IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 21, 2020, accepted July 11, 2020, date of publication July 20, 2020, date of current version July 30, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3010313

An Energy Efficient Routing Protocol Based on Improved Artificial Bee Colony Algorithm for Wireless Sensor Networks

ZONGSHAN WANG[1], (Member, IEEE), HONGWEI DING[1], (Member, IEEE), BO LI[1], (Member, IEEE), LIYONG BAO[1], (Member, IEEE), AND ZHIJUN YANG[2], (Member, IEEE)

[1]School of Information Science and Engineering, Yunnan University, Kunming 650500, China
[2]Yunnan Education Department, Kunming 650500, China

Corresponding author: Hongwei Ding (wzs694513739@163.com)

This work was supported in part by the National Natural Science Foundation of China named Research on Theory and Control Protocol of Convergence Multiple Access Communication Network under Grant 61461053, in part by the National Natural Science Foundation of China named Research on the Evolution of Polling System Theory and Application Control Protocol under Grant 61072079, in part by the Natural Science Foundation of Yunnan Province under Grant 2010CD023, and in part by the Financial Support of Yunnan University under Grant XT412004.

ABSTRACT Clustering sensor nodes is an effective method in designing routing algorithms for Wireless Sensor Networks (WSNs), which improves network lifetime and energy efficiency. In clustered WSNs, cluster heads are the key nodes, they need to perform more tasks, so they consume more energy. Therefore, it is an important problem to select the optimal cluster heads. In this paper, we propose a clustering algorithm that selects cluster heads using an improved artificial bee colony (ABC) algorithm. Based on the standard ABC algorithm, an efficient improved ABC algorithm is proposed, and then the network cluster head energy, cluster head density, cluster head location and other similar factors are introduced into the improved ABC algorithm theory to solve the clustering problem in WSNs. In the network initialization period, all nodes have the same energy level, the improved ABC algorithm is used to optimize fuzzy C-means clustering to find the optimal clustering method. We also propose an energy-efficient routing algorithm based on an improved ant colony optimization for routing between the cluster heads and the base station. In order to improve energy efficiency and further improve network throughput, in the stable transmission phase, we introduce a polling control mechanism based on busy/idle nodes into intra-cluster communication. The performance of the proposed protocol is evaluated in several different scenarios. The simulation results show that the proposed protocol has a better performance compared to a number of recent similar protocols.

INDEX TERMS WSN, clustering, energy efficiency, network lifetime, high throughput, polling, routing algorithm, artificial bee colony.

I. INTRODUCTION

The world is developing towards the interconnection of all things. The Internet of Things (IoT) has become a research hotspot in the information field. Wireless sensor networks play a key role in promoting the development of the IoT [1], [2]. Under this background, the large-scale applications of wireless sensor networks (WSNs) has been pushed to a new height. WSN is a multi-hop self-organizing network system formed by a large number of cheap micro sensor nodes through wireless communication. It integrates sensor technology, embedded computing technology, modern network and wireless communication technology, and distributed information processing technology and other fields of technology. The purpose of deploying WSN is to collaboratively collect information about the perceived objects in the monitoring area, convert the monitored data into electrical signals, and send them to the base station through wireless multi-hop communication. It has the characteristics of self-organized routing, no wiring, dynamic network, strong anti-destruction ability, etc. It is suitable for environmental monitoring, medical care, military field, industrial

The associate editor coordinating the review of this manuscript and approving it for publication was Ilsun You.

monitoring and other fields [3], [4]. In WSNs, the computing power of sensors nodes is limited, the energy is limited and the battery is hard to replace. When some network nodes run out of energy, the network topology changes. Too many dead nodes in the network may even cause the network system to be paralyzed and unable to operate normally. Therefore, it is of great significance for WSNs to design energy balanced and energy efficient routing protocols to maximize the network lifetime [5], [6]. The network lifetime is generally defined as the time until a certain proportion of nodes die, such as the time until the first node dies, or the time until 75 percent of nodes die, or the time until the last node dies. After the death of the first node, the stability of the network will decrease dramatically, and the overall performance of the network will be much worse than before [7]. Balancing the energy consumption of nodes and improving energy efficiency can effectively prolong the lifetime of the network. Hierarchical clustering protocols extend the network lifetime by dividing nodes into multiple clusters [8]. In the clustering protocol, the cluster head is the key node in the network, which is responsible for collecting the data perceived by the member nodes and sending the gathered data to the base station. Member nodes only need to communicate with their respective cluster heads for a short distance and consume less energy. There are many ways for the cluster head to communicate with the base station, such as sending data directly to the base station, or using other nodes as the next hop to send the data indirectly to the base station. The clustering protocols try to select the optimal cluster head set and rotate the role of cluster head among all nodes to balance the energy consumption of nodes. Fig. 1 shows a clustered WSN.

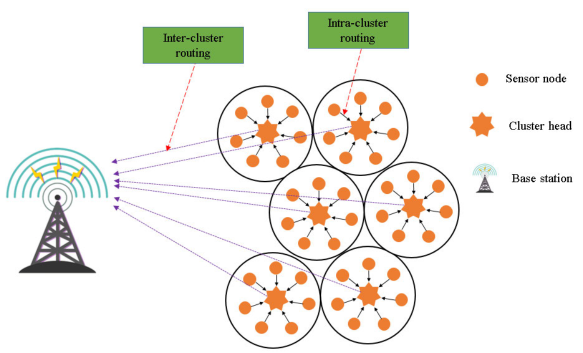

FIGURE 1. A clustered WSN.

The selection of cluster heads has an important impact on the performance of a clustering protocol. There are C_n^m possibilities to select m nodes as cluster heads among n network nodes, which is a NP-hard problem [9], and classical optimization algorithms are powerless for this kind of problems [10]. As efficient methods to obtain feasible solutions, heuristic and metaheuristic algorithms are widely used in the problem of optimal cluster head selection, and have achieved varying degrees of success. Artificial bee colony (ABC) algorithm is an efficient metaheuristic intelligent swarm method, which is inspired by the behavior of bees collecting honey in nature [11]. Compared with other swarm intelligence methods, artificial bee swarm algorithm can balance local exploration and global development, and can achieve good optimization results. At the same time, it has few parameters and is easy to implement.

