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Wireless sensor network routing optimization based on improved ant colony algorithm in the Internet of Things

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A R T I C L E I N F O

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A B S T R A C T

The Internet of Things (IoT) connects devices, enabling real-time data acquisition, automation, and collaboration. Wireless sensor networks are one of the important components of the Internet of Things, consisting of many wireless sensor nodes distributed in space. These nodes can perceive environmental information and transmit it to other nodes through wireless communication. In wireless sensor network routing optimization methods, improved ant colony algorithm can be used to find the optimal routing scheme. Ant colony algorithm simulates the behavior of ants in the process of searching for food, and optimizes factors such as transfer probability and pheromone concentration to enable ants to find the shortest path. In wireless sensor networks, node positions can be used as reference nodes and anchor nodes, combined with the objective function of wireless sensor network routing optimization, and improved ant colony algorithm can be used to solve the optimal path, thus obtaining the optimal wireless sensor network routing optimization scheme. Through experimental results, it can be found that the proposed method performs well in terms of energy consumption, transmission delay, number of dead nodes, and network throughput. These optimization results have positive implications for the sustainable development and practical application of the Internet of Things, which can improve the development of the digital economy and enhance the construction of smart cities.

1. Introduction

At present, wireless sensor networks have been widely applied in various fields such as environmental monitoring, agriculture, and the Internet of Things. In these applications [1,2], wireless communication between nodes in wireless sensor networks plays a crucial role. The Internet of Things has characteristics such as connectivity, intelligence, and real-time. It connects devices through wireless communication technology and endows them with perception, computing, and decision-making capabilities. This enables the Internet of Things to obtain and transmit data in real-time, automate collaboration and data sharing, improve production and operational efficiency, and reduce costs. At the same time, the Internet of Things utilizes big data analysis and predictive maintenance to provide insight into market trends and user needs, helping enterprises make more accurate decisions. In addition, the application of the Internet of Things in fields such as smart homes and health monitoring is improving people's quality of life and promoting the process of sustainable development. Therefore, the Internet of Things has significant advantages in improving efficiency, reducing costs, enhancing insight, improving quality of life, and promoting sustainable development. The routing optimization of wireless sensor

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networks has become an important and challenging issue due to the limited energy of sensor nodes, wide and random distribution of nodes, and other characteristics. The goal of wireless sensor network routing optimization is to improve network performance and energy utilization efficiency by selecting appropriate paths, minimizing energy consumption, maintaining low latency, and maximizing network lifespan [3]. It involves techniques and mechanisms such as path selection and transmission scheduling to ensure efficient and accurate data transmission between nodes. The research on routing optimization in wireless sensor networks is of great significance for improving network performance, extending network lifespan, providing reliable data transmission, and supporting real-time applications. By adopting effective routing optimization algorithms and mechanisms, more reliable, intelligent, and efficient wireless sensor network systems can be achieved. Wireless sensor network routing optimization plays an important role in the Internet of Things, as it can improve network performance and energy utilization efficiency, extend network lifespan, provide reliable data transmission and support real-time applications for various application fields. Therefore, routing optimization in wireless sensor networks is of great significance in promoting the development and application of animal networking [4,5].

Many research work has been carried out on the optimization of wireless sensor network routing. For example, reference [6] proposed a routing optimization method for wireless sensor networks based on grey prediction. Firstly, the characteristics of wireless sensor networks and the background of routing optimization problems were introduced, and the principle and application of grey prediction method were elaborated in detail. Then, a routing optimization method for wireless sensor networks based on grey prediction was proposed, which mainly utilizes the established grey prediction model to predict the status and communication load of nodes in the network, and makes routing decisions and optimizations based on the prediction results. Select nodes with lower load and energy consumption on the communication path as relay nodes to achieve network load balancing and energy conservation, in order to achieve the goal of optimizing network routing. However, after the application of this method, the network transmission delay increases. Reference [7] proposed a routing optimization method for wireless sensor networks based on energy and path constraints. Firstly, the energy constraints between nodes are considered, and through the use of energy balance strategies, the energy resources of nodes are reasonably allocated and managed to avoid situations where energy depletion leads to node failure or inability to complete tasks. Secondly, this method combines path constraints and considers factors such as distance between nodes and communication consumption in the optimization routing process to select the optimal transmission path. Energy and distance weights are added to ensure a uniform and reasonable energy distribution between network nodes, thus achieving wireless sensor network routing optimization. However, during testing, it was found that there were a large number of node deaths in the application of this method, which still lags behind the ideal application goal. Reference [8] proposed a wireless sensor network routing optimization method based on an improved grey wolf optimization algorithm. Initialize a group of virtual grey wolf representative nodes in a wireless sensor network and give them random position, speed, and fitness values. By simulating the search behavior of grey wolves, the optimization algorithm updates the speed and position of each grey wolf based on its position in the current solution space, and calculates its fitness value. Define a fitness function based on the routing optimization objective to evaluate the quality of each grey wolf's solution. In the process of updating the location of the grey wolf, combining competition strategy and cooperation mechanism, the grey wolf can conduct local and global searches based on the information of neighboring nodes to obtain better optimization solutions. Applying this method to practical applications, it was found that this method has the problem of low network throughput, and the actual application effect is not good.

Wireless sensor network routing optimization faces problems such as energy constraints, network topology dynamics, bandwidth and capacity limitations. Improving ant colony algorithm can help solve these problems [9,10]. In wireless sensor network routing optimization, improving ant colony algorithm can improve the performance and effectiveness of wireless sensor network routing optimization. However, unlike the improved approach of introducing the alternating search strategy of regional ants and public ants in Ref. [10] and limiting the number of candidate nodes for public ant search, in this study, the ant colony algorithm was improved by optimizing the transfer probability and pheromone concentration. Optimizing the transition probability can effectively guide ants to better choose paths during the search process. By adjusting the concentration of pheromones, the importance of different paths can be dynamically adjusted during the search process. The method of optimizing pheromone concentration can make ants more intelligent in updating pheromones and guide other ants to pay more attention to passing through high-quality paths in subsequent searches. In this way, the optimized ant colony algorithm can more accurately find better solutions and reduce the exploration of invalid paths. This algorithm can fully consider energy constraints, dynamic network topology, and resource constraints, and can achieve self-adaptability and distributed properties during the search for the optimal path. Therefore, a new routing optimization method for wireless sensor networks based on improved ant colony algorithm is proposed. The innovative technology route is as follows.

(1) Edge computing and intelligent perception: push computing power to IoT nodes to enable them to have intelligent perception and decision-making capabilities. This allows for real-time data processing and analysis on the device side, reducing the pressure of data transmission and cloud computing, and improving response speed and energy efficiency.
(2) Artificial intelligence and machine learning: Apply artificial intelligence and machine learning to IoT systems, enabling them to have autonomous learning and adaptability. By extracting patterns from massive data, discovering patterns, and automatically adjusting and optimizing the system, intelligent decision-making, automated management, and predictive maintenance functions are achieved.
(3) Security and privacy protection: With the increasing number of IoT devices and data, security and privacy have become important considerations. The innovative technological path should include strengthening the security of IoT devices and communication networks, adopting data collection and processing methods that comply with privacy protection standards, and promoting technological innovation in identity verification, encryption, and vulnerability repair.

