is the cumulative sum of distances from node i to the Sink node, θ denotes the search angle between node i and the next-hop node j obtained by utilizing the distance bands, and γ is the defined constant indicating the extent of θ's influence on routing.

3.2.3. State Transfer Equation Improvement

In this paper, a pseudo-random proportional estimation strategy with energy factor is introduced to optimize the state transfer formula, which enables the ants to quickly concentrate on the path with the highest probability and improve the convergence speed of the algorithm in the early stage of the algorithm when the role of pheromone and heuristic information of each path is not obvious. At the same time, balancing the energy consumption of nodes on the optimal path with less node energy but frequently visited by ants, prolonging the network lifetime and avoiding premature stagnation of the algorithm.

$$\kappa_{ej} = \frac{\left| E_j(t) - E_i(t) \right|}{E_0} \times 100\% \tag{22}$$

$$j=\begin{cases}\underset{j\in A_k^{\text{allowed}}}{\operatorname{argmax}}\{[\sigma_{ij}(t)]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}\left[\kappa_{ij}(t)\right]^{\gamma}\},q\leqslant q_0\\ S,q>q_0\end{cases} \tag{23}$$

Where, q is a random number generated by the path-finding ants before choosing the next hop node, and $q\in(0,1],q_0\in[0,1],\alpha,\beta,\gamma$ are the weight coefficients of pheromone concentration, heuristic function, and energy influencing factor, respectively, and the larger its value, the higher the degree of importance attached to the item, $E_i(t)$ denotes the residual energy of the source node i and $E_j(t)$ denotes the residual energy of the candidate node j. If the random number q generated by the ant at the current node satisfies $q\leqslant q_0$, then the choice $\left[\sigma_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}\left[\kappa_{ij}(t)\right]^{\gamma}$ the largest node as the next hop, otherwise the next hop is selected according to equation (24).

$$p_{ij}^{m}=\begin{cases}\dfrac{\sigma_{iu}(t)\big]^{\alpha}\left[\eta_{iu}(t)\right]^{\beta}\left[E_{iu}(t)\right]^{\gamma}}{\left.\sum\limits_{u\in A_k^{\text{allowed}}}\sigma_{is}(t)\right]^{\alpha}\left[\eta_{is}(t)\right]^{\beta}\left[E_{is}(t)\right]^{\gamma}},j\in A_k^{\text{allowed}}\\ 0,j\notin A_k^{\text{allowed}}\end{cases} \tag{24}$$

3.2.4. Pheromone update rule improvements

In terms of the biological characteristics of ACO, the pheromone update of ants is a positive feedback process, after ants complete the search for the shortest path, the pheromone released by the ants attracts a large number of ants to join the path, resulting in the nodes of the "best" path to die prematurely because of energy exhaustion. In addition, from the perspective of algorithm operation, the pheromone of traditional ACO adopts a cumulative approach to continuously increase the pheromone concentration on the optimal path found in the previous round, which causes the algorithm to easily fall into the local optimization instead of the global optimization. In particular, for the densely distributed "hot" nodes near the Sink node, although their pheromone concentration volatilizes at a certain rate, the number of pheromone increases is higher than the volatilization amount, and the network nodes have sufficient energy. At this time, the non-optimal path closest to the Sink node becomes the best path for the ants to make the next hop. At the same time, the path from the source node to the Sink node also suffers from uneven energy consumption and low global activity of the network, while in the "hot zone" near the Sink node, there are paths with more routing hops and smaller node intervals, which affects the accuracy of $\Delta\tau_k$.

In this paper, the deviation value of node energy from the average energy is utilized as a reference factor for the pheromone increment formula. When the deviation value is large, the incremental pheromone will be reduced accordingly, enabling the fallback ants to adaptively adjust to avoid the source node joining the paths with too large an energy difference when sending the next round of ant packets. The specific calculation process is as follows:

$$\tau_{ij}(t)=(1-\rho)\times\tau_{ij}(t)+\Delta\tau_{ij}(t) \tag{25}$$

$$\Delta\tau_k=\frac{1}{C-\dfrac{E_{\min k}-F_{d_k}}{E_{\text{avg}k}-F_{d_k}}}+\frac{1}{\sigma_k(s)} \tag{26}$$

where F_{d_k} denotes the energy consumption of the path-finding ants, $\sigma_k(s)$ denotes the deviation of the source node's energy e_s from the path-averaged energy $E_{\text{avg}k}$ as the fallback ant k returns from the Sink node to the source node, and $\sigma_k(s)$ is calculated as follows:

$$\sigma_k(s)=\left(e_s-E_{\text{avg}k}\right)^2 \tag{27}$$

The increments of the pheromone function are calculated as follows:

$$\tau_{ij}(t+n) = (1-\rho)\times\tau_{ij}(t) + \mu\times\frac{E_{\text{avg}}^k \times E_{\min}^k}{E_{\text{sum}}^k \times H_{\min}^k} \tag{28}$$

Where, E_{avg}^k and $E_{\min}^k$ denote the average and minimum value of the remaining energy of the nodes in the passage path of the fallback ant k respectively, E_{sum}^k denotes the total energy consumed in the passage path and μ is a constant. A higher value of $\frac{E_{\text{avg}}^k \times E_{\min}^k}{E_{\text{sum}}^k \times H_{\min}^k}$ indicates more sufficient energy in the passage path. Paths with higher E_{avg}^k and $E_{\min}^k$ and shorter length are filtered out and these paths are given additional pheromone compensation.

