

Research Article

Low-Energy Secure Routing Protocol for WSNs Based on Multiobjective Ant Colony Optimization Algorithm

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As one of the three pillars of information technology, wireless sensor networks (WSNs) have been widely used in environmental detection, healthcare, military surveillance, industrial data sampling, and many other fields due to their unparalleled advantages in deployment cost, network power consumption, and versatility. The advent of the 5G standard and the era of Industry 4.0 have brought new opportunities for the development of wireless sensor networks. However, due to the limited power capacity of the sensor nodes themselves, the harsh deployment environment will bring a great difficulty to the energy replenishment of the sensor nodes, so the energy limitation problem has become a major factor limiting its further development; how to improve the energy utilization efficiency of WSNs has become an urgent problem in the scientific and industrial communities. Based on this, this paper researches the routing technology of wireless sensor networks, from the perspective of improving network security, and reducing network energy consumption, based on the study of ant colony optimization algorithm, further studies the node trust evaluation mechanism, and carries out the following research work: (1) study the energy consumption model of wireless sensor networks; (2) basic ant colony algorithm improvement; (3) multiobjective ant colony algorithm based on wireless sensor routing algorithm optimization. In this study, the NS2 network simulator is used as a simulation tool to verify the performance of the research algorithm. Compared with existing routing algorithms, the simulation results show that the multiobjective ant colony optimization algorithm has better performance in evaluation indexes such as life cycle, node energy consumption, node survival time, and stability compared with the traditional algorithm and the dual cluster head ant colony optimization algorithm.

1. Introduction

Wireless sensors are an important component and application unit in Internet technology, which have become the latest technology for collecting data from remote locations by interacting with physical phenomena in the surrounding environment and relying on a large number of low-cost devices working in concert. Typically, WSNs consist of hundreds or thousands of low-cost sensor nodes, each with an embedded processor, a wireless interface for communication, a nonreplenishable energy source, and one or more on-board sensors such as temperature, humidity, motion, speed, photo, and piezoelectric detectors that detect environmental or physical conditions such as heat, light, sound,

pressure, vibration, and electromagnetism. Once deployed, a sensor node can collect information of interest from its onboard sensors, perform local processing of this data, including quantization and compression, and forward the data wirelessly to a base station either directly or through a neighboring relay node. The ability to interact directly with physical phenomena allows wireless sensor networks to be of significant value in multiple domains, such as military operations, commercial, industrial, medical, disaster, and rescue operations. The composition of a wireless sensor network includes aggregation nodes, communication nodes, and acquisition nodes. The aggregation nodes are mainly responsible for receiving signals and transmitting signals; the communication nodes are mainly responsible for

TABLE 1: FRID nodes, wireless sensor network nodes, wireless mesh nodes, and comparison.

Standard	FRID node	Wireless sensor network nodes	Wireless mesh node
Cost	Relatively low	Relatively low	High
Mobility	Both nonremovable and removable	Both nonremovable and removable	Movable
Wireless range	Moderate	Smaller	Larger
Volume size	Embeddable	Smaller	Larger
Energy source	Not required	Power supply with capacity limit	Rechargeable
Computing power	Limited	Weaker	Cannot handle large protocols such as TCP/IP

interacting with each other over the Internet, and the acquisition nodes are mainly responsible for collecting information, tasks, and interactions.

There are also differences between FRID, wireless sensor network nodes, and mesh network nodes in terms of various attribute characteristics (as shown in Table 1).

The multiobjective ant colony optimization algorithm is a heuristic intelligence algorithm that simulates the behavior of an ant colony searching for food processes. Ant colony algorithm can solve many problems by simplifying complex problems. For WSN node energy is very restricted, considering the distributed, positive feedback characteristics of the ant colony algorithm can solve the WSN routing design problems, ACO algorithm has great potential. An algorithm applied to WSN has the characteristics of adaptive, real-time, local work, support multipath, and dynamic topology. It can better balance the network load, improve the reliability of data transmission, and better reduce the energy consumption of the network. Therefore, the use of the ACO algorithm to solve the difficult problems in routing protocol design has become the focus and hotspot of WSN routing protocol research, which has good research value for satisfying the application and better performance of routing protocol design.