The last stage of each round in the hierarchical clustering protocol is the stable transmission phase. In this phase, the member nodes send the perceived data information to the corresponding cluster head, and then the cluster head sends the gathered data to the base station [12]. Generally speaking, the distance between the member nodes and their respective cluster heads is very close, and intra-cluster communication uses a single-hop method. However, the distance between the cluster heads and the base station is generally far. If single-hop communication is used, the excessive energy consumption of the cluster heads will be aggravated. In large-scale WSNs, the distance between the cluster head and the base station may even exceed the maximum radio range of the sensor node [13]. Therefore, hierarchical clustering protocols generally need a routing algorithm to find an appropriate path between each cluster head and the base station, so that the cluster head can send data to the base station in a multi-hop way. In this way, the excessive energy consumption of the cluster head far away from the base station can be avoided.

In this paper, we propose an energy-efficient and energy-balanced clustering routing protocol, which uses an improved artificial bee colony algorithm to select the optimal cluster heads, and the member nodes join the appropriate cluster heads, thus dividing the network into several clusters. In order to avoid excessive energy consumption of cluster heads far from the base station, an efficient routing algorithm is proposed to find the optimal path between the cluster heads and the base station. The cluster head uses multi-hop communication method to send the fused data to the base station. The intra-cluster communication mechanism of many clustering protocols uses the TDMA mechanism, which is very advantageous under ideal circumstances, that is, when all nodes can always collect valid data [14]. However, in reality, it is often difficult to achieve this ideal state, some nodes may not perceive useful data for a period of time, but they will still be awakened in their own time slots, which will generate unnecessary energy consumption and waste time slots. To solve this problem, in the stabilization phase, we introduce a polling control mechanism based on busy/idle nodes into intra-cluster communication to balance the network energy consumption and improve the network throughput.

The main contributions of this paper are as follows:

- A novel and efficient improved artificial bee colony algorithm is proposed, which is combined with fuzzy C-means clustering to solve the first round energy efficient clustering problem. Under the condition that all nodes have the same energy level, the optimal cluster heads can be selected and the clustering can be optimized.

- In order to solve the clustering problem of subsequent rounds, an optimal clustering method based on an improved artificial bee colony algorithm is proposed. The honey source updating principle in artificial bee colony algorithm is combined with the parameterization of cluster head energy, cluster head location and cluster head density in the WSN, and the Gini coefficient in economics is introduced to optimize clustering.
- An energy-efficient routing algorithm based on an improved ant colony optimization is proposed to find the optimal path from each cluster head to the base station.
- In the intra-cluster communication phase, a polling control mechanism based on busy/idle nodes is introduced to reduce network energy consumption and improve network throughput.
- A clustering routing algorithm based on artificial bee colony optimization is proposed. Simulation results show that the proposed algorithm can effectively balance network energy consumption, improve network throughput, and extend network lifetime.

The rest of the paper is arranged as follows. The second part introduces the related work. The third part introduces the network model and energy consumption model used in this paper. The fourth part summarizes the improved artificial bee colony algorithm. The fifth part describes the energy efficient clustering routing protocol based on the improved artificial bee colony algorithm. In the sixth part, the proposed algorithm is simulated and compared with other existing protocols. The seventh part summarizes the work of the whole paper and puts forward the next research work.