3.3. Algorithm Flow

3.3.1. Specific realization steps

The specific implementation steps of the E-EEABR algorithm in this paper are as follows:

Step 1: Initialize the parameters. At the moment $t = 0$, set the initial energy of the node to E_0, the initial pheromone concentration $\tau_{ij}(0) = 0$, the number of iterations to be $N = 0$, and the maximum number of iterations allowed to be $N_{\max}$.

Step 2: The deployed m ants are randomly placed at n nodes with iteration number $N = N + 1$ until all nodes are traversed, and a different initial node position is placed in each ant's T_k^{tabu}.

Step 3: The ants search the route according to $k = k + 1$.

Step 4: Find the optimal range of paths for the next hop according to the deployed hierarchical band, search angle and distance factor. If the ant generates a random number $q \leqslant q_0$, the node j is transferred according to Eq. (23), otherwise it is transferred according to Eq. (24), where $j \in A_k^{allowed}$.

Step 5: Update the node's T_k^{tabu} and incentive values, etc.

Step 6: Determine whether the ants reach the Sink node, i.e., whether $k < m$ is satisfied. If it is not satisfied, return to step 3 to continue execution, otherwise go to step 7.

Step 7: Continue to execute Step 1~Step 6 until k ants can all reach the Sink node.

Step 8: Determine the possible paths that the ants in the region may pass through, and if there are ants, perform the pheromone update using Eq. (25) and Eq. (26).

Step 9: Continue executing Step 2 to Step 8 until the number of ant iterations $N < N_{\max}$, clear T_k^{tabu} and return to Step 3, otherwise end the loop.

3.3.2. Improved E-EEABR algorithm flow

The flow of the improved E-EEABR algorithm in this paper is shown in Fig. 6.