2. Current Status of Domestic and International Research

WSNs are widely used to benefit all aspects of people's lives, the field is highly interdisciplinary, integration of communications, microelectromechanical systems, embedded computing, and other technologies; with the development of technology, the field will accommodate more new technologies and new areas of crossfertilization; the field gradually scales industrialization and commercialization and has attracted the attention of a large number of countries and concerns. For the characteristics and application requirements of wireless sensor networks, domestic and foreign researchers have proposed routing protocols for wireless sensor networks, which are usually divided into three routing protocols: planar, hierarchical, and bionic intelligence. Early wireless sensor networks are small in scale; routing protocols generally use planar routing protocols; in the protocol, each node is equal; the network does not need to set up special functions of the node, generally, through the gradient interest as a reference element and broadcast to the

network; this routing protocol robustness is better; simple implementation, but serious energy consumption, scalability is poor, such as flooding protocol, directed diffusion protocol, rumor protocol, and SPIN protocol. Hierarchical routing protocol network structure is divided into backbone and subnetwork and establishes clustering mechanism, which has better scalability and reduces the number of data transmission by data fusion within the cluster, thus reducing the network energy consumption and balancing the energy consumption of each node, which is suitable for large-scale networks, but its disadvantage is that the implementation is more complex and may reduce the routing efficiency. Typical hierarchical routing is LEACH protocol, TEEN protocol, and PEGASIS protocol.

Ant colony optimization algorithm with its distributed, self-organizing, scalable, and other characteristics in the design of WSN routing protocols have been widely used. The research on WSN routing algorithms based on ant colony optimization in China started late. Literature [1] proposed a routing algorithm based on fuzzy theory and ant colony optimization to select the next-hop node by fuzzy comprehensive evaluation method and use the low energy node dormancy working mechanism during data transmission, to achieve the purpose of balancing the energy consumption of network nodes; literature [2] used an improved nonuniform clustering method to cluster the network, considering the remaining energy of nodes and the distance between nodes and base stations to reduce the energy consumption of nodes and uses an improved ant colony optimization algorithm to search for intercluster multi-hop paths. With the consideration of routing security problem, the ant colony secure routing algorithm came into being; literature [3] based on the ant colony optimization algorithm, the comprehensive trust degree derived from the evaluation of packet forwarding rate, packet repetition rate, and packet consistency is introduced as a heuristic factor into the ant colony algorithm to establish node-trusted ant colony secure routing.

Many foreign scholars have also studied the application of ant colony algorithm in routing protocols in order to improve the search efficiency of wireless sensors. Literature [4] proposed an ant colony energy-efficient routing algorithm for wireless sensor networks, which introduced node energy as a heuristic into the ant colony algorithm and effectively reduced the energy consumption of the network; literature [5] used node energy as the main criterion for routing

selection and considered node energy in the pheromone update phase as a way to reduce the energy consumption of the network; literature [6] introduced a fuzzy system into the directional diffusion protocol by path hop count and minimum node energy to evaluate the routing quality and automatically adjust the system of fuzzy rule base using ant colony optimization algorithm to improve the routing decision and energy efficiency. Some studies further apply the ant colony optimization algorithm to the secure routing problem by combining optimization methods to solve the security problem of routing. Literature [7] proposed a secure routing protocol based on ant colony algorithm, setting security value for each path taken by ants, the fewer the path obstacles, the higher the security, setting encryption mechanism when the security value is lower than the threshold, and selecting the two paths with the highest security value as the final routing paths; literature [8] proposed a secure routing algorithm for ant colony based on fuzzy logic theory, using a fuzzy logic controller based on the energy consumption rate, packet loss rate, node life cycle, and other indicators to calculate the node trust value and use the path with the highest trust level as the routing path.

3. Low-Energy Secure Routing for Wireless Sensor Networks Based on Multiobjective Ant Colony Optimization Algorithm

3.1. Energy Consumption Model for Wireless Sensor Networks. For the overall network, this chapter proposes the idea of transmission energy region division as shown in Figure 1, which plans the data transmission direction in conjunction with the destination node to exclude loops and prevents node *iv* from sending data to nodes in the direction farther away from the destination node than itself, saving unnecessary energy consumption and also reducing algorithm's computational effort. The specific method is as follows:

With the destination node *Q* as the center of the circle and the distance d (*Q*, *M*) between *Q* and *M* as the radius to intersect *m* concentric circles, for practical application, the transfer energy region division can be regarded as the sector ring $XYZ\gamma$ formed by the intersection region of the target transfer probability circle region and the circle *Q*. The value of the jump probability P_i is related to the area of the region where the circle is located because the area of the sector ring region divided is proportional to the area of the circle region, so the probability P_i is also adapted to the sector ring region division, where *X* and γ are the outer intersection points of the largest circle of circle *Q* and the target transfer probability circle region, and *Y* and *Z* are the inner intersection points of *X*, γ and the target transfer probability circle region, respectively. Generally, when the destination node is located in the sector *BC*, then the sensor node *iv* establishes a path directly with the destination node.