II. RELATED WORK

The clustering routing protocols reduce network energy consumption while facilitating network management. In recent years, many different routing protocols have been proposed. The classic clustering routing protocol is the LEACH protocol proposed by Heinzelman et al in 2000 [15]. The LEACH protocol introduces the concept of ''round'', and each round is divided into two phases: a clustering phase and a stabilization phase. LEACH can balance the energy consumption of the network to each node by periodically changing the cluster heads, and effectively extend the lifetime of the network. Data fusion technology used in LEACH protocol effectively reduces the amount of data transmission and avoids unnecessary energy consumption caused by redundant data transmission. However, the LEACH protocol randomly selects cluster heads without considering the residual energy and location of the nodes, resulting in uneven distribution of cluster heads and unreasonable number of clusters, shortening the lifetime of the network. In [16], the LEACH algorithm is improved and a centralized clustering algorithm LEACH-C (LEACH-centralized) is proposed. At the start of each round, the base station launches the clustering process according to the location and energy of the nodes. The clustering algorithm uses the simulated annealing method to divide the network nodes into a predetermined number of clusters, which ensures the energy of the cluster head while minimizing the inter-cluster distance. However, the single-hop routing mechanism will aggravate the fast energy consumption of nodes far away from the base station, which brings some limitations to the protocol. In [17], a clustering routing protocol based on Grey Wolf Optimizer (GWO) is proposed, it makes use of the infinite computing power and infinite energy of the base station to accurately calculate the energy that the network will consume in the next round, and the corresponding fitness function is proposed. The GWO is used to find the optimal solution of the problem, so as to select the optimal cluster head set. In order to further prolong the network lifetime, the protocol does not select cluster heads in each round. It only executes the setup phase when the remaining energy of the cluster heads in the last round is insufficient, which avoids frequent clustering and saves network energy consumption. In order to avoid the fast energy consumption of cluster heads far away from the base station, this protocol proposes a dual-hop routing method, selects a relay node for each cluster head, and finds the optimal drop point of the relay node based on the minimum energy consumption and energy balance, and then maps this point to the cluster head node in the network. This protocol prolongs the network lifetime to some extent, but when selecting relay node, not all cluster heads can find a relay that meets the conditions, which will lead to some cluster heads have to communicate directly with the base station. This will aggravate the excessive energy consumption of this part of cluster heads. In addition, when the application scenario is large, the distance between the cluster heads and the base station may exceed the maximum radio distance of the sensor node. If these cluster heads fail to find a relay, the data collected by this cluster cannot be successfully sent to the base station, which makes the monitoring data received by the base station incomplete. FIGWO [18] is another GWO-based protocol to prolong network lifetime. In order to optimize the cluster structure, the prey position of GWO is improved, and an improved GWO based on energy and position is proposed. And considering the residual energy and the distance from the base station, the fitness function is designed to evaluate the quality of the solution generated by the GWO. It first uses a median algorithm to divide the network nodes into several uniform clusters, and then performs an improved GWO within each cluster to select the optimal cluster head. FIGWO successfully prolongs network lifetime by optimizing the cluster structure, but it does not take into account any routing algorithm, that is, the cluster head sends data directly to the base station. This will lead to uneven energy consumption, and the cluster heads far from the base station will die prematurely due to a large amount of energy consumption, which will shorten the network lifetime and affect the scalability and stability of the network. ABC-SD [19] is a clustering routing protocol designed to prolong the lifetime of the network. In this protocol, artificial bee colony algorithm is used to solve clustering and routing problems. By considering the energy of nodes and the neighborhood information, an efficient fitness function for ABC is designed to solve the clustering problem. To further improve network energy efficiency, a Cost-based Function for routing problems is presented, which takes into account both the energy efficiency and the number of hops, and the inter-cluster routing is established. The protocol uses a combination of centralized clustering and distributed routing, which effectively prolongs the network lifetime and improves the network throughput. However, the protocol does not consider the load balance between cluster heads, which affects the network performance. The clustering routing protocol proposed in [20] uses an improved particle swarm optimization (PSO) to select the optimal cluster heads. Considering the energy and location of the nodes, a fitness function of PSO is designed to select the optimal cluster heads with high residual energy and close to the base station. To reduce the energy consumption of cluster heads, the protocol selects a relay node for each cluster head. A fitness function of particle swarm optimization algorithm for routing problem is designed by considering the residual energy and geographic location of nodes, and the nodes with high residual energy and close to the cluster head are selected as relays. This protocol effectively prolongs the network lifetime. However, due to some limitations of the particle swarm optimization algorithm, there is no guarantee that the selected clustering and the selected relays are the best possible solution. A novel cluster-based routing protocol proposed in [21] uses a Fixed-Parameter Tractable (*fpt*) approximation algorithm with an approximation ratio of 1.1 to solve the load balancing problem. In addition, a virtual grid infrastructure containing multiple equal-sized cells is introduced, and the algorithm runs independently for each cell to make the *fpt*-approximation algorithm suitable for large-scale WSNs. In order to balance the energy consumption between nodes and prolong the network lifetime, considering the average energy of nodes in the cell, the distance between the cell center and the base station, and the initial energy of the gateway, a merit is designed to evaluate the cell. Cluster heads find the suitable next-hop according to each cell's merit to complete the data transmission. This protocol can effectively solve the problem of load balancing and prolong the network lifetime. EB-CRP [22] is a centralized clustering routing protocol, clustering and routing are executed inside the base station. In order to balance the load of gateways, a *fpt*-approximation algorithm with an approximation ratio of 1.1 is used to assign network nodes to different gateways to complete the construction of clusters. With the goal of energy efficiency and energy balance, the inter-cluster routing is constructed. First, a virtual square infrastructure is constructed with the center of the sensor field as the center point, and then the nodes close to the diagonal of virtual square are selected to form the main path. The base station selects the next hop on the main path for the nodes according to the merit value to complete the data transmission. To balance the energy consumption of nodes near the base station, the routing algorithm rotates the virtual square every certain number of rounds to update the main path. The proposed algorithm effectively solves the problem of load balancing and constructs efficient inter-cluster routing, which improves the energy efficiency and prolongs the network lifetime. Like EB-CRP, CFPT [23] also aims to minimize the load of gateways, a *fpt*-approximation algorithm is used to assign network nodes to different gateways to form network clustering, but the approximation ratio of the *fpt*-approximation algorithm is 1.2. Simulation results show that the proposed clustering method can effectively balance the load of gateways. In order to balance the network energy consumption to each node and ensure the energy efficiency, a routing algorithm is proposed. After every certain round, nodes calculate the merit value of their neighbor nodes according to the location information and residual energy, so as to build a path with high residual energy and short distance, and complete the construction of inter-cluster routing. EB-CRP solves the problem of load balancing and effectively prolongs the network lifetime. In [24], the concept of partitioning is introduced, and CEB-UC algorithm is proposed. This algorithm divides the WSN into different areas, the cluster size in the partition close to the base station is smaller and the cluster size is larger in the partition far from the base station, which balances the network cost and prolongs the network lifetime. In [25], an iterative clustering routing algorithm based on quantum genetic algorithm (QGEEIC) is proposed. This algorithm selects the optimal cluster heads iteratively based on energy efficiency, and improves the clustering parameters by using quantum genetic algorithm. Simulation results show that QGEEIC effectively extends the network lifecycle and reduces the total network energy consumption. In order to strengthen the robustness of the routing protocol, reference [26] proposed an energy-efficient routing protocol EECRP based on the center of mass, which considers the residual energy of nodes when selecting cluster heads, and adds a protection mechanism in the proposed protocol. By shortening the communication distance, the energy consumption of cluster heads is reduced, and the network performance is effectively improved. In [27], an improved hybrid leapfrog algorithm is used to select the optimal cluster heads, and considering the residual energy and the density of nodes, an efficient fitness function is designed to evaluate the quality of the solution produced by the algorithm. This algorithm effectively balances the load of cluster heads in the network, thereby extending the network's lifetime. In [28], an energy-efficient clustering routing protocol based on ant colony algorithm is proposed. According to the energy and distance between nodes, a new pheromone updating scheme is designed. In combination with the pseudo-random routing discovery algorithm, the energy consumption of sensor nodes is effectively balanced. In addition, the algorithm uses an opportunistic broadcast mechanism replace the flooding mechanism when transmitting control packets, further reducing network energy consumption and extending network lifetime. In [29], an improved LEACH algorithm based on non-uniform clustering is proposed to solve the problem of uneven distribution of cluster heads. First, the improved algorithm adds the energy factor to the random number generated by the nodes, which ensures that the nodes with more residual energy have a greater probability of being selected as cluster heads. Secondly, when the cluster heads transmit data to the base station, they use the combination of single hop and multi hop to make the network load more balanced and avoid the network hot spot problem. Reference [30] improved the LEACH algorithm and optimized the method of cluster head election. In the cluster head election phase, the proposed algorithm considers the geographical position of the nodes and the remaining energy of the nodes, and uses the quantum artificial bee colony algorithm to select the optimal cluster heads for each round. This algorithm makes the cluster heads distributed evenly, thus effectively prolonging the network lifetime. In reference [31], an energy-efficient clustering routing protocol based on glowworm swarm optimization is proposed. This algorithm optimizes the clustering by considering the remaining energy of the nodes, the density of the nodes, and the compactness of the clusters. In the communication phase, the energy consumption of nodes is balanced by the combination of single hop and multi-hop. The proposed algorithm significantly improves network performance and extends network lifetime. In [32], a new energy-efficient regional source routing protocol is proposed, which balanced the energy consumption of the network by dynamically selecting the nodes with high remaining energy in the wireless sensor network as cluster heads. In addition, An ant colony algorithm based on distance is used to find the global optimal transmission path for each node, so as to shorten the data transmission distance and reduce the energy consumption when the node transmits data. This algorithm has a better performance in terms of network lifetime and throughput.