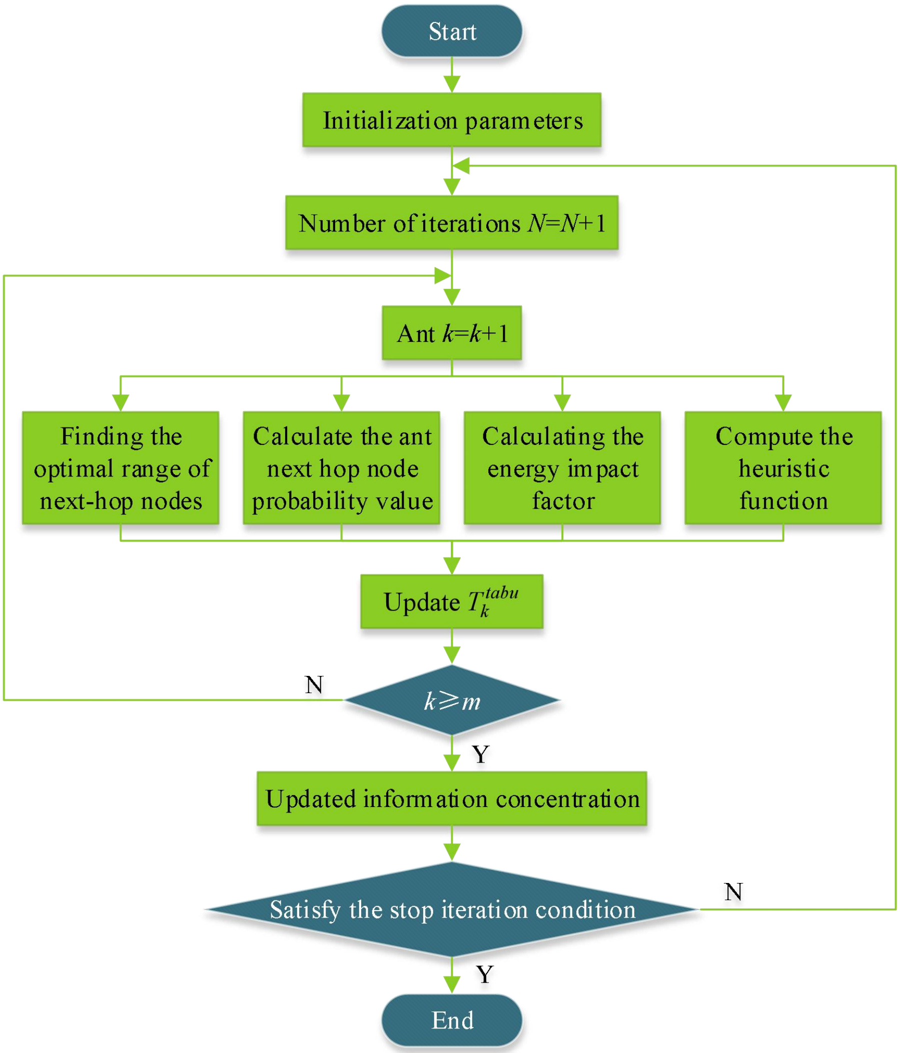


Figure 6. Procedure of E-EEAB Ralgorithm.

3.4. Optimization of Ant Colony Parameters

3.4.1. Simulation Experiments on the Effect of Ant Colony Parameters on Protocol Performance

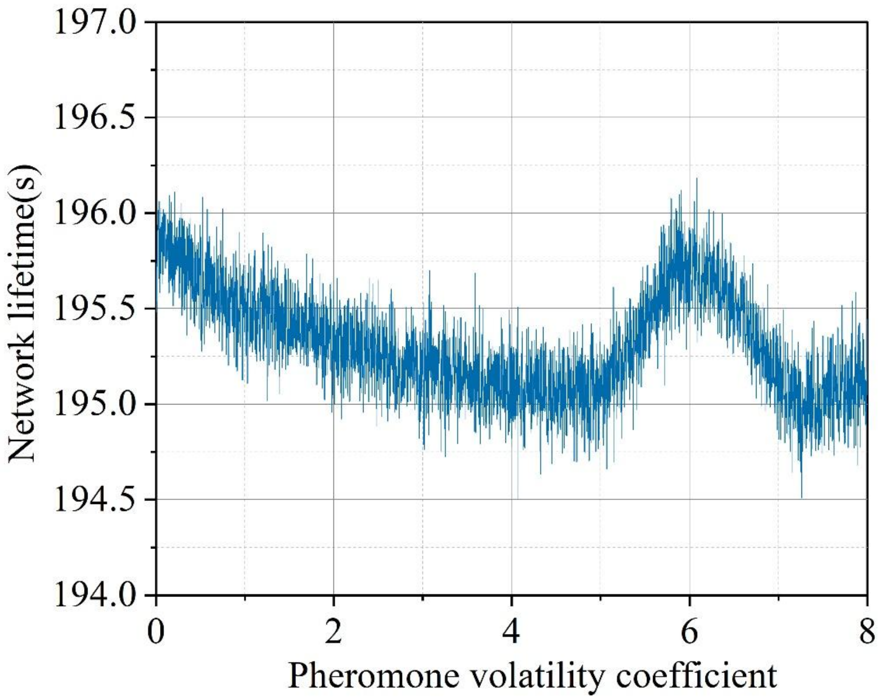
Due to the strong correlation between the parameters of the ACO algorithm, how to determine the optimal parameter combination to make the best solution performance is a very complex optimization problem. There is no mathematical basis for the selection method of ACO parameters, which is usually based on experience. The parameter selection is mainly based on simulation experiments and experience. And for different specific problems, the configuration scheme of each parameter is different. Therefore, this paper investigates the optimal value setting range of ρ , α and β in the E-AODVR protocol through simulation experiments.

Simulation experiments using the current more popular NS2. wireless propagation model selection Two-ray Ground Reflection, 20 nodes in the 800 × 800m² rectangular area randomly distributed, node transmission radius of 280m, node movement model selection Random waypoint, node movement speed in the 0-12m/s between random change, pause time interval is 0, MAC layer selection IEEE805.11DCF mode, link bandwidth is 1.5Mbit/s, application layer data is 50 CB CB/s. 12m/s, node moving speed varies randomly between 0 and 12m/s, pause time interval is 0, MAC layer selects IEEE805.11DCF mode, link bandwidth is 1.5Mbit/s, application layer data is 50 CBR connections, CBR packet length is 536byte, sending rate is 1packet/s, initial energy of node is 205J, minimum speed is 0, maximum speed is 10m/s and simulation time is 255s.The main parameters of E-EEABR protocol take values as shown in Table 1.