The transmitting energy consumption in wireless sensor networks mainly includes the energy consumption of the RF module and the signal amplifier module, and the receiving energy consumption mainly includes the energy consump-

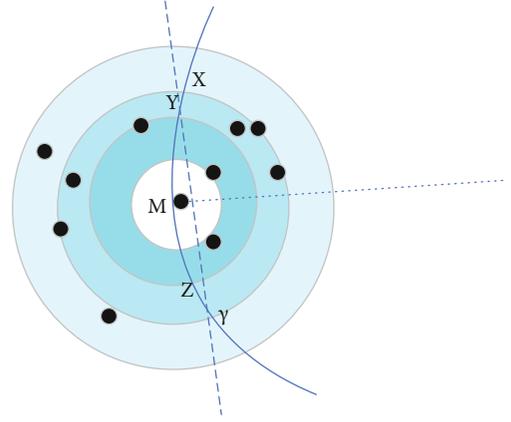


FIGURE 1: Diagram of optimal transmission energy region division.

tion of the receiving circuit and the energy consumption of the data fusion [9]. The energy consumption of the sensor node to send x bit data at a distance d . E_{tx} is calculated as

$$E_{tx}(x, d) = \begin{cases} E_e \times x + \epsilon_{free} \times x^2 \times d^{1/2}, & d \leq d_0, \\ E_e \times x + \epsilon_{decay} \times x^2 \times d^2, & d > d_0, \end{cases} \quad (1)$$

where $E_e = 72\text{ nJ/bit}$ denotes the RF energy consumption coefficient, and the energy consumption coefficients for the free-space model and the multipath fading model power amplifier circuit are $\epsilon_{free} = 30(\text{PJ} - \text{m}^2)/\text{bit}^2$, and $\epsilon_{decay} = 0.0039/(\text{m} - \text{bit})^2$, d_0 , respectively, which are distance thresholds, calculated as

$$d_0 = \sqrt[3]{\left(\frac{\epsilon_{decay}}{\epsilon_{free}}\right)^2} \quad (2)$$

Therefore, the calculated value is about $d_0 = 390\text{ m}$. The energy consumption of the sensor node receiving x bit data is given by

$$E_r = E_e \times x. \quad (3)$$

The energy consumption of sensor nodes for data fusion of data of size l bit is calculated as

$$E_{all} = E_{contest} \times x. \quad (4)$$

Among them, $E_{contest} = 8 \times 10^{-7} \text{ J/bit}$.

Therefore, the total energy consumption of the wireless sensor network in a given time is

$$E_{all} = \sum_{i=0}^R (E_{contest} \times x + E_e \times x + \epsilon_{free} \times x^2 \times d_i^{1/2}) + \sum_{i=0}^K (4E_e \times x + \epsilon_{decay} \times x^2 \times d_i^2), \quad (5)$$

where R is the number of common nodes in the network and K is the number of cluster head nodes in the network.

3.2. Ant Colony Model for Wireless Sensor Networks. In the search of the behavior of ants foraging, an ant colony optimization algorithm was obtained, which is highly innovative and has been applied to various optimization fields. The ant colony algorithm was originally applied to traveler's problem (TSP) [10], in which a traveler starts from a city, visits each of the n cities in turn, and returns to the starting city to find the shortest route. Since many problems can be abstracted as solutions to the TSP, the traveler problem is introduced to illustrate the system model of the basic ant colony algorithm.

Let $x_i(t)$ denote the number of ants located in the city at time t , then the $n = \sum_{i=0} x_i(t)$ total number of ants in the colony. $\alpha(t)$ is the heuristic factor on the path at moment t , and $\beta(t)$ is the pheromone content on the path at moment t . In the process of movement, A randomly chooses the next location to be visited according to the amount of information on the path and the heuristic factor, then the probability of ant A moving from the city a to city b at moment t is

$$P_{ab}^A(t) = \frac{\partial \left(\left([\alpha_a^2(t)]^k [\beta_b^2(t)]^j \right) / \left(\sum_{m \neq a, n \neq b} [\alpha_m^2(t)]^k [\beta_n^2(t)]^j \right) \right)}{\partial t} \quad (6)$$

To avoid overwhelming the inspired information when there is too much residual pheromone, which causes the system to stall, a one-step turn is realized in each ant. After a move or end of a cycle, the pheromone is to be updated. Therefore, the number of pheromones on the path at moment t can be updated according to Equations (7) and (8).

$$\kappa(t+n) = (1-\eta)\kappa(t) + \Delta\kappa_{ij}(t), \quad (7)$$

$$\Delta\kappa_{ij}(t) = \frac{\sum_{i=0, j=0} \kappa_{ij}(t)}{t}, \quad (8)$$

where $\eta \in (0, 1)$ is the pheromone volatility factor and η is the pheromone residual factor and provides a certain survival time for each path found by the ants by adjusting the pheromone volatility rate; $\Delta\kappa_{ij}(t)$ is the total pheromone increment on the path in this cycle, and the initial value is 0; $\Delta\kappa_{ij}^m(t)$ represents the information left on the path by the ant in this cycle. The usual $\Delta\kappa_{ij}^m(t)$ update strategy includes three cases of ant perimeter model, ant volume model, and ant density model.