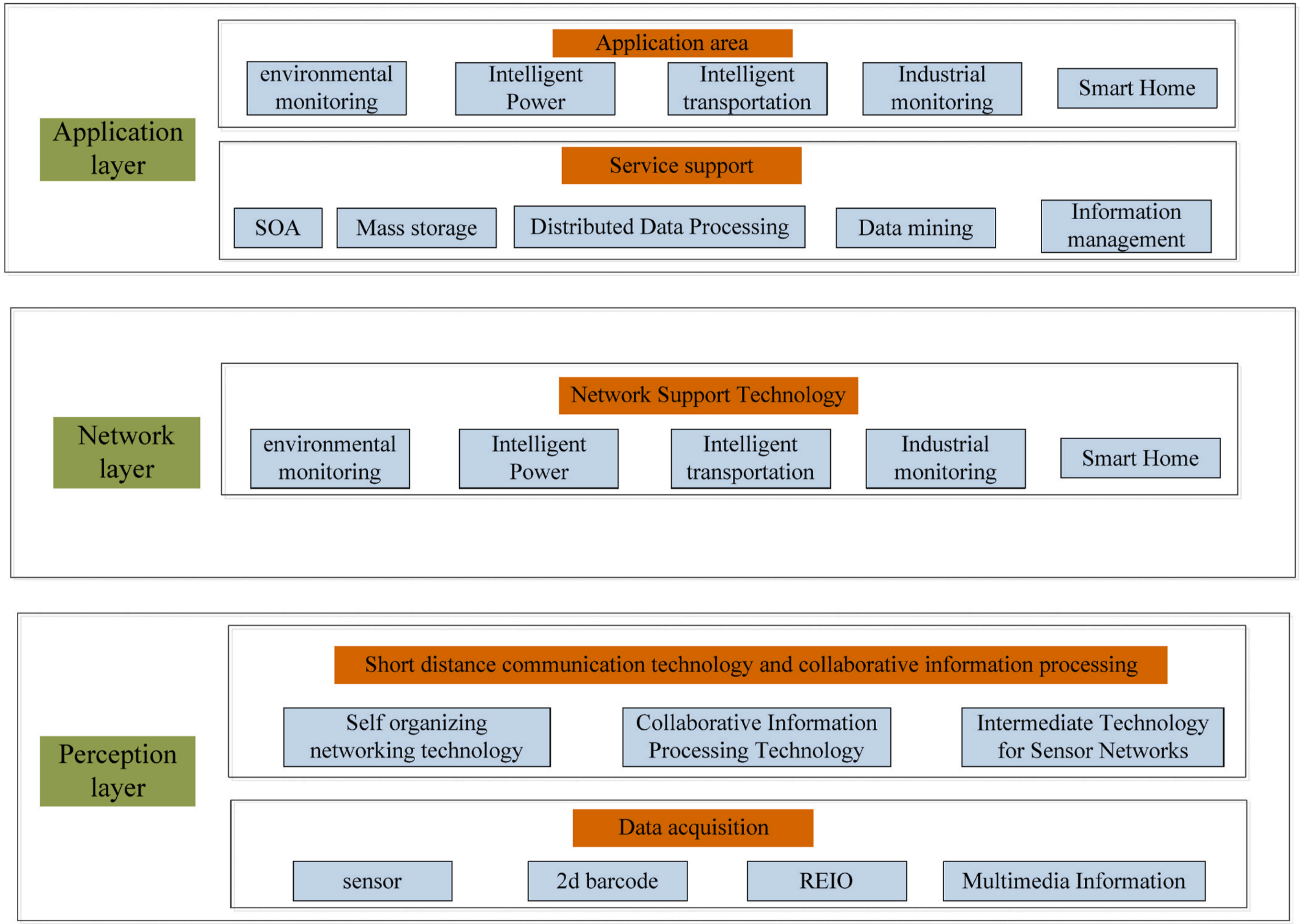

Fig. 1. IoT architecture.

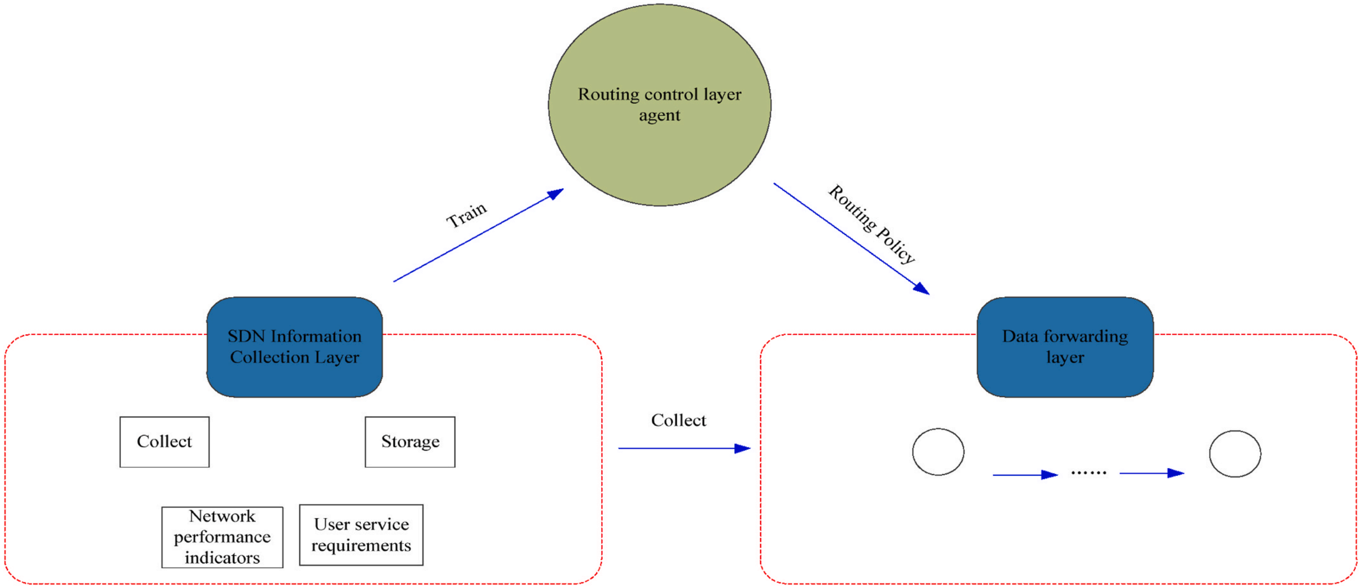

Fig. 2. Wireless sensor network routing model.

(4) Cloud edge collaboration and resource optimization: By optimizing the collaborative work between cloud and edge devices, efficient utilization of resources and distributed computing can be achieved. This can reduce network transmission latency and provide a better user experience and flexibility.
(5) Integrated application and scenario innovation: Promote the integration of animal networking with other fields, such as smart cities, healthcare, industrial manufacturing, etc. By innovating applications and scenarios, the Internet of Things can be widely applied in different fields, further improving efficiency, reducing costs, and contributing to sustainable development.