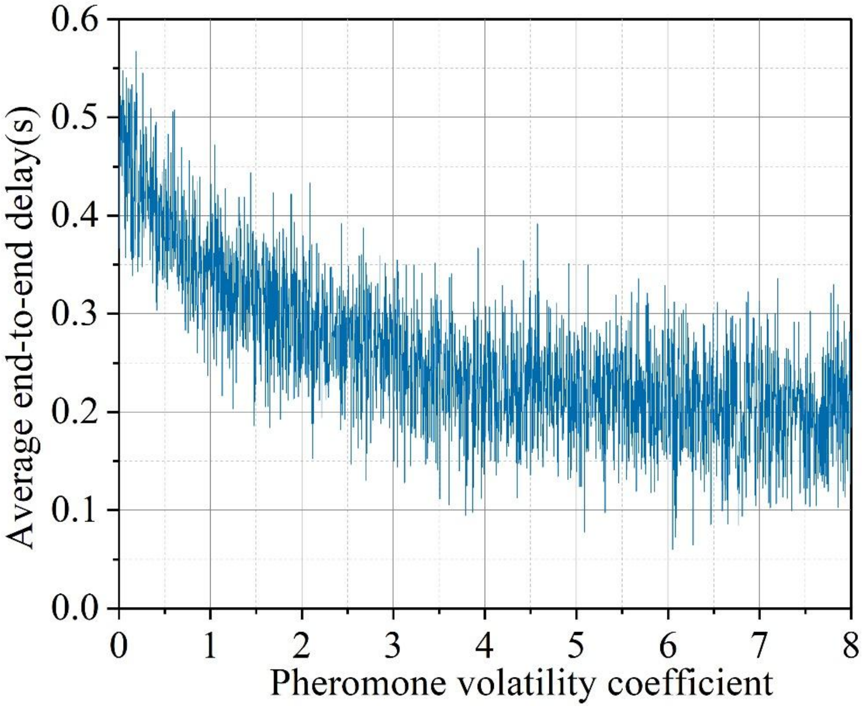
Table 1. The main parameter values of the E-AODV protocol.

Parameter name	value	Parameter name	value	Parameter name	Value
$\tau_{\min}$	0.01	τ_{init}	0.1	μ	0.2
TTL	16	$\mathrm{NUM}_{\mathrm{nbr}}$	3	HELLO_INTERVAL	5 sec
ACTIVE_INTERVAL	4 sec	WAIT_TO_SLEEP_INTERVAL	4 sec	SLEEP_INTERVAL	3 sec

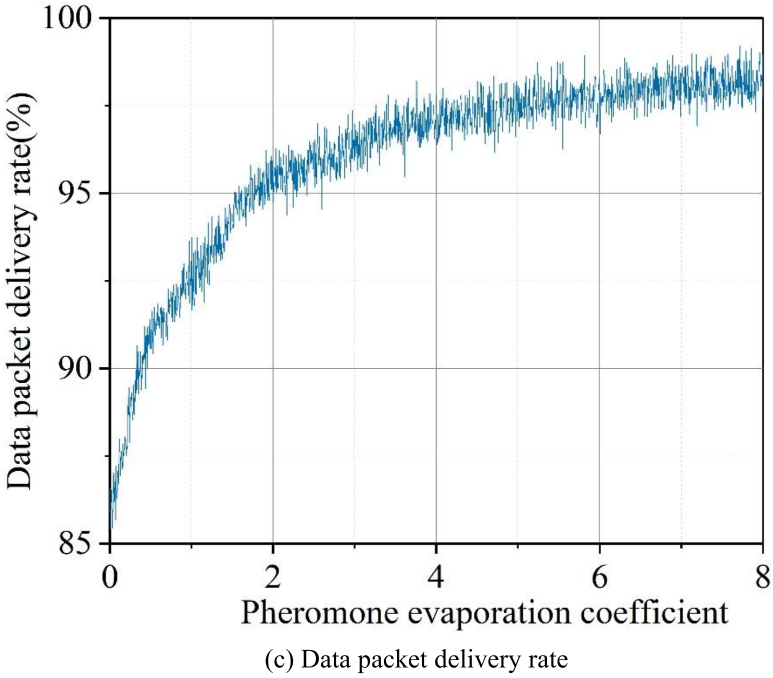
This set of experiments $\alpha = 1$, $\beta = 0.5, \rho$ take values ranging from 0 to 10 with a step size of 0.1, and a total of 100 experiments are conducted. The effect of pheromone volatilization coefficient ρ on the protocol performance is shown in Fig. 7 (Figs. a~c are network survival time, average end-to-end delay, and packet delivery rate, respectively). The pheromone volatility coefficient ρ has a very large impact on the protocol performance. As ρ increases, the volatilization rate accelerates, the average end-to-end delay and packet delivery rate performance improves (the average end-to-end delay decreases, and the packet delivery rate increases), the network survival time performance decreases, and the overall performance of the protocol is better when ρ is in the interval of 5.1~6.6.



(a) Network survival time



(b) Average end-to-end delay



(c) Data packet delivery rate

Figure 7. The effect of the pheromones on the performance of the protocol.