3.3. Optimization Strategy of Ant Colony Algorithm. Since its introduction in 2011, the refinement and optimization of the ACO have been attracting domestic and international attention. The optimization ideas of the ACO are generally in line with the strategy of "internal refinement and external optimization."

Firstly, secondary applications are made to the ant colony fixed step size, search radius, and generating solution generation mechanism as well as to the concentrated formula to improve the disadvantages of rapid convergence and weak local search ability of ant colony. Secondly, we

consider enhancing the external application of ACO algorithm by integrating multiple algorithms and introducing mature algorithmic frameworks or mathematical mechanisms into the sniffing and visual search mechanism of ACO algorithm, such as classical difference algorithm and genetic variation mechanism; we use uncertainty theory such as chaos theory and cloud model to improve the generation mechanism of candidate solutions. The above two approaches effectively improve the local search capability of the ant colony optimization algorithm and improve the stability and search accuracy of the search. In this paper, the following strategies are proposed to optimize the classical ant colony algorithm through the study of its defects.

- (1) Efficient algorithm combination. Combining multiple algorithms to optimize and complement each other is popular in current algorithm research. The concept of population suitability variance is proposed in the literature [11], where the variance value is used as an evaluation parameter to compare with the threshold value of the algorithm, and when the variance is small, the depth-seeking algorithm of the contraindicated search is adopted, and when the judgment value is large, the search strategy of the ant colony optimization algorithm is adopted. The core of the combination is to complement each other's strengths and maintain the advantages of the respective algorithms themselves. In the future, we will continue to study the mix of ACO and simulated annealing, particle swarm, and other algorithms to improve the external performance of ACO
- (2) Developed based on mature theory. On the other hand, the drawbacks of fast convergence of ant colony optimization algorithm and weak randomness and stability of the search phase are solved when combined with mature theory algorithms. The mechanism of using cloud architecture to generate candidate solutions is proposed in the literature [12], where a normal cloud generator is adopted in the process of designing the concentration determination function, introducing uncertainty in the search radius, requiring a large search in the early stage and a detailed search in the later stage, and introducing the concept of dynamic programming to quickly seek optimal solutions
- (3) Increase the population diversity. In the face of the above problem for the high-dimensional complex function ant colony algorithm is difficult to find global optimization, increasing the global diversity is one of the methods to solve such problems. In the literature [13], it is proposed to incorporate the traditional algorithmic idea of difference into the ant colony algorithm by introducing the difference factor F , which replaces the concentration formula. The iteratively generated positions are generated based on the optimal position coordinates of the previous generation, which increases the diversity of the

population and does not lead to the convergence of individuals and localization in the same direction compared to the original ant colony algorithm. There are not many research articles on this strategy, and this paper will conduct an in-depth study in this area to propose a reasonable coordinate transformation formula and design a suitable variant location

- (4) Introducing a new flight strategy. The core of the change lies in adding randomness to the flight distance and flight direction in the flight strategy, while reasonably allowing the ant colony to jump out of the limitations of the local optimum through the mutation algorithm. The ant colony algorithm is a new type of algorithm designed based on the inspiration of ant colony foraging strategy, which can draw on the behavioral research of nature for ant colony algorithm and use the forward principle of a frog hopping and chromosome crossover variation strategy for the later stage of the algorithm to accelerate the convergence speed

As shown in Figure 2, when node M selects a path in the transmission direction to destination node P, node N acts as its potential next-hop node, and when node N selects a path in the transmission direction to source node O, node M acts as its potential next-hop node. At this point, nodes N and M can be preferred as each other's optimal position, and they take into account the advantages of energy and time delay in each other's division area, so when the optimal position is updated through these two points, this path can be saved as the value of the global optimal solution dimension.

- (5) Update the concentration determination formula. The determination formula of the algorithm concentration in the ant colony optimization algorithm is the core calculation formula in the guaranteed flight strategy. Through the innovation and development of the formula, the ant colony optimization algorithm is effectively regulated at the height of global search and local search balance optimization. The concentration determination formula, as the core problem of the ant colony algorithm, has been the focus of research in the algorithm community. In the literature [14], the distance value between the current coordinate position of the ant colony and the origin is defined as an escape parameter, and the defined parameter is introduced into the regulation when the concentration determination formula is updated, and a parameter is a random number in the interval [0,1], thus solving the problem that the candidate solution can be negative. The concentration judgment formula is as follows:

$$H(x) = \sum_{i=1}^n p_i \ln \frac{1}{P_i}, \quad (9)$$

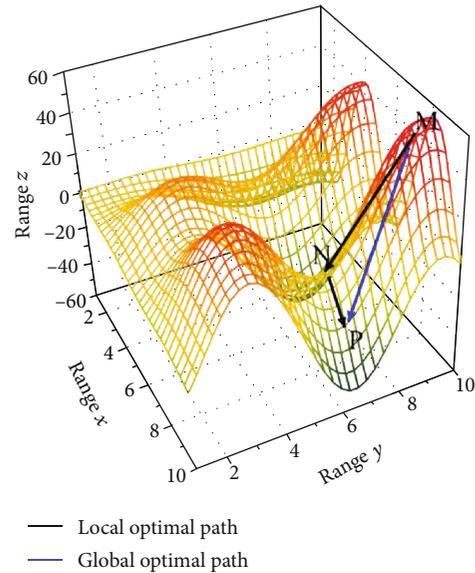


FIGURE 2: Global optimal solution location selection.

- (6) Multiobjective ant colony algorithm has efficient searchability based on the traversal of the algorithm; however, the multiobjective ant colony algorithm does not involve the global optimal position, which makes the ants find the new position far from the optimal solution and ineffective [15–17]. To address this problem, we propose to improve the accuracy of searching the global optimal solution by giving the ants a stronger ability to search the potential space and changing the original strategy to focus on the neighboring candidate solutions, thus inducing an adaptive perturbation strategy

3.4. Multiobjective Ant Colony Secure Routing Model. Traditional optimization algorithms by themselves do not solve multiobjective optimization problems [18–21]. Multiple objective functions can be transformed into but one objective problem by the form of the weighting method or constraint method, which is handled by the traditional solution method. However, in a multiobjective optimization problem, it is impossible to find a single optimal solution that can best satisfy all objectives because the objectives are juxtaposed and equal and in conflict. Therefore, the practice of converting a multiobjective problem into a single objective to find a single solution is flawed. The solution of a multiobjective optimization problem is to find a Pareto optimal solution set consisting of many “noninferior solutions” and to provide a reliable basis for practical problem decisions by effectively finding the Pareto frontier of the multiobjective optimization problem.

The multiobjective optimization problem is to find the global optimal solution of multiple objectives, not the local optimal solution, which may even be contradictory or even opposite to the optimal solution locally. Unlike ordinary single-objective optimization problems, it is not a matter of finding an optimal solution, but a noninferior set of