2. Routing optimization method for wireless sensor networks

Wireless sensor network routing based on improved ant colony algorithm under the Internet of Things has multiple advantages. Firstly, the algorithm is self adaptive and can adjust routing choices in real-time according to environmental changes, thereby improving network performance. Secondly, distributed decision-making enables each sensor node to make independent decisions, reducing network load and enhancing network robustness. In addition, improved ant colony algorithm can quickly find the optimal path, improve routing efficiency, and improve energy efficiency through energy balancing and optimizing data forwarding paths. Finally, the algorithm also has strong fault tolerance and can adaptively bypass faulty nodes or links, ensuring the correct transmission of data. To ensure the security of user information, attention should be paid to data encryption and privacy protection. In summary, wireless sensor network routing based on improved ant colony algorithm will provide reliable, efficient, and energy-saving communication solutions for the Internet of Things.The architecture diagram of the Internet of Things is shown in Fig. 1.

2.1. Construction of wireless sensor network routing model

Building a wireless sensor network routing model is of great necessity for optimizing network routing, which is mainly reflected in the following aspects [11].

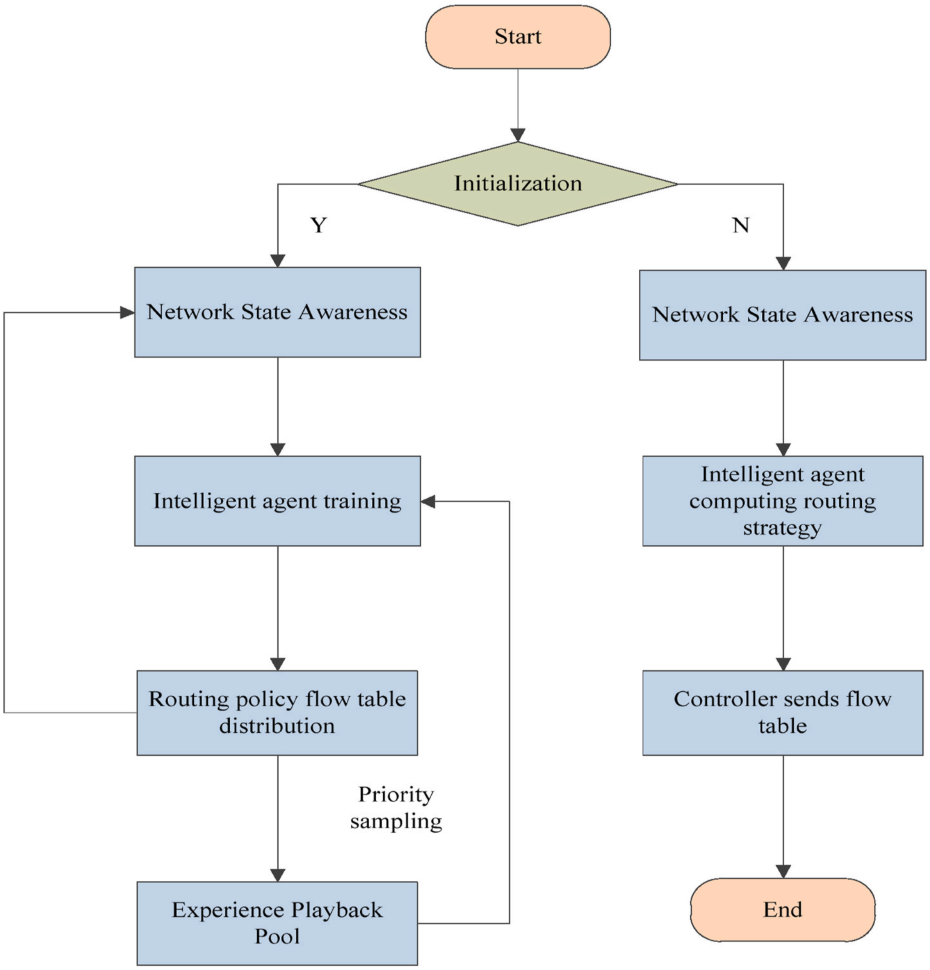

Fig. 3. Execution process of wireless sensor network routing model.

(1) Analyzing network topology: By constructing a wireless sensor network routing model, one can gain a deeper understanding of the entire network topology, which helps determine appropriate routing strategies and algorithms, and evaluate the performance of the network.
(2) Evaluating security and stability: In wireless sensor networks, security and stability are crucial factors. By constructing a routing model, data transmission paths and communication behaviors between nodes can be analyzed to identify potential security vulnerabilities or unstable factors, and corresponding measures can be taken to improve them.
(3) Optimizing network topology and node layout: The topology and node layout of wireless sensor networks directly affect the performance of the network. By constructing a routing model, network topology can be optimized, and the location and density of nodes can be reasonably planned to improve network coverage, transmission efficiency, and energy utilization.
(4) Improving routing efficiency and energy consumption: Optimizing routing is an important task in wireless sensor networks, which can reduce data transmission latency, reduce energy consumption, and improve network throughput and performance. By constructing a routing model, different routing algorithms and strategies can be analyzed and the optimal routing scheme suitable for specific application scenarios can be selected.

Based on the above analysis, a wireless sensor network routing model [12] was constructed, which mainly consists of three layers: routing control layer, SDN information collection layer, and data forwarding layer. The wireless sensor network routing model is shown in Fig. 2.

(1) The routing control layer is the core of the entire model, and the routing control layer of the wireless sensor network routing model can manage and optimize network routing, providing reliable support for the normal operation of the wireless sensor network.
(2) The DN collection layer plays a connecting role. This layer can provide various training parameters for the routing control layer, as well as collect and store various network performance parameters collected from the data forwarding layer, as well as special network service requirements and network status. The DN collection layer implements the collection, aggregation, compression, and processing of data generated in wireless sensor networks to improve network performance, energy efficiency, and data transmission efficiency [13].
(3) The data forwarding layer is used to execute routing strategies, achieving reliable forwarding and effective transmission of data in wireless sensor networks, ensuring data transmission efficiency and security.

The execution process of the wireless sensor network routing model is shown in Fig. 3.

Assuming $G = (V, E, W)$ represents a wireless sensor network, where V represents a set of v nodes in the network, i.e. $v \in V$; E represents a set of e links in a network, where the connection between two forwarding nodes defines a link, i.e. $e \in E$. Assuming that F represents the traffic size matrix of node $N \times N$ in the graph, and f_{ij} represents the traffic from source node s_i to destination node s_j, the node traffic expression shown in equation (1) can be constructed:

$$f_{ij} = \begin{cases} f_{ij} \in R^+, e_{ij} \in E \\ 0, else \end{cases} \tag{1}$$

The traffic from the source node to the target node can be determined through equation (1). In equation (1), R^+ represents the traffic matrix, and e_{ij} represents the number of links from source node s_i to destination node s_j [14].

Assuming that B represents the bandwidth size matrix of $N \times N$ for nodes in the graph, and b_{ij} represents the bandwidth from source node s_i to destination node s_j, then the bandwidth expression shown in equation (2) can be constructed:

$$b_{ij} = \begin{cases} f_{ij} b_{ij} \in R^+, e_{ij} \in E \\ 0, else \end{cases} \tag{2}$$

By equation (2), the bandwidth from the source node to the target node can be determined considering the size of traffic.