3.4.2. Comparative analysis of protocol performance before and after ACO parameter optimization

Based on the range of optimal value settings for ρ, α and β identified in the previous paper, the optimal values of the parameters in this paper are set to $\rho = 8$, $\alpha = 2$ and $\beta = 0.8$. To compare the parameters before and after optimization the impact of the performance of E - EEABR, this experiment take $\rho \in \{0.6, 2, 8\}$, $\alpha \in \{0.6, 2, 5\}$, $\beta \in \{0.2, 0.8, 2\}$, The values of the experimental environment parameters and the main parameters of E-EEABR were the same as those in the previous text. A total of 30 experiments were conducted. The performance comparison of the E-EEABR protocol before and after the optimization of ant colony parameters is shown in Table 2. From the experimental results, it can be seen that when ρ = 8, α = 2, and β = 0.8, the overall performance of the E-EEABR is better compared with other combinations of values.

Table 2. Performance comparison of the E-EEABR protocol.

Experiment number	ρ	α	β	Network survival time (s)	Average end to end delay (s)	Packet delivery rate (%)
1	0.6	0.6	0.2	195.26046	0.3862	87.44
2	0.6	0.6	0.8	195.26669	0.2526	88.67
3	0.6	0.6	2	195.93343	0.3127	88.27
4	0.6	2	0.2	195.52801	0.3843	89.6
5	0.6	2	0.8	195.6813	0.2587	88.54
6	0.6	2	2	195.43114	0.291	91.65
7	0.6	5	0.2	194.97185	0.3431	91.89
8	0.6	5	0.8	195.29984	0.4192	92
9	0.6	5	2	195.07922	0.4208	90.58
10	2	0.6	0.2	195.21004	0.1741	95.52
11	2	0.6	0.8	194.79923	0.1815	94.5
12	2	0.6	2	195.00918	0.2748	95.31
13	2	2	0.2	195.22946	0.2173	95.6
14	2	2	0.8	195.02613	0.3152	96.23
15	2	2	2	195.08842	0.3639	96.52
16	2	5	0.2	195.38833	0.1266	98.38
17	2	5	0.8	195.41113	0.157	96.58
18	2	5	2	195.28961	0.167	95.81
19	8	0.6	0.2	195.53075	0.2935	96.73
20	8	0.6	0.8	195.51808	0.2119	99.16
21	8	0.6	2	195.60617	0.0963	97.96
22	8	2	0.2	195.80393	0.16	97.04
23	8	2	0.8	196.28054	0.1723	98.79
24	8	2	2	195.93863	0.2394	97.78
25	8	5	0.2	195.32494	0.1914	96.32
26	8	5	0.8	194.96691	0.2505	99.94
27	8	5	2	195.73761	0.1996	98

3.4.3. Optimization Steps for Ant Colony Parameters of the E-EEABR Protocol

On the basis of simulation experiment analysis, this paper summarizes the specific steps for setting the optimal parameter combination method of ACO algorithm as follows:

The first step is to preliminarily determine the approximate value ranges of ρ , α and β of ACO algorithm based on experience.

The second step is to take a fixed value unchanged in the value range of α and β respectively, adjust the value of ρ , and find out the more desirable value of ρ after several experiments to get a better solution.

In the third step, ρ is set to the value found in the second step, and a more suitable combination of α and β is found by constantly adjusting the values of α and β .

4. Simulation experiment and analysis

4.1. Validation of algorithmic energy optimization

There are 16 Micaz nodes placed in the wireless sensor network, in which node 1 is the source node, which utilizes the light intensity data of the surrounding environment collected by the mts500 sensors, which reaches the destination node, i.e., node 16, after multihop transmission from the intermediate nodes, which first transmits the data to the computer through the MIB510 programming board, and then changes the type of the message packet from forward to backward, and returns it to the source node in accordance with the original path back to the source node. The content of the message packet is shown in Table 3. This is one of the message packets sent by the source node. At the beginning stage, the source node selects the next hop node based on the distance between the nodes and the remaining energy of the node, and the message packet records six types of data, in which the type of the message packet is divided into Forward and Backward, i.e., Front and Latter, which are equivalent to Forward ants and Backward ants in the Ant Colony Algorithm, and the ID number of the node visited records the nodes visited by this message packet, which facilitates the recording of the message packet passing through the The ID number of the visited node records the node visited by the message packet, which is convenient to record the path that the message packet has passed through, and it is also convenient for the backward message packet to return in accordance with the original path. Time records the time elapsed since the source node sent the message packet. The destination node ID number is node 16 and the source node ID number is node 1. Each sensor node records the information about the neighboring nodes with an array recording the distance between each pair of nodes, the pheromone concentration on the path between the nodes, the remaining energy of the nodes as well as the neighboring nodes. The distance between the nodes and the nodes as well as the initial pheromone concentration on the path between the nodes and the initial residual energy of the nodes are all set in the program. The energy consumption formula of the nodes as well as the pheromone change formula is the same as presented in Chapter III. The source node is set to send a message packet to the destination node at the rate of one message packet every 1s, and the two attacking nodes masquerade as the source node's ID number 0001 and set to send a message packet to all nodes in the wireless sensor network at the rate of one message packet every 0.25s, and the data strength is set to be constant to weak. The initial energy of all nodes is 2J, distributed in an area of 10M*10M, the initial message packet sent by the source node has a length of 64bit, with the increase in the number of accessed nodes, the data content of the column of visited node ID in the message packet increases, and the length of the message packet is getting bigger and bigger.