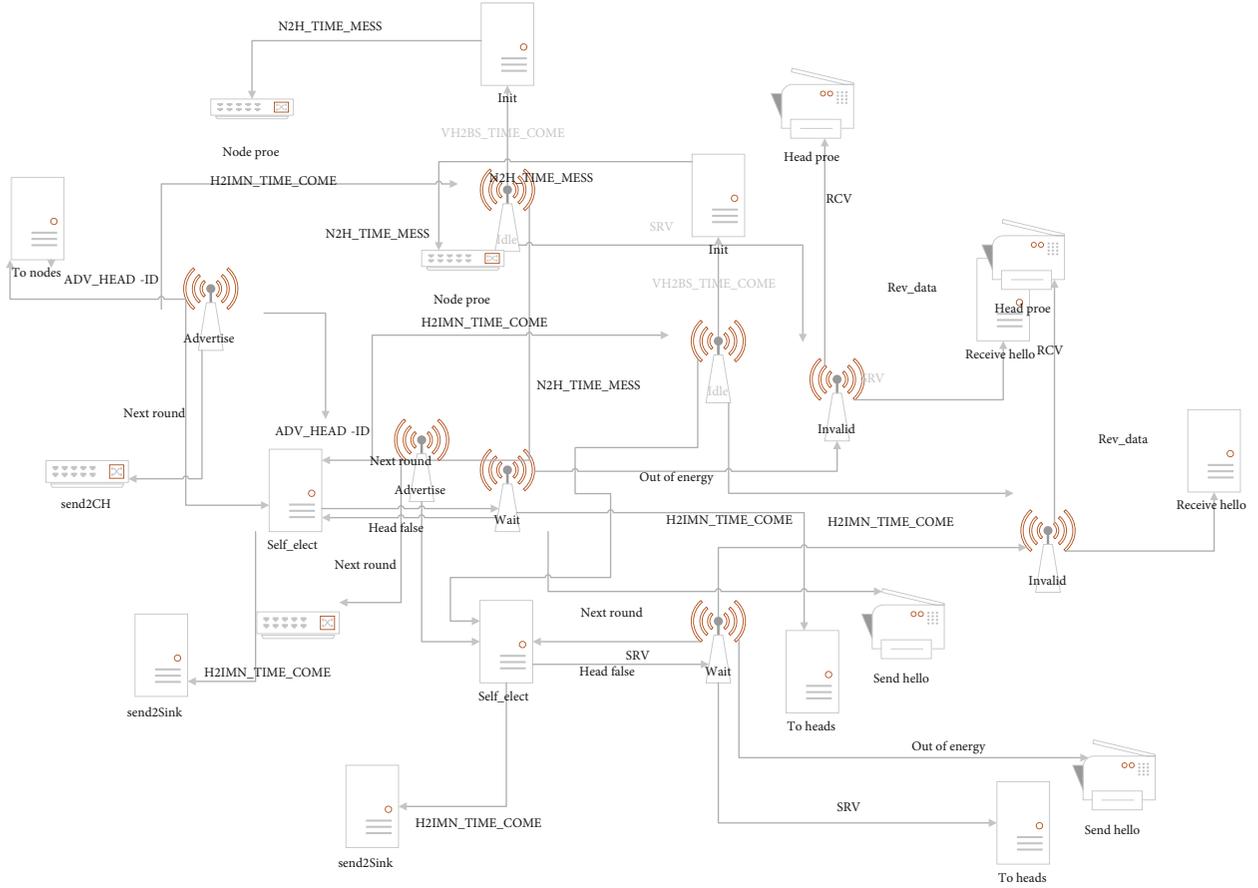


FIGURE 3: A process model of AMAPTEEN protocol.

solutions that compromises these objectives [22–24]. In practical applications, wireless sensor network routing is often exposed to unknown risks of attacks, leading to various unpredictable losses. So, how to improve the security of wireless sensor networks is also a very urgent and important topic. However, the improvement of security often comes at the cost of excessive energy consumption. Therefore, a multiobjective optimization strategy needs to be introduced to

make improvements on the existing single-objective ant colony optimized routing algorithm with two designed objective functions: node residual energy and trust value, as the node performance indicators that constitute the optimal routing path.

According to the multiobjective optimization algorithm, Equations (5) and (6) can be optimized as follows, respectively

$$E_{\text{all}} = \prod_{D_{ij}} \frac{\partial \left(\sum_{i=0}^R (E_{\text{contest}} \times x + E_e \times x + \epsilon_{\text{free}} \times x^2 \times d_i^{1/2}) + \sum_{i=0}^K (4E_e \times x + \epsilon_{\text{decay}} \times x^2 \times d_i^2) \right)}{\partial x}, \quad (10)$$

$$P_{ab}^A(t) = \frac{\partial \left(\left([\alpha_a^2(t)]^k [\beta_b^2(t)]^j \right) / \left(\sum_{m \neq a, n \neq b} [\alpha_m^2(t)]^k [\beta_n^2(t)]^j \right) \right)}{\partial t}. \quad (11)$$

4. Simulation Analysis Based on Multiobjective Ant Colony Optimization Algorithm

The multiobjective ant colony optimization algorithm AMAPTEEN is further optimized based on the traditional APTEEN optimization algorithm. a new AMAPTEEN scenario is created on the OPENT platform and improved

based on the ant colony dual-cluster head model ADCAPTEEN process layer model. The AMAPTEEN algorithm process layer model is shown in Figure 3.

Compared with the traditional APTEEN process model, the AMAPTEEN protocol process model shown in Figure 3 differs mainly in the states of self-elect, receive-hello, send data to an intermediate node, send to Sink, and so on.

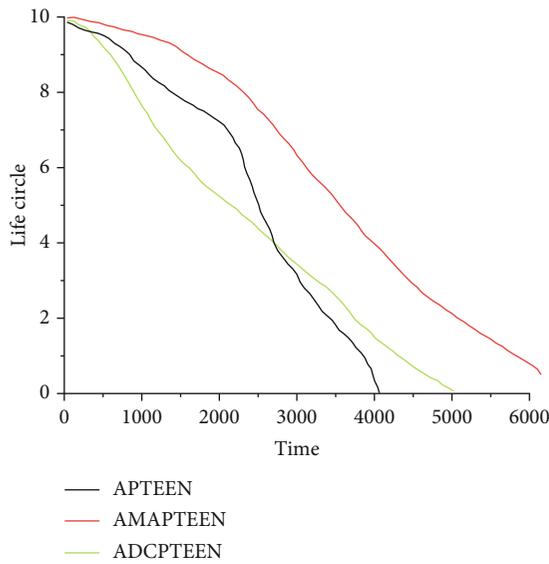


FIGURE 4: Comparison of the network life cycle of APTEEN, ADCPTEEN, and AMAPTEEN.