Assuming that R represents the remaining traffic size matrix of node $N \times N$ in the graph, and r_{ij} represents the remaining bandwidth from source node s_i to destination node s_j. Then the expression for the remaining bandwidth as shown in equation (3) can be constructed:

$$r_{ij} = \begin{cases} r_{ij} - u_{ij}, r_{ij} \in E \\ 0, else \end{cases} \tag{3}$$

By equation (3), the remaining bandwidth from the source node to the target node can be determined. In the equation, u_{ij} represents the bandwidth used between nodes i and j.

Assuming that W represents a weight matrix with a link forwarding size of $N \times N$ for the graph, and w_{ij} represents the weight of links between nodes i and j for links.The calculation equation for link node weights is shown in equation (4):

$$w_{ij} = \begin{cases} r_{ij} w_{ij} \in R^+, e_{ij} \in E \\ 0, else \end{cases} \tag{4}$$

By calculating equation (4), the weights between different link nodes were determined.

Assuming that f_{ij}^k represents the weight of the transmitted data stream on k-th path, and $w_{e_{ij}}^k$ represents the weight of the sub stream split into f_{ij} selected for transmission on k-th path. Then equation (5) can be constructed to calculate the path transmission weight:

$$w_{e_{ij}}^{k} = \frac{f_{ij}^{k}}{\sum_{k=1}^{K} w_{ij} f_{ij}^{k}} \tag{5}$$

Assuming that D_{end} represents the end-to-end delay of traffic from source node s_i to destination node s_j in the network, then it can be calculated using equation (6):

$$D_{end} = \sum_{i,j=1}^{V} \sum_{e \in k}^{E} d_{ij} \tag{6}$$

Calculate the traffic transmission delay from the source node to the target node based on the transmission delay using equation (6). In the equation, d_{ij} represents the transmission delay between nodes i and j. Assuming that T_{end} represents the end-to-end throughput of traffic from source node s_i to destination node s_j in the network, the calculation equation can be expressed as equation (7):

$$T_{end} = \sum_{i,j=1}^{V} \sum_{e \in k}^{E} t_{ij} \tag{7}$$

In equation (7), the calculation of traffic throughput from the source node to the target node was completed based on network throughput. In the equation, t_{ij} represents the network throughput between nodes i and j. In wireless sensor networks, effective policy algorithms can reduce the latency and packet loss rate of traffic transmission, improve network throughput, and other network performance. The mathematical expression of the wireless sensor network routing model is shown in equation (8):

$$E_R = \alpha D_{end} - \beta T_{end} + \gamma \frac{C_e w_{e_{ij}}^{k}}{L_{end}} \tag{8}$$

In equation (8), the construction of a wireless sensor network routing model was completed, taking into account delay and packet loss rate. In the equation, L_{end} represents the packet loss rate of the wireless sensor network data flow, $\alpha, \beta, \gamma \in [0,1]$ represents the weights of D_{end}, T_{end}, and L_{end}, and C_e represents the total link capacity.

2.2. Wireless sensor network routing optimization objective function

In the wireless sensor network routing model, it is assumed that there are n reference nodes, m anchor nodes, and l unknown nodes. The calculation equation for the characteristic membership degree μ_k^{ij} of the distance relationship between anchor node j and reference node i and unknown node k is shown in equation (9):

$$\mu_k^{ij} = \frac{r_{ij} \wedge r_{kj}}{\max r_{ij} \wedge r_{kj}} \tag{9}$$

In equation (9), the calculation of feature membership is completed through fitting between different data. In the equation, r_{ij} represents the data fit between i and j, and r_{kj} represents the data fit between k and j.

The calculation equation for the deviation of membership degree between i and other reference nodes is shown in equation (10):

$$d_{ij}^{k} = \sum_{p \neq i} \left| \mu_{ij}^{k} - \mu_{pj}^{k} \right| \tag{10}$$

In equation (10), the calculation of membership deviation was completed by calculating the difference in membership degrees of the distance relationship features between different nodes. In the equation, μ_{pj}^{k} represents the distance relationship feature membership degree between i and other reference nodes [15].

The calculation equation for the deviation between j and all reference nodes and other points is shown in equation (11):

$$d_j^{k} = \sum_{i=1}^{n} \sum_{p \neq i} \left| \mu_{ij}^{k} - \mu_{pj}^{k} \right| \tag{11}$$

By calculating the distance relationship feature membership degree of equation (11), the deviation between the reference node and other nodes was calculated.

Assuming that the membership weights of each node are different, the calculation equation for the total weighted deviation of all nodes is shown in equation (12):

$$d^{k}(w) = \sum_{j=1}^{m} w_j d_j^{k} \tag{12}$$

In equation (12), the calculation of the weighted total deviation was completed by combining the node deviation and weight. The relationship between nodes is shown in Fig. 4.

As for the anchor node, if $\mu_{ij}^{k} \rightarrow 1$, it can be inferred that the position of unknown node k is near the circumference with anchor node j as the center and r_{ij} as the radius. But it does not mean that unknown node k stands near node i. Because the knowledge of a single anchor node is not sufficient to determine the location of unknown nodes, it is necessary to integrate more anchor node knowledge. Sensors first perceive the information they obtain, and then through negotiation between the sensor and the server, they can determine the location of unknown nodes [16,17].

The specific implementation process for locating nodes with the goal of obtaining more accurate node positions is as follows:

Assuming the distance between unknown node k and anchor node j is d_j^k, while the distance between reference node i and anchor node j is d_j^i. Among all virtual reference nodes, the larger the attribute v_{ij}^k, the more similar the reference nodes d_j^i and d_j^k are, so the closer the reference node i is to the unknown node k. If positive ideal solution V_k^+ is the solution closest to the membership degree of unknown node k, and negative ideal solution V_k^- is the reference node farthest from the membership degree of unknown node k, the calculation equations for positive and negative ideal solutions are shown in equation (13):