Table 3. Message packet content.

Destination ID number	Source ID number	Message package type	The access node id number	Data intensity	Time(s)
0016	0001	Front	0001 0002	Strong	0.5
0016	0001	Front	0001 0002 0010	Strong	0.6
0016	0001	Front	0001 0002 0010 0006	Strong	0.7
0016	0001	Front	0001 0002 0010 0006 0010	Strong	0.8
0016	0001	Front	0001 0002 0010 0006 0010 0015	Strong	0.9
0016	0001	Front	0001 0002 0010 0006 0010 0015 0016	Strong	1
0001	0016	Latter	0016	Strong	1.1
0001	0016	Latter	0016 0015	Strong	1.2
0001	0016	Latter	0016 0015 0010	Strong	1.3
0001	0016	Latter	0016 0015 0010 0006	Strong	1.4
0001	0016	Latter	0016 0015 0010 0006 0010	Strong	1.5
0001	0016	Latter	0016 0015 0010 0006 0010 0002	Strong	1.6
0001	0016	Latter	0016 0015 0010 0006 0010 0002 0001	Strong	1.7

The comparison of residual energy of the nodes after wireless injection attack and the delay in the data generated is shown below:

(1) Comparison of residual energy of nodes

The residual energy of the nodes after being attacked is shown in Table 4. It can be seen that the residual energy of the nodes under the E-EEABR algorithm after the attack is well maintained and relatively balanced, no node's energy is depleted, and the residual energy of the nodes under the traditional ACO algorithm after 20 minutes of attack on the attacked nodes is not balanced, and some of the nodes have particularly low energy depletion including nodes No. 10 and 12, and some nodes are depleted including nodes No. 6, 8, and 11. No. 6, No. 8, and No. 11. The effect of the attack also shows that the E-EEABR algorithm is beneficial for the energy equalization of the nodes of the wireless sensor network as well as saving the energy consumption.

Table 4. The remaining energy of the node after being attacked.

Node ID number	E-EEABR	On the traditional ant colony algorithm
1	1.20	0.98
2	0.87	0.65
3	0.74	0.49
4	0.88	0.77
5	1.00	0.32
6	0.62	0.00
7	0.50	0.10
8	1.16	0.00
9	0.96	0.71
10	0.69	1.75
11	0.52	0.00
12	0.82	1.87
13	0.72	0.55
14	0.81	1.01
15	0.53	0.69
16	1.32	1.62

(2) Comparison of data delay

Comparison of data delay after the attack is shown in Table 5. 2 algorithms under the attack node within 2 minutes of the attack there is no delay in receiving data, 2 minutes after the traditional ACO algorithm there is a delay in the data situation, and as the node attack time grows the data delay is getting higher and higher. In E-EEABR algorithm after 5 minutes of attack there is a data delay condition, with the growth of attack time the delay is getting higher and higher, but the growth rate is much lower than the growth rate of data delay under the traditional ACO algorithm. After the wireless injection attack on both algorithms, both the residual energy of the nodes and the data delay comparison degree reflect that the E-EABR algorithm has a great improvement in energy optimization compared to the traditional ACO algorithm, which indicates that the E-EABR algorithm is also much stronger than the traditional ACO algorithm in withstanding the attack.

Table 5. Comparison of data delay after being attacked.

Attack time/minute	E-EEABR	On the traditional ant colony algorithm
2	0.00	0.00
5	1.49	4.67
8	2.16	8.51
11	6.84	13.02
14	10.19	22.39
17	12.85	38.76
20	20.54	51.48

4.2. Simulation analysis of E-EEABR incorporating ACO algorithm

4.2.1. Average residual energy of nodes

The average residual energy of the nodes is shown in Fig. 8, which shows that the average residual energy of the nodes of E-EEABR decreases slower than that of the SEP algorithm. From the specific data again, when the network runs to 120 rounds, the average node residual energy of SEP algorithm is about 0.47J, while at this time, the average residual energy of nodes of E-EEABR is still about 0.5J or so, and the residual energy of all the nodes is still in a more saturated state. And by 200 rounds, the average residual energy of nodes of E-EABR algorithm is reduced to 0.47J, having the same energy but E-EABR makes the network run for nearly 80 rounds more, and the node energy utilization is improved by 66.7%

compared with SEP algorithm. The simulation results illustrate that comparing with SEP algorithm, E-EABR algorithm saves energy consumption by considering node distance and energy by re-selecting the cluster mechanism, and at the same time invoking a combination of single-hop and multi-hop approach in transmitting data reduces the amount of communication and equalizes the energy consumption of the cluster head, making the network energy consumption more energy efficient.