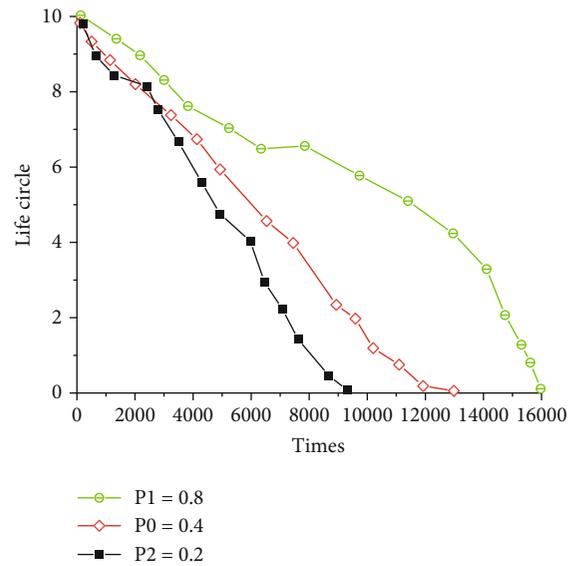


FIGURE 6: Life cycle comparison of multiobjective optimization ant colony algorithm with different elected cluster head probabilities.

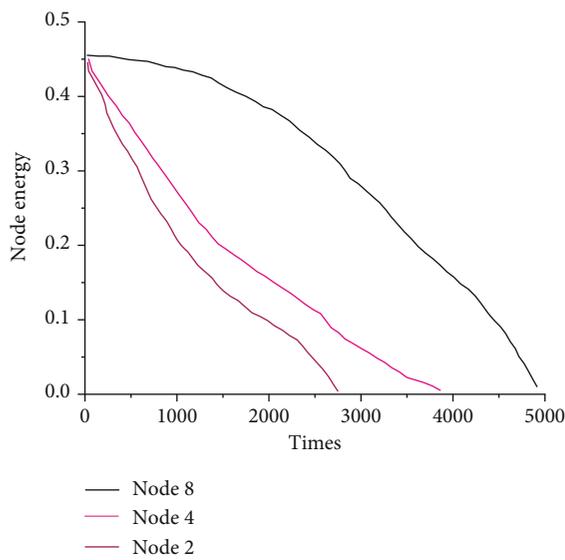


FIGURE 5: Multiobjective ant colony optimization algorithm node energy consumption.

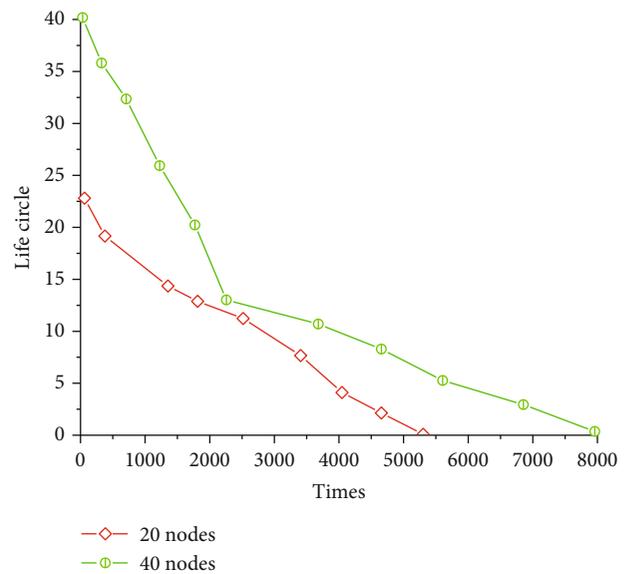


FIGURE 7: Total node survival time of multiobjective ant colony optimization algorithm.

Firstly, in the bootstrap state, the CH campaign no longer uses the traditional threshold but uses a modified threshold formula to campaign the CH, taking into account the remaining energy of the node and the distance to the Sink node. Secondly, bootstrap state CH receives hello from CM; in this state machine, CH gets the pheromone concentration value based on its remaining energy and distance from CM to Sink and the increase of pheromone concentration in the Hello packet sent by CM. The intermediate node selection is performed according to the pheromone concentration. In ADCAPTEEN, VCH selects one campaign per round, while the intermediate node is selected each time as long as the soft and hard thresholds or counting time

requirements are met, and there is data transmission to the Sink node, instead of waiting until the next round for the intermediate node selection. The work of the intermediate node to forward CH to the Sink node is implemented in the send data to intermediate node and send data to Sink node states.

The AMAPTEEN protocol network topology is constructed, and the experimental parameters are set in the same way as in ADCPTEEN. Firstly, the network life cycle is compared between algorithms as shown in Figure 4. Since APTEEN is the direct communication between CH and Sink nodes, which causes high energy consumption and is not very energy efficient, the ADCPTEEN algorithm selects the

TABLE 2: Comparison of multiobjective ant colony optimization algorithm, traditional algorithm, and dual cluster head ant colony algorithm.