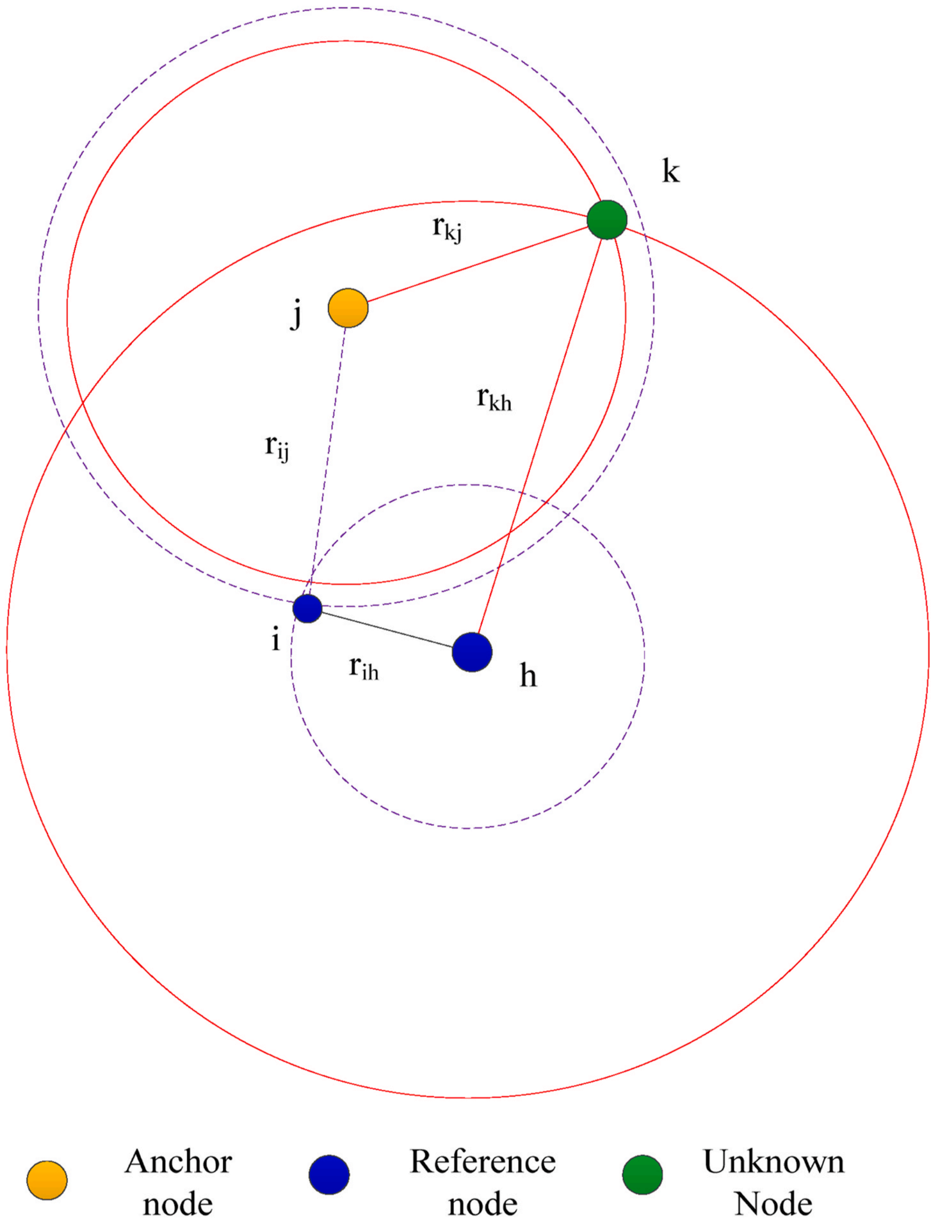

Fig. 4. Relationship between nodes.

$$\begin{cases} V_k^+ = \{v_{k1}^+, v_{k2}^+, \cdots, v_{km}^+\} \\ V_k^- = \{v_{k1}^-, v_{k2}^-, \cdots, v_{km}^-\} \end{cases} \tag{13}$$

According to the positive and negative ideal solutions obtained from equation (13), the distance between the reference node and the unknown node can be calculated.

The distance between reference node i and unknown node k is calculated using equation (14):

$$\begin{cases} d_{i+}^k = \|V_i^k - V_k^+\| = \sqrt{\sum_{j=1}^{m} \left(v_{ij}^k - v_j^{k+}\right)^2} \\ d_{i-}^k = \|V_i^k - V_k^-\| = \sqrt{\sum_{j=1}^{m} \left(v_{ij}^k - v_j^{k-}\right)^2} \end{cases} \tag{14}$$

According to the calculation results of equation (14), it can be seen that virtual reference nodes with larger d_{i-}^k and smaller d_{i+}^k are closer to unknown node k. Assuming that the defined matching degree C_i^k represents the positional similarity between reference node i and unknown node k, the matching degree C_i^k can be calculated using equation (15):

$$C_i^k = \frac{d_{i-}^k}{d_{i+}^k + d_{i-}^k} \tag{15}$$

According to the matching degree C_i^k calculated by equation (15), the reference nodes are arranged in descending order, and then the coordinates of the K virtual reference nodes located in the front row are calculated using equation (16):

$$(x_k, y_k) = \left(\frac{\sum_{i=1}^{K} C_i^k x_i}{\sum_{i=1}^{K} C_i^k}, \frac{\sum_{i=1}^{K} C_i^k y_i}{\sum_{i=1}^{K} C_i^k} \right) \tag{16}$$

By using equation (16), the coordinates of virtual reference nodes can be calculated based on matching degree. In the equation, (x_i, y_i) represents the ideal position of unknown node k.

Based on the above analysis, establish an objective function for wireless sensor network routing optimization, and the expression of the objective function is shown in equation (17):

$$W = \left\{\max \sum m_i m_j, \min \sum u_i, \min \sum h_i, \max \sum r_i r_j\right\} \tag{17}$$

Equation (17) simultaneously considers node distance, energy consumption, transmission delay, transmission energy, and transmission efficiency, which can meet the requirements of wireless sensor network routing optimization from multiple perspectives. In the equation, m_i and m_j represent the connection quality and distance between nodes, u_i represents the energy consumption of nodes, h_i represents the delay between nodes, and r_i and r_j represent the remaining energy and transmission efficiency of nodes, respectively.

2.3. Routing optimization based on improved ant colony algorithm

The improved ant colony algorithm has the advantages of global search ability, adaptability, robustness, and parallel computing ability. This makes ant colony algorithm widely applied and innovative in fields such as travel salesman problems, network routing optimization, resource scheduling and task allocation, and social behavior simulation. By improving algorithm strategies, parameter settings, and innovation in application fields, the performance and applicability of ant colony algorithm can be further improved, unleashing its enormous potential in solving practical problems. Traditional ant colony algorithm has shown good performance in some optimization problems, but it has problems such as slow convergence speed, poor search ability, and weak robustness. In order to overcome these shortcomings and further improve the performance and application range of the algorithm, improvements have been made to the algorithm. The improved ant colony algorithm is based on heuristic rules of ant colony behavior, simulating the behavior of ants searching for food in the environment during the problem solving process. The application of improved ant colony algorithm in wireless sensor network routing optimization has the following advantages.

(1) Distributed optimization: Wireless sensor networks typically consist of a large number of nodes, and traditional centralized optimization algorithms are not suitable for such distributed networks. Improved ant colony algorithm can run and optimize in a distributed environment, and each node can make autonomous decisions using local information to achieve distributed routing optimization.
(2) Adaptability and robustness: The improved ant colony algorithm can adapt to the dynamic changes of the network and has good robustness against node failures, energy constraints, and other situations. It continuously updates and adjusts pheromones and path selection strategies, making network routing adaptive and able to cope with complex network environments.

(3) Efficiency and low overhead: Improved ant colony algorithms typically have high resolution efficiency and low computational overhead. The parallel search of ants and the local update strategy of pheromones enable the algorithm to quickly find high-quality solutions without requiring a large amount of computing resources and energy consumption.
(4) Global optimal solution ability: Improved ant colony algorithm can conduct global search throughout the entire network, and guide ants' exploration through pheromone accumulation and update strategies, making the algorithm have high global search ability and convergence, and can find routing solutions close to the optimal solution.