The clustering routing protocol is an important part of the IoT routing protocol. In the clustering routing protocol, the functions of the cluster members are simple and do not need to maintain complex routing information. The network is highly scalable. However, the cluster heads in the network need to perform many tasks, such as collecting the data collected by the nodes in the cluster, fusing redundant data, communicating with the base station etc., so each round of energy consumption is more than that of member nodes, and cluster head may become the bottleneck of the network. Therefore, selecting appropriate cluster heads can effectively improve the overall performance of WSN. In this paper, an improved artificial bee colony algorithm is proposed to solve the problem of cluster head selection. In addition, in order to evaluate the quality of the solutions produced by the improved artificial bee colony algorithm, this paper proposes a new type of highly efficient fitness function to optimize the cluster heads selected in each round. In the network initialization period, all nodes have the same energy level, and an improved artificial bee colony algorithm is used to optimize the fuzzy C-means clustering to select cluster heads for first round. Each round of cluster heads is centrally selected by the base station. When selecting cluster heads, a large number of calculation is completed by the base station with infinite energy, so that the nodes have more energy for transmitting data. In order to avoid the fast energy consumption of the cluster heads far from the base station, an efficient routing algorithm based on ant colony optimization is proposed to find the optimal path between the cluster heads and the base station. In order to further improve the network throughput and reduce the network energy consumption, a polling control mechanism based on busy/idle nodes is introduced into intra-cluster communication. In each round, member nodes send their perceived data to their respective cluster heads using their polling schedule, and the cluster heads send the gathered data to the base station in the way of multi-hop routing. Compared with other similar protocols, the energy-balanced and energy-efficient clustering routing protocol proposed in this paper has a better performance.

III. SYSTEM MODEL

In this section, we introduce the network energy consumption model used in this paper, and make some settings for the WSN and sensor nodes to facilitate the subsequent work.

A. ENERGY CONSUMPTION MODEL

This paper adopts the First Order Radio Model introduced in [33]. The transmission process of data and the energy consumption of each step are shown in Fig. 2.

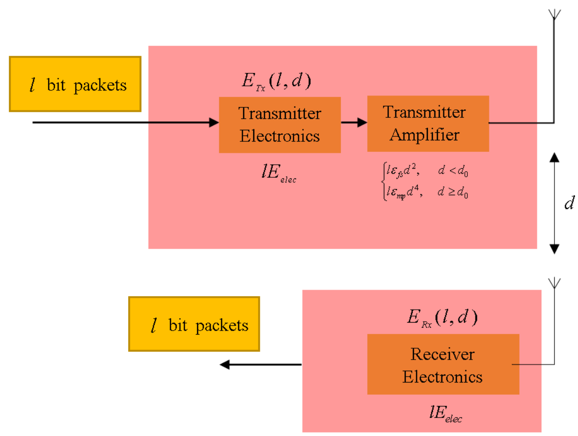

FIGURE 2. Data transmission process and energy consumption.

The energy consumed by a node to send l-bit data mainly includes two parts: energy loss of sending l-bit data and the energy loss of the power amplifier circuit. The energy consumed by a node to receive data only includes the energy consumption of the receiving circuit. Assume that the channel is symmetrical, that is, the energy consumed by node i to send data to node j is equal to the energy consumed by node j to send data to node i. The energy consumed by a node to send l-bit data through distance d is

$$E_{Tx}(l,d) = \begin{cases} lE_{elec} + l\varepsilon_{fs}d^2, & d < d_0 \\ lE_{elec} + l\varepsilon_{mp}d^4, & d \geq d_0 \end{cases} \tag{1}$$

The energy consumed by the node to receive l-bit data is

$$E_{Rx}(l, d) = lE_{elec} \tag{2}$$

The energy consumed by the cluster head to fuse l-bit data is

$$E_{Fx}(l, d) = lE_{DA} \tag{3}$$

where E_{elec} is the energy consumed for transmitting 1-bit data, E_{DA} is the energy consumed for fusing 1-bit data, and d_0 is the threshold for distinguishing between the two energy attenuation models of the signal amplifier, and the value is $d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$. When the transmission distance is less than d_0, a free space fading model is selected, and the energy required for power amplification is ε_{fs}. When the transmission distance is greater than d_0, a multipath attenuation model is selected, and the energy required for power amplification is ε_{mp}.

B. NETWORK MODEL

We make the following assumptions on WSNs and network nodes:

- N sensor nodes are randomly and uniformly distributed in the monitoring area of $M \times M$, each node has a unique network ID, the base station is located at the center of the monitoring area, all nodes are fixed, and no human intervention is performed after network deployment.
- All sensor nodes are homogeneous, that is, the initial energy is the same, the processing and communication capabilities are equal, and energy cannot be supplemented.
- All nodes can sense their own residual energy, and calculate the distance between themselves and the signal sending end according to the received signal strength.
- Each node can communicate with the base station directly, and the node can merge data and choose transmission power independently according to the communication distance.
- The computing power and energy of the base station are unlimited.

IV. GLOBAL ARTIFICIAL BEE COLONY ALGORITHM BASED ON CROSSOVER AND TABU

In this part, we first introduce the standard artificial bee colony (ABC) algorithm, and then, aiming at the shortcomings of the algorithm, we propose a global artificial bee colony algorithm based on crossover and tabu.

A. STANDARD ARTIFICIAL BEE COLONY ALGORITHM

The ABC algorithm is a kind of swarm intelligence optimization algorithm inspired by bee's behavior of collecting honey in nature. Compared with other intelligent algorithms such as genetic algorithm and particle swarm algorithm, ABC algorithm has the advantages of low complexity, strong robustness, less set parameters and strong optimization ability. It can be well applied to artificial neural network training, combination optimization, system and engineering design and many other fields [34].