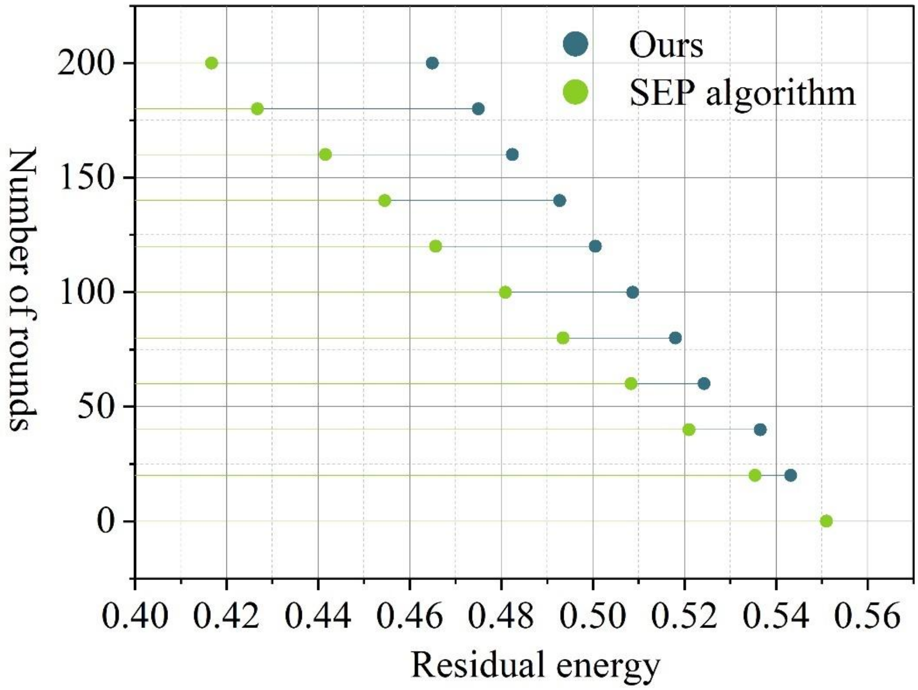


Figure 8. Average residual energy of nodes.

4.2.2. Communication packets between cluster head and Sink node

The cluster head and Sink node communication packets are shown in Fig. 9, the experiment will run the network for 200 rounds, we can see that in SEP algorithm, the cluster head and Sink node communication packets fluctuates a lot and its average transmission packets are about 9.8, the reason is that SEP algorithm elects the cluster head by using single-hop approach to communicate data with the Sink node. As for the E-EEABR algorithm, the fluctuation in the number of cluster heads communicating with Sink is almost non-existent, and its average transmitted packets are about 12. The reason is that the use of single-hop and multihop methods results in the fact that not all the cluster heads communicate with the Sink node directly for data communication, and therefore the above phenomenon will be caused. With this set of comparisons, we can see that the SEP algorithm fluctuates a lot in the number of cluster heads, which is not conducive to the balance of the network, whereas the E-EEABR algorithm utilizes a combination of single-hop and multi-hop means to balance the network load.

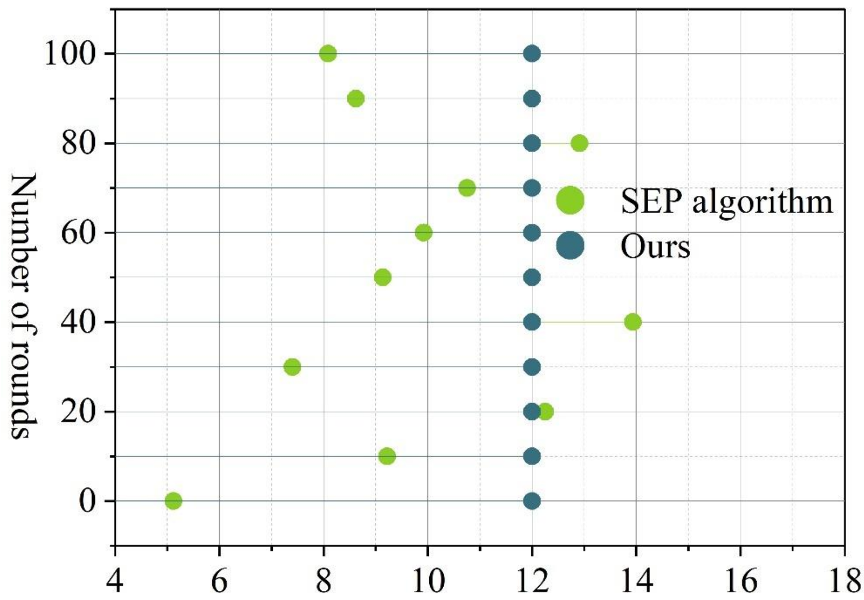


Figure 9. The cluster head communicates data packets with the Sink node.