In order to gain a deeper understanding of the system model of ant colonies, first n target points are given, and an ant randomly selects a certain target point a to start. It is required to traverse all elements in n once (without repetition), and finally return to a to find the shortest path. Assuming $C = \{c_1, c_2, ..., c_n\}$ represents a set of n target point elements, $L = \{l_{ij} | c_i, c_j \subset C\}$ represents the set formed by the pairwise connected target point elements in set C, and $d_{ij}(i, j = 1, 2, ..., n)$ is the Euclidean distance of l_{ij}, The calculation equation for Euclidean distance d_{ij} is shown in equation (18):

$$d_{ij} = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2} \tag{18}$$

In equation (18), the Euclidean distance is calculated by the unknown position of the virtual reference node and the target node.

During the crawling process, individual $k(k = 1, 2, ..., m)$ in the ant colony determines its next jump direction by analyzing the remaining pheromone concentration on each path. Use Taboo List $tabu_k(k = 1, 2, ..., m)$ to record the set of elements that an individual has already selected, and dynamically adjust it with changes in $tabu_k$. During the entire search process, the ant determines the element to be transferred in the next step when selecting the current element through equation (19):

$$p_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta}{\sum\limits_{s \subset allowed_k} [\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta}, if \ \ j \subset allowed_k \\ \qquad 0, other \end{cases} \tag{19}$$

In equation (19), the determination of ant transfer elements is achieved by combining the control of pheromones with the unselected set of elements. In the equation, $allowed_k$ represents the set of elements that individual k has not yet selected, α represents the control factor of pheromones, β represents the control factor of prior knowledge, and $\eta_{ij}(t)$ represents the heuristic function. The calculation process of the heuristic function $\eta_{ij}(t)$ is shown in equation (20):

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \tag{20}$$

In equation (20), the construction of the heuristic function was completed through Euclidean distance.

The layout strategy adopted imitates the laws of human memory, and as new pheromones begin to enter the brain, the effect of older pheromones gradually weakens or even disappears. At time $t + n$, the pheromone concentration adjustment equation on path (i, j) is shown in equation (21):

$$\tau_{ij}(t + n) = (1 - \rho).\tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{21}$$

In equation (21), the adjustment of pheromone concentration was completed by comprehensively considering the increase in pheromone content and volatility coefficient. In the equation, $\tau_{ij}(t)$ represents the concentration of pheromones on nodes i and j at time t, ρ represents the volatility coefficient, $\rho \subset [0, 1]$, $\Delta\tau_{ij}(t)$ represents the increase in pheromones, and $\Delta\tau_{ij}^k(t)$ represents the average amount of pheromones.

The calculation equation for the increase in pheromones is shown in equation (22):

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^k(t) \tag{22}$$

In equation (22), the amount of pheromone increase was calculated by the mean of pheromone amounts in different paths. In equation (22), $\Delta\tau_{ij}^k(t)$ represents the mean pheromone quantity.

Due to the fact that the basic ant colony algorithm can cause the energy consumption of nodes on the shortest path to be too fast, which may lead to node failure, this article has made the following improvements to the transfer probability. The calculation process of the improved transfer probability is shown in equation (23):

$$p_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}(t)]^\beta [E_j(t)]^\gamma}{\sum\limits_{s \subset alloeed_k} [\tau_{is}(t)]^\alpha [\eta_{is}(t)]^\beta [E_s(t)]^\gamma}, ifj \subset allowed_k \\ 0, other \end{cases} \tag{23}$$

In equation (23), the calculation of transfer probability is completed through probability transfer factor, importance coefficient, and energy consumption heuristic factor. In the equation, $E_j(t)$ represents the remaining energy of the j-th node at time t. The parameters α, β, and γ are mainly used to measure the importance coefficient of the corresponding term in the transition probability. $\eta_{ij}(t)$

represents the heuristic factor for the energy consumption of the path between node i and node j. The calculation equation is shown in equation (24):

$$\eta_{ij}(t) = \begin{cases} 1/d_{ij}^2(4), d_{ij}(t) < d_0 \\ 1/d_{ij}^4(4), d_{ij}(t) \geq d_0 \end{cases} \tag{24}$$

The values of the three parameters α, β, and γ in traditional ant colony algorithm are fixed and unchanged. During the traversal process, it is hoped that their values can adapt to changes in the number of traversals. α is used to measure the proportion of pheromone concentration. At the beginning, it is hoped that the proportion of pheromone concentration will be large, and at the end, it is hoped that the proportion of pheromone concentration will be small. This can accelerate the search speed at the beginning, and at the end, it can search slowly, and the search scope will be wider, It can avoid falling into local optima. The update process of α is shown in equation (25):

$$\alpha(n) = \alpha_0 + \alpha_1 e^{-Kn}, 0 \leq n < N \tag{25}$$

By equation (25), the proportion of pheromone concentration was updated under multiple parameter constraints.

In the equation, α_0, α_1, K represent different constants, n represents the number of iterations of the ant colony, and N represents the total number of iterations. It can be seen that the larger the value of n, the smaller the value of $\alpha(n)$, so that the proportion of pheromone concentration can adapt to changes in the number of iterations.

In order to avoid excessively high pheromone concentration on the shortest path or too low pheromone concentration on the longest path, which may cause the algorithm to converge too quickly, the pheromone concentration is limited to between. The pheromone concentration update process on the local path is shown in equation (26):

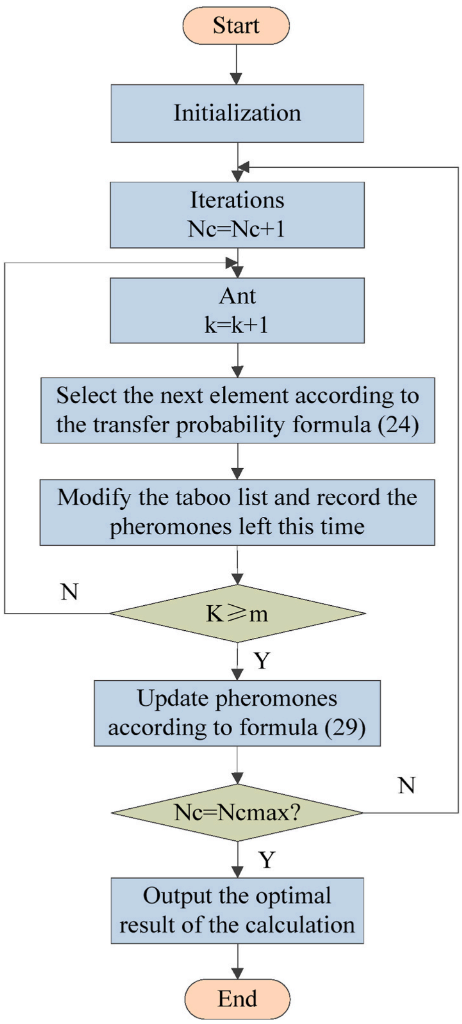

Fig. 5. Flow of solving the objective function for wireless sensor network routing optimization.

$$\tau_{ij}(t+1) = \max\{\tau_{\min}, \min[(1-\rho)]\tau_{ij}(t) + \rho\Delta\tau, \tau_{\max}\} \tag{26}$$

In equation (26), the pheromone concentration on the local path is updated under the constraints of the maximum and minimum pheromone values.