Standard	Multiobjective ant colony optimization algorithm	Traditional algorithms	Double cluster head ant colony algorithm
Life cycle (s)	4578	1629	3794
Node energy consumption	Low energy consumption, long life	High energy consumption	Lower energy consumption
Total node survival time (10 nodes)	4276 s	1392 s	3328 s
Total node survival time (20 nodes)	7849 s	2431 s	5986 s
Stability	Very stable	More volatile	More stable

VCH by the main MCH to jointly perform the data communication task between MCH and Sink nodes. A huge number of communication consumptions are performed by VCH, and MCH energy consumption is reduced to a large extent. Otherwise, VCH does not change until it enters the next round, so it has to complete multiple data transmissions. This reduces the energy efficiency and reliability of the network. However, the AMAPTEEN algorithm proposed in this chapter states that each time data transmission between CH and Sink nodes is executed, and IM-node is selected, forming multiple data transmission paths. Meanwhile, the algorithm proposed in this paper optimizes the calculation of the threshold value, taking into account the remaining energy of the node and the distance to the Sink. The proposed AMAPTEEN has a longer network life cycle than the traditional algorithm. From the simulation results, it can be seen that the network life cycle of the AMAPTEEN algorithm extends about 0.15 times longer than that of ADCPTEEN. AMAPTEEN is effective in extending the network life cycle of the whole network and is better than ADCPTEEN in terms of energy efficiency.

Figure 5 shows the energy consumption of AMAPTEEN nodes; node 2, node 4, and node 8 have similar energy consumption curves to the nodes of the dual cluster head ant colony algorithm. The two energy consumption curves of node 4 and node 8 steadily decrease as the simulation time increases, and the energy consumption curve of node 1 starts to show a decreasing trend but plummets at about 4200 s. Compared with the dual cluster head ant colony algorithm, the survival time of node 2 and node 4 can be seen to be prolonged because the AMAPTEEN algorithm uses a multipath approach to equalize the energy consumption. The energy consumption of individual nodes is reduced.

Figure 6 compares the energy consumption of the AMAPTEEN protocol for the three cases of 0.2, 0.4, and 0.2 elected cluster head probability. Comparing with the dual cluster head ant colony algorithm, it can be seen that AMAPTEEN survives longer than ADCAPTEEN for the cases of 0.4 and 0.8 elected cluster head probability. However, the simulation results at 0.2 show that AMAPTEEN nodes survive for a smaller time than ADCAPTEEN nodes. The reason is that when the probability of elected cluster head is small, the CH campaign threshold is relatively small, which leads to no CH election for a long time and no effective cluster forma-

tion. Therefore, a reasonable selection of the elected cluster head probability is very critical to improve the network performance and improve the network rationality.

Figure 7 shows the comparison of the total survival time of 20 nodes with 40 nodes for the AMAPTEEN algorithm. Consistent with the trend of the network life cycle curve shown for the dual cluster head ant colony algorithm, the AMAPTEEN protocol thus retains the effectiveness and scalability of the network. In comparison with the ADCAPTEEN protocol, both 10-node and 20-node network topology network survival times are extended. Therefore, AMAPTEEN is better than ADCAPTEEN protocol not only in terms of energy efficiency but also scalability.

Table 2 shows the comparison of the life cycle, node energy consumption, and total node survival time of the multiobjective ant colony optimization algorithm compared to the traditional algorithm and the two-cluster head ant colony algorithm. The multiobjective ant colony algorithm has several superiorities, including high stability, low consumption, and long life cycle.

5. Conclusion

Wireless sensor networks have a wide range of applications in time synchronization, positioning algorithms, routing protocols and error control, and routing technology, as a core issue of wireless sensor networks relates to the reliability, integrity, and security of communication data and is the key to ensuring safe and effective network communication. For resource-constrained WSN networks, routing issues are studied in two main areas: security issues and energy consumption issues. This paper focuses on these two issues of routing protocols from the aspect of improving network security and energy effectiveness. The node trust evaluation model is studied and applied to the ant colony optimization algorithm, which is widely used to solve the WSN routing problem, to derive a node-trusted secure routing protocol based on the ant colony optimization algorithm, which uses the concept of multiobjective to achieve multiobjective ant colony secure routing.

In this paper, a node-trusted secure routing protocol based on a multiobjective ant colony optimization algorithm is studied. To address the problem of insider attacks in the network, a simple trust assessment model is used to calculate the direct and indirect trust values of nodes and weight the

node integrated trust value as a measure of node security. In this paper, we propose a low-cost, high-efficiency, high-security, and high-stability wireless routing algorithm based on the traditional ant colony algorithm by analyzing the integrated trust value, node residual energy, path average energy, and minimum energy and incorporating them into the pheromone update. The superiority of the algorithm in this paper is verified by a large number of experiments through the experimental verification of life cycle, node energy consumption, node survival time, and stability indexes.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of 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.

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