The standard ABC algorithm [35], [36] divides bees into three types: employed bee, onlooker bee and scout bee. Generally, the number of employed bee and onlooker bee is equal, accounting for half of the total bee colony. The number of nectar sources is equal to the number of employed bees and onlooker bees. The position of the nectar source represents the feasible solution of the optimization problem, and the amount of nectar from the nectar represents the fitness function value (the quality of the feasible solution). At the initial moment, all bees are scouts, and SN food source location are randomly generated in the search space according to formula (4).

$$x_{ij} = L_j + rand(0, 1)(H_j - L_j) \tag{4}$$

where x_i is the location of the food source i, the range of the search space is $[L_j, H_j]$, $j = 1, 2, \ldots, D$ is a component of the d-dimensional solution vector, and $rand(0, 1)$ is a random value between [0, 1].

According to formula (5), each employed bee is searched near the current nectar source to generate a new food source location.

$$new\_x_{ij} = x_{ij} + rand()(x_{ij} - x_{kj}) \tag{5}$$

where new_x_{ij} is the location of the new food source, x_{ij} is the location of the old food source, x_{kj} is the location of randomly selected food source, $j \in \{1,2,\ldots,D\}$, $k \in \{1,2,\ldots,SN\}$, and $k \neq i$. j and k are randomly generated, and $rand()$ is a random number between [0,1], the value determines the magnitude of the perturbation. When the amount of nectar from the new nectar source is better than that of the old nectar source, the employed bee uses the greedy strategy to replace the old nectar source with the new nectar source and reserve it for the next generation of the population, otherwise the new nectar source is abandoned and the old nectar source is retained. After all the employed bees have completed their search, they return to the dancing area to share their food source information. The onlooker bee chooses the employed bee to follow according to the nectar information shared by the employed bee, and the following probability is calculated according to the formula (6).

$$P_i = fit / \sum\nolimits_{n=1}^{SN} fit_n \tag{6}$$

where fit_i is the fitness value of the i-th solution. This method of choosing employed bees to follow is called roulette, which can ensure that individuals with large fitness values are more likely to be followed by onlooker bees. The onlooker bee chooses employed bee i to follow with probability P_i, and the role of this bee will be changed to employed bee, and perform the corresponding operation of employed bee.

In the process of searching, if the number of stay times of the employed bees and onlooker bees in the vicinity of a nectar source exceeds the maximum limit of $Limit$, and no better food source is found, it is considered that the food source has been exhausted. The employed bees abandon the food source and change their roles to scout bees. According to formula (4), a new food source is randomly generated.

B. GLOBAL ARTIFICIAL BEE COLONY ALGORITHM BASED ON CROSSOVER AND TABU

The standard ABC algorithm has a strong search ability, but the global search ability is insufficient. When it is close to the global optimum, the search speed becomes slower and the individual diversity decreases, which leads to the algorithm easily falling into the local optimal solution. The ABC algorithm only uses the strategy of scout bees to randomly generate new nectar sources during global detection. It is difficult for the randomly generated new nectar sources to be superior to other nectar sources with multiple iterations, that is, the randomly generated solution is difficult to be superior to the local optimal solution with multiple iterations, which limits the global search ability of the algorithm. To solve this problem, this paper improves the global search strategy of the algorithm. introduces the cross operation of genetic algorithm and the tabu search idea of tabu algorithm based on the global artificial bee colony (GABC) algorithm [37], and proposes the global artificial bee colony algorithm based on the crossover and tabu search (CGTABC).

CGTABC algorithm combines genetic algorithm, tabu search algorithm and GABC algorithm, while improving the global optimization ability of the algorithm, it also enhances the neighborhood search ability of the algorithm. Genetic algorithm is a method for searching the optimal solution by simulating the natural evolution process. It has adaptive and self-organizing capabilities, including three operations of selection, crossover and mutation. It is widely used to solve complex optimization problems [38]. Tabu search is a combination of artificial intelligence and local search algorithm. It is a global search algorithm that uses memory mechanism to jump out of local optimal value [39]. Firstly, the CGTABC algorithm adds a global guide item to the employed bee search. Secondly, after the employed bee search, the new solution will cross with the global optimal solution, further enhancing the global optimization ability of the algorithm. In order to coordinate the neighborhood search ability and global optimization ability of the algorithm, a new parameter cross coefficient is introduced. Finally, the tabu idea of tabu search algorithm is introduced, and a tabu table is added on the premise of keeping the whole process of the original algorithm unchanged. When the location of a certain nectar source is not updated after a continuous *Limit* disturbance, the food source is liberated into the tabu list, and the scout randomly generates a new solution. If the fitness value of the new solution is less than the threshold value (the fitness value of the optimal solution in the current tabu list is set as the threshold value), the new solution is considered unqualified, and a new solution is generated again until the new solution is greater than the threshold value. If the new solution generated by the scout bees is less than the threshold for continuous σ times, the optimal solution in the tabu list is used as the new solution generated by the current scout bee. Because the quality of the solutions in the tabu list is generally poor, the length of the taboo list is infinite. Except that the optimal solution in the tabu list has a certain probability of being pardoned, the rest of the solutions will always be banned. The details of using CGTABC algorithm to select the optimal cluster heads will be explained in Section V.

V. PROPOSED PROTOCOL

In the proposed protocol, we adopt the concept of ''round'' in LEACH, and each round is divided into a setup phase and a stabilization phase. In the setup phase, the base station uses the CGTABC algorithm to select the cluster heads based on the location and energy of the nodes, and uses the proposed ACO-based routing algorithm to find the proper paths between each cluster head and the base station. In the stabilization phase, the members send the perceived data to the corresponding cluster head, and the cluster head sends the gathered data to the base station by using the proposed ACO-based routing algorithm. In this section, we first introduce how to use CGTABC to solve the problem of optimal cluster head selection, and then we elaborate on the ACO-based routing algorithm. Finally, we describe the polling control mechanism based on busy/idle nodes, and introduce the workflow of using the proposed polling mechanism in the intra-cluster communication phase.