In the equation, $\tau_{\min}$ represents the minimum value of pheromones, $\tau_{\max}$ represents the maximum value of pheromones, and $\Delta\tau$ represents the increment of pheromones. The calculation process for the degree of superiority and inferiority of each path is shown in equation (27):

$$v_a = \frac{E_{average} \times E_{\min}}{E_{sum}} \tag{27}$$

In formula (27), the ratio of the average remaining energy of the path and the lowest remaining energy to the total energy consumption is comprehensively considered, and the calculation of the degree of superiority and inferiority of the path is completed. In the equation, $E_{average}$ represents the average remaining energy of the ant on its path, $E_{\min}$ represents the minimum remaining energy, and E_{sum} represents the total energy consumption.

Select the path with the highest value of v_a as the optimal path through comparison, and then globally rearrange the pheromone concentration on this path. The layout calculation equation is shown in equation (28):

$$\tau_{ij}(t+1) = \max\{\tau_{\min}, \min[(1-\rho)\tau_{ij}(t) + \rho\Delta\tau, \tau_{\max}]\} \tag{28}$$

In equation (28), the pheromone concentration was rearranged to improve the ant colony algorithm. By using the improved ant colony algorithm to solve the objective function shown in equation (18), the optimization of wireless sensor network routing is completed.

The solution process for the objective function of wireless sensor network routing optimization based on improved ant colony algorithm is shown in Fig. 5.

3. Experimental design

3.1. Experimental setup

In order to verify the effectiveness of the routing optimization method for wireless sensor networks based on improved ant colony algorithm designed in this article, relevant experiments were conducted. The specific experimental settings are as follows:

Network simulation refers to the evaluation and analysis of the performance, behavior, and characteristics of a computer network through simulation and experimentation. In the wireless sensor network routing optimization experiment, the network simulation parameters are set as shown in Table 1.

The location and distribution of nodes are shown in Fig. 6.

Setting parameters such as the initial position and energy state of nodes and establishing connections between nodes is an important step in wireless sensor networks. In the network deployment phase, it is necessary to consider factors such as the location distribution and energy state of nodes to ensure that the network coverage and communication quality meet the requirements. Select appropriate routing optimization methods based on specific research objectives to achieve optimal network performance. During node operation, data packets are sent and received according to the routing protocol. Through routing protocols, nodes can determine the optimal data transmission path to achieve efficient data communication. At the same time, nodes will also collect network performance indicators and sensor data, including distance between nodes, data transmission delay, energy consumption and other indicators. These collected data can be used to analyze and evaluate the performance of the network, in order to further optimize and improve the routing scheme of wireless sensor networks. The specific experimental data types are shown in Table 2.

Using energy consumption, network latency, packet loss rate, and network coverage as indicators, validate the effectiveness of grey prediction based methods, energy and path constraints based methods, improved grey wolf optimization based methods, and the proposed methods, in order to compare the practical application effects of different methods.

3.2. Experimental result

Energy consumption is an important performance indicator in wireless sensor networks and a key consideration factor in the design and optimization of wireless sensor networks. Measuring the energy consumption of nodes during communication and data

Table 1
Network simulation parameters.

Simulation parameters	Parameter Value
Monitoring scope	200*200
Number of nodes	25
Number of running rounds	1200r
Node initial energy	0.45J
Packet size	4000bit
Control packet size	100bit

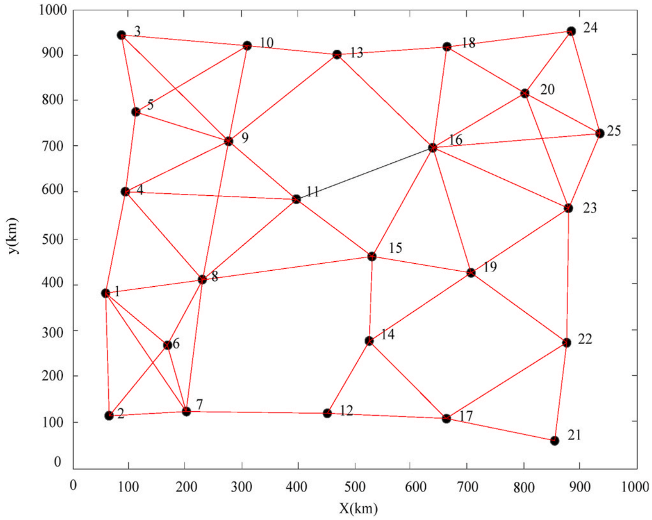

Fig. 6. Node location and distribution.

Table 2
Data types used in the experiment.

Experimental data type	Experimental data type
Topology data	Including location information of nodes and connections, neighbor relationships, etc. These data are used to construct network topology and serve as the basis for routing protocols
Sensor data	Wireless sensor networks are typically used to collect physical or environmental parameters in the environment. Sensor nodes collect various perceptual data and transmit it to base stations or other target nodes through routing protocols
Routing control data	These data are used to control the behavior of routing protocols, mainly including routing requests exchanged between nodes, routing update messages, and decisions about which path to forward through
System Configuration Data	Covering some basic configuration information of wireless sensor networks, such as the initial position and energy state of nodes, communication range settings, node power levels, etc
Debugging and log data	Used for diagnosing and debugging the operation of routing protocols, as well as recording events and error messages that occur in the network

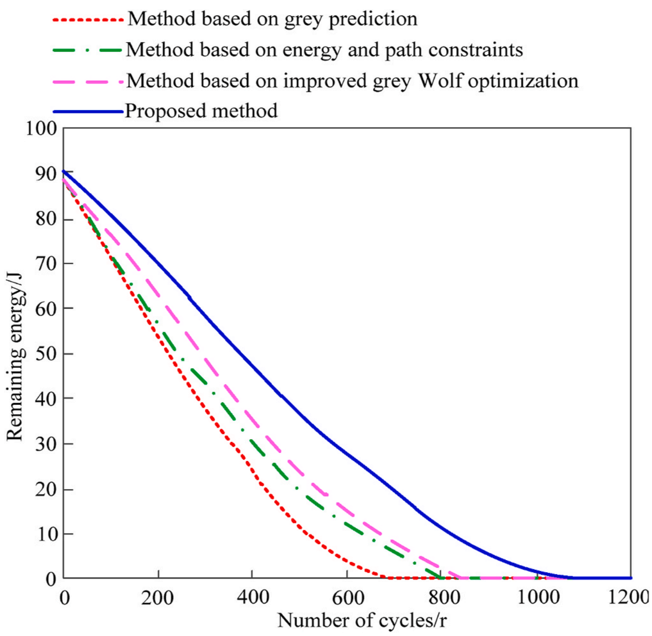

Fig. 7. Energy consumption comparison of four methods.

transmission, routing optimization methods should be able to reduce the energy consumption of nodes and extend the lifespan of the network. The energy consumption comparison of the four methods is shown in Fig. 7.

According to the analysis of the data in Fig. 7, when the number of rounds reaches 690 times, the energy value of the node becomes 0 after the application of the method based on grey prediction, indicating that the node energy is exhausted at this time. When the number of rounds reaches 800, the energy value of the node becomes 0 after the application of the method based on energy and path constraints, indicating that the node energy is exhausted at this time. When the number of rounds reaches 840, the node energy value based on improved grey Wolf optimization becomes 0 after application, indicating that the node energy is exhausted at this time. When the number of cycles reaches 1040, the node energy value after the application of the proposed method becomes 0, indicating that the node energy is exhausted at this time, indicating that the node energy consumption speed of the proposed method is slow, indicating that the design and optimization of the proposed method makes the network more durable and reliable, thus prolonging the life cycle of the whole network and providing longer service.