4.2.3. Average cluster head energy consumption

Since there is no node death before the network runs, we take the average energy consumption of the cluster head in the first 100 rounds as a comparative parameter for the experiments, and the average energy consumption of the cluster head is shown in Fig. 10, from which it can be seen that the level of the average energy consumption of the cluster head of the E-EABR algorithm is lower than that of the SEP algorithm as a whole, with the maximum energy consumption of about 2.35×10^{-3} J and the minimum of about 1.85×10^{-3} J. While the SEP algorithm's average cluster head energy consumption is about 8.7×10^{-3} J at maximum and 3.3×10^{-3} J at minimum.In these 200 rounds of simulation experiments, the average cluster head energy consumption of E-EEABR algorithm is about 2.1×10^{-3} J, while the average cluster head energy consumption of SEP algorithm is about 5.0×10^{-3} J, which saves 58% of the energy consumption in the cluster head in each round. Meanwhile, observing the curves, it can be clearly found that the data fluctuation of the E-EEABR algorithm is much smoother, which also indicates that it is better in terms of network balance. From both the data and the curve, it can be seen that the E-EABR algorithm outperforms the SEP algorithm in terms of cluster head energy consumption, effectively reduces the average energy consumption of the cluster head and balances the network energy consumption.

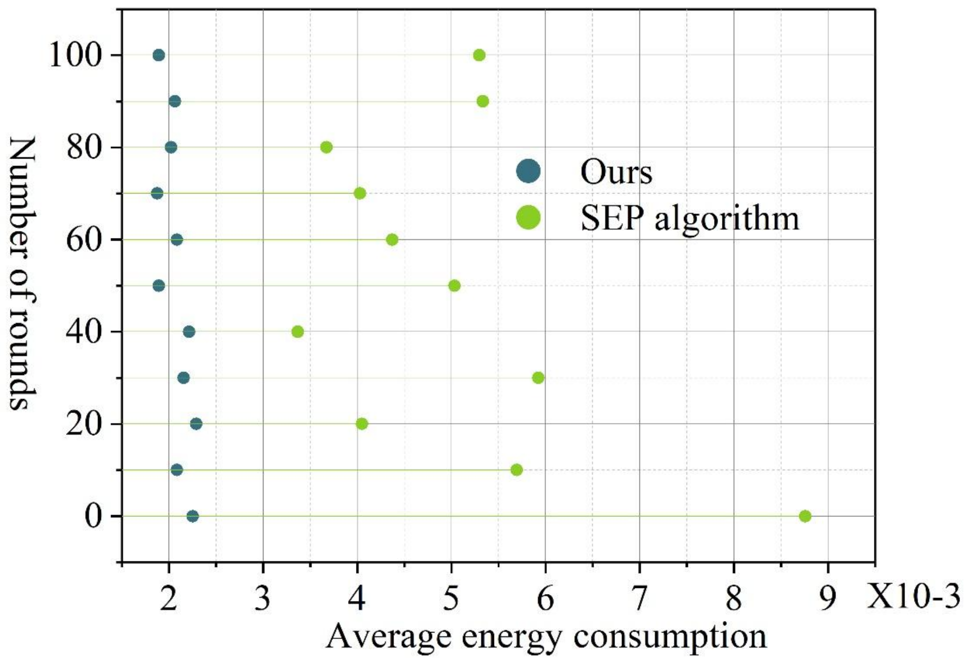


Figure 10. Cluster average energy consumption.

5. Conclusion

In this paper, the relevant principles of EAODV routing protocol are analyzed in depth. And on this basis, the ant colony algorithm is improved by using a combination of distance bands, restricted search angle and distance factor to reduce the energy consumption of nodes, and a pseudo-random scaling rule containing energy factor to optimize the probability transfer function in order to enhance the algorithm's ability of searching for excellence. The main conclusions of the study are as follows:

(1) Through the performance comparison experiments of EAODV protocol before and after ACO parameter optimization, it is found that when ρ =8, α =2, and β =0.8, the overall performance is better when compared with the other combinations of values.

(2) This paper's algorithm by 200 rounds, its average residual energy of the nodes is reduced to 0.47J, node energy utilization on the SEP algorithm improved by 66.7%, through simulation experiments to prove the feasibility and superiority of this paper's algorithm, which indeed reduces the energy loss of the network, increases the uniformity of the distribution of the clusters, and effectively prolongs the network's survival cycle, improves the node's survival rate, and improves the network's performance.

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