A. THE CGTABC ALGORITHM IS USED TO SELECT CLUSTER HEADS FOR THE FIRST ROUND

First, we will record the CGTABC algorithm used in the first round of cluster head selection as CGTABC1. In homogeneous WSN, the initial energy of all nodes is the same. In this case, reference [26], [40], [41] and so on adopt the random selection method in the first round of cluster head selection, but this method will cause uneven distribution of cluster heads and unreasonable clustering, thus increasing the network energy consumption. In order to solve this problem, the fuzzy C-means clustering (FCM) algorithm is used to cluster the network nodes in the initialization phase, and the node nearest to the cluster center is the cluster head. However, the FCM clustering algorithm is sensitive to the initial clustering center and is easy to converge to the local optimal solution. To solve this problem, CGTABC1 is used to optimize the initial clustering center of FCM, so that the clustering effect is better, the cluster heads are evenly distributed, and the nodes in the cluster are closer. FCM clustering needs to specify the number of clusters, and the optimal number of clusters of FCM is the optimal number of cluster heads of the current network, which is determined by the predetermined proportion of cluster heads. In the first round of cluster head selection, the optimal cluster heads are selected when all nodes have the same energy level, and the network energy consumption is effectively reduced by minimizing the communication distance between nodes.

1) FCM CLUSTERING ALGORITHM

Fuzzy C-means (FCM) clustering is a kind of unsupervised clustering algorithm. The idea of FCM is to make the similarity between objects divided into the same category the largest, but the similarity between different categories the smallest [42]. When FCM is applied to the clustering of WSN nodes, the network nodes can be divided into several tight clusters to minimize the transmission distance when the members send data to the cluster head, so as to reduce the communication energy consumption within the cluster. The clustering loss function of FCM is

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2, \quad 1 \le m \le \infty \tag{7}$$

where x_i is the i-th sample point, c_j is the $j-th$ cluster center, $||x_i - c_j||$ is the distance from the sample i to the cluster center c_j, generally using Euclidean distance, u_{ij} is the degree of membership of the sample i to the cluster center j, m is the weighting factor (it's usually 2), N is the number of samples, C is the number of clusters. The clustering process of FCM is a process of minimizing the clustering loss function J_m through continuous iteration. With each iteration, the membership matrix is updated according to formula (8).

$$u_{ij} = 1/[\sum_{k=1}^{C} (\left\| x_i - c_j \right\| / \left\| x_i - c_k \right\|)^{2/(m-1)}] \tag{8}$$

The cluster center c_j is updated according to formula (9).

$$c_j = (\sum_{i=1}^{N} u_{ij}^m \cdot x_i)/(\sum_{i=1}^{N} u_{ij}^m) \tag{9}$$

The condition for the end of the iteration is

$$\max(\left| u_{ij}^{(k+1)} - u_{ij}^{k} \right|) < \varepsilon \tag{10}$$

where k is the number of iteration steps, ε is the error threshold. The above formula indicates that if you continue to iterate, the degree of membership will not change greatly, that is, the algorithm is considered to have reached convergence.

2) CGTABC1 OPTIMIZES FCM CLUSTERING

The performance of the FCM algorithm is affected by the selection of the initial clustering center, and it easily converges to the local optimal solution. In this paper, CGTABC1 is used to optimize the FCM algorithm. First, CGTABC1 is used to get the initial clustering center of FCM, and then the standard FCM algorithm is used to get the final classification results.

In reference to particle swarm optimization (PSO) algorithm, a global optimal solution guided artificial bee colony algorithm (GABC) is proposed in reference [37], which enhanced the search ability near the global optimal solution to a certain extent. Its search is shown in equation (11). However, GABC will reduce the global optimization ability of the algorithm to a certain extent, that is, the algorithm has strong exploration ability near the iterative optimal solution, but the global development ability is not sufficient. Although it has global guidance and fast convergence speed, it is easy to converge near the iterative optimal solution. In order to make the algorithm not weaken its global exploration ability under the guidance of the global optimal solution, this paper proposes formula (12). After the employed bee searches for a new solution new_x_{ij} by equation (5), a random number between [0,1] is randomly generated and compared with the cross coefficient cr. If the random number is less than cr, then the employed bee will cross the solution new_x_{ij} and the global optimal solution according to formula (12) to generate a new solution $new\_x_{ij}\_crossover$. If the generated random number is greater than cr, then no cross is performed.

$$\begin{aligned} &GABC\_new\_x_{ij} \\ &\quad = x_{ij} + rand()(x_{ij} - x_{kj}) + \delta(x_j^{global} - x_{ij}), \quad k \neq i \end{aligned} \tag{11}$$

$$\begin{aligned} &new\_x_{ij}\_crossover \\ &\quad = \begin{cases} new\_x_{ij}, & rand < cr \\ rand()(x_j^{global} - x_{ij}) + \delta(x_j^{global} - new\_x_{ij}), & otherwise \end{cases} \end{aligned} \tag{12}$$

where $\delta \in [0, C]$ and C are non-negative constants. cr is the cross coefficient, used to coordinate the search ability and global optimization ability of the algorithm. The smaller the cr is, the stronger the search ability of the algorithm near the iterative optimal solution is, but the global development ability is weaker, and vice versa.

The fitness function of CGTABC1 is designed as

$$f_{CGTABC1} = 1/(J_m + 1) \tag{13}$$

According to equation (13), the fitness function of CGTABC1 is inversely proportional to the clustering loss function of FCM, which ensures that the better the clustering effect of FCM is, the greater the fitness value is.

In the standard ABC algorithm, the probability that an onlooker bee selects a food source is calculated according to formula (6), but, when the fitness values are close to each other, the calculated follow probability is not distinguishable, that is, it is difficult to distinguish the good and bad food sources. In order to make high-quality nectar sources attract more onlooker bees, a new probability selection model is proposed, as shown in equation (14).

$$P_{CGTABC1(i)} = \sin(\frac{fit_i - fit_{\min}}{fit_{\max} - fit_{\min}}) \tag{14}$$

where fit_i represents the fitness value of the i-th solution, fit_{max} and fit_{min} represent the fitness values of the current optimum solution and the current worst solution, respectively, and $P_{CGTABC1(i)}$ represents the probability that the i-th nectar source is selected by the onlooker bee. It can be known from equation (14) that the function independent variable takes values between [0,1], and the sine function is constant greater than zero and monotonically increases in this interval, which ensures that the greater the fitness value of the solution, the more likely it is to be chosen by the onlooker bee. The proposed probability selection model effectively enhances the convergence speed and optimization ability of the algorithm. The pseudo code of CGTABC1 to optimize FCM is shown in Algorithm 1.