The transmission delay after routing optimization in wireless sensor networks refers to the delay in data transmission from the source node to the target node. The optimized routing scheme can reduce retransmission and error detection time during transmission, improve packet transmission efficiency, and reduce transmission delay. The transmission delay comparison results of the four methods are shown in Fig. 8.

The analysis of the results in Fig. 8 shows that with the increase of the number of rounds, the transmission delay of the four methods shows an increasing trend. Among them, the transmission delay of wireless sensor network varies between 149 ms and 386 ms after the application of the method based on grey prediction, and the transmission delay of wireless sensor network varies between 277 ms and 445 ms after the application of the method based on energy and path constraints. The transmission delay of wireless sensor network varies between 92 ms and 395 ms after the application of the improved grey Wolf optimization method, while the transmission delay of wireless sensor network varies between 25 ms and 81 ms after the proposed method, and the transmission delay is the lowest, indicating that this method can not only improve the performance and efficiency of wireless sensor network. At the same time, it can meet the needs of users for fast response and high-quality experience.

With the operation of wireless sensor networks, dead nodes refer to nodes that, due to various reasons, cannot operate normally or run out of energy, thus unable to participate in network communication and data transmission. The comparison of the number of dead nodes for the four methods is shown in Table 3.

According to the analysis of the results in Table 3, when the number of rounds is 200, there are no dead nodes under the application of the four methods; when the number of rounds is 400, there are 5 dead nodes in the wireless sensor network under the application of the grey prediction method, and 12 dead nodes in the wireless sensor network under the application of the energy and path constraint method. However, the method based on improved grey Wolf optimization and the proposed method do not appear dead nodes. When the number of rounds is 600 and 800, more dead nodes appear in the wireless sensor network under the application of the method based on grey prediction, the method based on energy and path constraints, and the method based on improved grey Wolf optimization, and the number of dead nodes under the application of the proposed method is still 0. When the number of rounds is 1000, a dead node appears in the wireless sensor network applied by the proposed method. When the number of rounds is 1200, all the nodes of the wireless sensor network die under the application of the grey prediction method and the energy and path constraint method, while

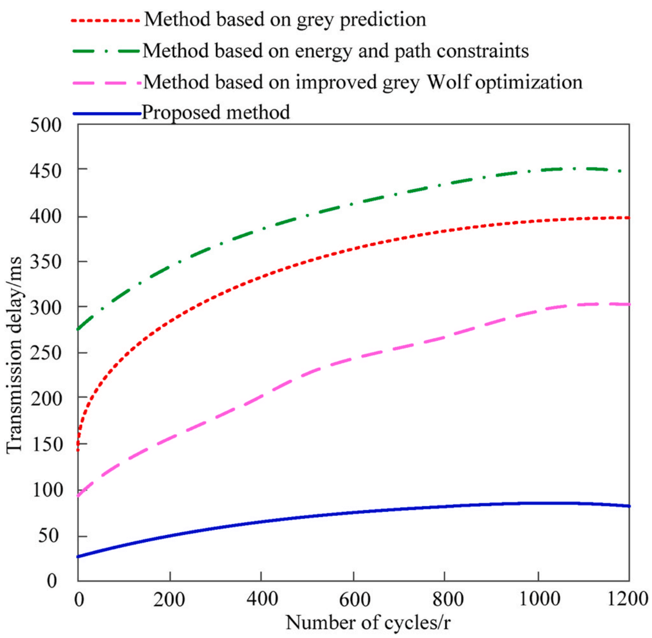

Fig. 8. Comparison of transmission delays among four methods.

Table 3
Comparison of the number of dead nodes among the four methods.

Number of rounds	Method based on grey prediction	Method based on energy and path constraints	Method based on improved grey Wolf optimization	Proposed method
200	0	0	0	0
400	5	12	0	0
600	8	16	2	0
800	12	18	7	0
1000	16	20	8	1
1200	25	25	10	2

the number of dead nodes under the improved grey Wolf optimization method is 10, and the number of dead nodes under the proposed method is 2, indicating that the wireless sensor network is in good health.

After optimizing the routing of wireless sensor networks, the network throughput indicators can be improved to a certain extent. Network throughput refers to the amount of data or tasks that a network can transmit or complete per unit of time. The network throughput comparison results of the four methods are shown in Table 4.

By analyzing the data in Table 4, we can see that with the increase of the number of rounds, the network throughput of the four methods shows an upward trend. When the number of rounds reaches 1200, the network throughput of the four methods reaches the maximum. Among them, the maximum network throughput based on grey prediction is 1.35×10^4bps, the maximum network throughput based on energy and path constraints is 1.76×10^4bps, and the maximum network throughput based on improved grey Wolf optimization is 1.49×10^4bps. The maximum network throughput of the proposed method is 2.03×10^4bps, indicating that the efficiency, performance and responsiveness of the wireless sensor network optimized by the proposed method have been significantly improved, which has a positive impact on providing high-quality data transmission, supporting a variety of application scenarios and meeting user requirements.

4. Conclusion

Wireless sensor network routing optimization is one of the key issues in the Internet of Things, which is of great significance for improving network performance, extending network lifespan, providing reliable data transmission, and supporting real-time applications. The current routing optimization methods have problems such as high energy consumption, high transmission delay, high number of dead nodes, and low network throughput. To address these issues, this article proposes a wireless sensor network routing optimization method based on improved ant colony algorithm in the Internet of Things. Through experimental testing, it has been proven that the proposed method has absolute advantages over the current method in terms of energy consumption, transmission delay, number of dead nodes, and network throughput. This research achievement can not only improve the energy efficiency of wireless sensor networks, but also improve the quality of data transmission and provide better support for real-time applications. At the same time, this method can also optimize network capacity and meet the network performance requirements of different application scenarios. These contributions provide important support for the reliability, intelligence, and efficiency of wireless sensor networks, and promote the further development of wireless sensor network technology in various application fields. However, there are still some challenges in the research of routing optimization in wireless sensor networks. For example, when optimizing routing in a dynamic environment, it is necessary to consider issues such as changes in network topology and the balance between energy consumption and data transmission quality. These challenges require further in-depth research to propose more comprehensive and adaptable routing optimization methods for wireless sensor networks, and to promote the development and application of animal networking technology.

Data availability statement

Data included in article/supp. material/referenced in article.

CRediT authorship contribution statement

Hongzhang Han: Writing – review & editing, Writing – original draft. **Jun Tang:** Software, Resources, Project administration, Formal analysis, Data curation, Conceptualization. **Zhengjun Jing:** Writing – review & editing, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 4
Comparison of network throughput of four methods (10^4bps).

Number of rounds	Method based on grey prediction	Method based on energy and path constraints	Method based on improved grey Wolf optimization	Proposed method
200	0.22	0.38	0.35	0.45
400	0.36	0.63	0.46	0.96
600	0.48	0.89	0.75	1.46
800	0.93	1.26	1.01	1.81
1000	1.22	1.58	1.36	1.92
1200	1.35	1.76	1.49	2.03

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