B. THE CGTABC ALGORITHM IS USED TO SELECT CLUSTER HEADS FOR SUBSEQUENT ROUNDS

We will record the CGTABC algorithm used when selecting cluster heads for subsequent rounds as CGTABC2. On the premise that the overall process of CGTABC algorithm is unchanged, CGTABC2 uses the network ID of the node as the identifier to select cluster heads for subsequent rounds. The following is an example of how CGTABC selects cluster heads.

Population initialization: randomly generate a population containing *SN* individuals, each individual represents a clustering result, and the dimension of individual vector represents the number of cluster heads. For example, according to the predefined percentage of cluster heads, if six nodes should be selected from all the surviving nodes to act as cluster heads, there will be 6 objects in each individual, then there are 6 objects in each individual, and the individual v={v_1,v_2,v_3,v_4,v_5,v_6} means that nodes with network ID of v_1, v_2, v_3, v_4, v_5, v_6 are selected as cluster heads.

The employed bee searches around the nectar source v and produces the new solution new_v, the corresponding practical operation is: randomly select an object from the surviving node set and replace an object in v to form the new solution new_v. For example, select an object v_m from the surviving nodes, replace an object v_3 in the solution v, and form a new solution $new\_v = \{v_1, v_2, v_m, v_4, v_5, v_6\}$. where v_m and v_3 are randomly selected, and $v_m \notin v$.

After the new solution is generated by the search of employed bee, the practical operation corresponding to the cross between the new solution and the global optimal solution is: assume that the global optimal solution is $v_{global} = \{v_{11}, v_{22}, v_{33}, v_{44}, v_{55}, v_{66}\}$, if the solution new_v generated by employed bee searching is not equal to the iterative optimal solution v_{global}, then an object in new_v is replaced by an object in v_{global} to form a new solution $new\_v\_crossover$. For example, after the employed bee generates a new solution $new\_v = \{v_1, v_2, v_m, v_4, v_5, v_6\}$ by searching, it is compared with the iterative optimal solution v_{global}. If $new\_v \neq v_{global}$, the employed bee selects an object v_2 in the individual and replaces it with an object v_{66} in v_{global} to form a new solution $new\_v\_crossover = \{v_1, v_{66}, v_m, v_4, v_5, v_6\}$, where v_{66} and new_v are randomly selected, and $v_{66} \notin new\_v$, when v_{66} and new_v have only one object different, $new\_v\_crossover = v_{global}$.

Tabu operation: In the process of searching, if the number of stay times of the employed bees and onlooker bees in the vicinity of a nectar source exceeds the maximum limit of *Limit*, and no better food source is found, this nectar source is liberated into the tabu list. For example: if nectar source $v = \{v_1, v_2, v_3, v_4, v_5, v_6\}$ has been searched for *Limit* times, and still hasn't been updated, then it is considered that the nectar source has been exhausted, and it is released into the tabu list. When the optimal number of clusters changes due to the death of a certain number of nodes, the tabu list is emptied

Algorithm 1 CGTABC1 Algorithm Optimizes FCM Clustering

```
1:Parameter initialization: Both the number of employed bees and onlooker bees are SN,the maximum number of times a nectar source can be mined repeatedly Limit, the maximum number of iterations maxCycle, the cross coefficient cr, the optimal number of clusters K, the fuzzy index m, and the error threshold ε.
2:Initialize the population, randomly generate a population containing SN individuals according to formula (4).
3:Calculate the fitness function value of all individuals according to equation (13), and remember the optimal solution
for iteration=1 to maxCycle
    Employed bee
    for i = 1 to SN
        Employed bee search operation according to formula (5)
        A new nectar source is obtained by cross operation between the nectar source searched by employed bee and the iterative optimal nectar source according to formula (12)
        Ensure the new nectar source is within the scope of optimized search
        The fitness value of the new nectar source is calculated by equation (13), and the better nectar source is retained according to the greedy strategy
    end
    for i = 1 to SN
        Calculate the probability P_CGTABC1(i) that the onlooker bee chooses the nectar source i according to equation (14)
    end
    Onlooker bee
    for i = 1 to SN
        The onlooker bee choose which employed bee to follow according to the probability P_CGTABC1(i)
        Onlooker bee becomes employed bee and perform operations corresponding to employed bees
    end
    if a nectar source meets the conditions of being abandoned, put
    it in the tabu list
    Scout bee
        The scout generates a new nectar source
        Ensure that this nectar source is available and replace the abandoned nectar source
    Remember the current optimal nectar source
end
Use the global optimal solution as the initial clustering center of FCM, execute the standard FCM algorithm, and complete the clustering
```

because the dimension of the solution vector stored in the current tabu list is no longer equal to the dimension of the individual vector in the later tabu list.

The actual operation corresponding to the operation performed by the scout is: the scout randomly selects six objects from the surviving nodes to form a new solution, and tests whether the new solution is qualified. If all σ consecutive solutions fail, think of the best solution in the tabu list as the new solution produced by the scout.

The search of employed bees strengthens the local exploration ability of the algorithm, and the cross with the global optimal solution ensures the global optimization ability of the algorithm. Because of the dimension limitation of individual vector, we set the number of cross objects to one. Too many cross objects will reduce the diversity of population and make the algorithm premature convergence. The search operation of employed bee and the process of crossing with the global optimal solution are shown in Fig. 3.

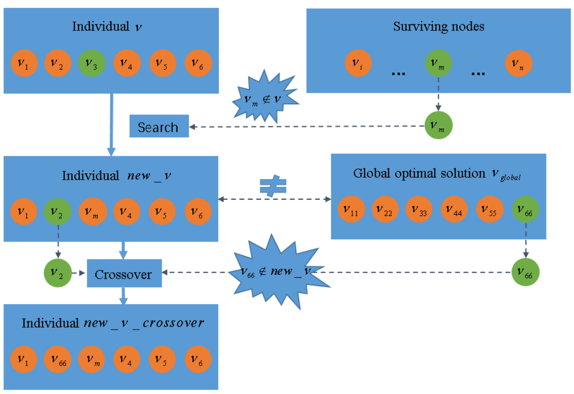

FIGURE 3. The process of searching and crossing by employed bees.

C. PROPOSED FITNESS FUNCTION

The key to selecting cluster heads using the CGTABC algorithm is how to define the fitness function, that is, how to measure the quality of a solution. The fitness function of CGTABC1 is shown in equation (13). Because the fitness function of CGTABC2 is complex and has many factors to consider, it will be introduced in detail in this section.

When CGTABC2 selects the optimal cluster heads, it needs to take into account the remaining energy of the nodes, the network load of the nodes, the average distance between the cluster heads, the energy balance between the clusters, the compactness of the clusters and other factors to design an efficient fitness function to evaluate the quality of CGTABC2's solution. It should be noted that the fitness function value of CGTABC2 is inversely proportional to the solution quality, that is, the smaller the fitness value, the higher the solution quality.

Balancing the energy consumption of the network can effectively extend the stability period of the network and achieve the goal of almost all nodes dying at the same time. Especially in the application scenarios with high requirements on reliability, the WSN can only work normally when all nodes are alive. Once a node dies, the work of the network is no longer meaningful. Therefore, balancing the energy consumption of the network is of great significance for WSNs. The Gini coefficient is a statistical indicator used to measure the degree of unequal income distribution in a region in economics. It can effectively reflect the difference of income distribution between individuals in a general and abstract way. A common formula for the Gini coefficient [43] is

$$G = \frac{1}{2n^2\mu} \sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j| \tag{15}$$

where n is the total number of people in the region, x_i is the income of the i-th person, x_j is the income of the j-th person, and μ is the average income of the people in the region.

From the description of the Gini coefficient, it can be seen that its characteristics are similar to the characteristics of the cluster. Therefore, energy Gini coefficient is proposed to estimate the equilibrium degree of energy in clusters. The calculation formula of energy Gini coefficient is as follows

$$E_{s(G)} = \frac{1}{2num^2(s)E_{ave}(s)} \sum_{i=1}^{num(s)} \sum_{j=1}^{num(s)} |E(i) - E(j)| \tag{16}$$

where $E_{s(G)}$ represents the energy Gini coefficient of the s-th cluster, $num(s)$ represents the number of nodes in the s-th cluster, $E_{ave}(s)$ represents the average residual energy of the s-th cluster, $E(i)$ represents the residual energy of node i.

After calculating the energy Gini coefficients of all clusters through equation (16), calculate the standard deviation of this group of energy Gini coefficients according to equation (17).

$$E_\sigma = \sqrt{\frac{\sum_{s=1}^{k} (E(s) - E_{ave})^2}{k}} \tag{17}$$

where k represents the number of cluster heads of the current network, $E(s)$ represents the remaining energy of the s-th cluster, and E_{ave} represents the average remaining energy of each cluster. E_σ is a measure of the degree of dispersion of the energy Gini coefficients of k clusters. The smaller E_σ is, the smaller the dispersion of energy Gini coefficients of all clusters is, that is to say, the energy balance of all clusters is similar, and the current clustering effect is better. Because in the cluster routing protocol, if each round can ensure the energy balance of all clusters is similar, then the energy consumption of the network can be well balanced in the whole network lifetime, so as to improve the network performance.

Based on the above analysis, the fitness function corresponding to the energy Gini coefficient is designed as

$$f_1 = \frac{e^k}{k} \cdot E_\sigma \tag{18}$$

When selecting cluster heads, the residual energy of nodes is an important index to be considered. According to Atkinson welfare index, formula (19) is designed to evaluate the energy balance of cluster heads. While considering the energy balance between cluster heads, it is necessary to ensure that cluster heads have as much residual energy as possible.

So formula (20) is proposed to evaluate the energy proportion of the cluster heads. By the way of weighted sum, the two optimization goals of the energy balance degree of the cluster head and the energy ratio of the cluster head are converted into a single objective optimization, as shown in equation (21), where ω_1 and ω_2 are weighting factors, and $\omega_1 + \omega_2 = 1$.

$$f_{21} = 1 - [\frac{1}{k}\sum_{s=1}^{k}(\frac{E_{CH}(s)}{E_{ave}(CH)})^{1-\varepsilon}]^{1/(1-\varepsilon)} \tag{19}$$

$$f_{22} = \frac{\sum_{i=1}^{n} E(i)}{\sum_{s=1}^{k} E_{CH}(s)} \tag{20}$$

$$f_2 = \omega_1 f_{21} + \omega_2 f_{22} \tag{21}$$

In formula (19), k is the number of cluster heads in the current network, $E_{CH}(s)$ is the residual energy of the s-th cluster head, $E_{ave}(CH)$ is the average residual energy of the cluster head, and ε is the inequality aversion parameter, which is 0.5. The smaller f_{21} is, the more balanced the energy between the cluster heads is. In equation (20), n is the number of surviving nodes in the current network, $\sum_{i=1}^{n} E(i)$ is the total energy of the current network, $\sum_{s=1}^{k} E_{CH}(s)$ is the total remaining energy of the cluster heads, and the smaller f_{22} is, the larger the total energy of the cluster heads is, and the better cluster heads are selected.

Index f_3 is used to evaluate the reasonable distribution of cluster heads in the network, which is obtained by dividing f_{32} by f_{31}. In equation (22), f_{31} represents the total distance between cluster heads, which is used to measure the inter-cluster load of the current network. The larger f_{31} is, the larger the total distance between cluster heads is, and the cluster heads are more evenly distributed. However, the total distance between cluster heads is easily affected by the extreme values, leading to inaccurate judgment. Therefore, the index f_{32} is designed, as shown in equation (23). f_{32} is the sum of the distance from each node to the cluster head of its own cluster, which is used to measure the compactness within the cluster. The smaller the f_{32} is, the closer the current cluster is. According to equation (24), the more compact the cluster is, and the larger the distance between the cluster heads is, the smaller f_3 will be, and the more reasonable the distribution of cluster heads is.

$$f_{31} = \sum_{s=1}^{k-1}\sum_{m=s+1}^{k} d_{CH}(s, m) \tag{22}$$

$$f_{32} = \sum_{i=1}^{k}\sum_{j=1}^{num(i)} d_{CN}(i, j) \tag{23}$$

$$f_3 = \frac{f_{32}}{f_{31}} \tag{24}$$

Balancing the load of cluster heads is very important for WSN. Compared with members, cluster heads need to perform more activities and consume more energy. Therefore, reducing the load of cluster head can effectively improve the performance of the network. Referring to reference [43], this paper uses the number of members in the cluster to measure the load of the cluster head.

$$num_{ave} = \frac{n-k}{k} \tag{25}$$

$$Th_{\max} = num_{ave} + \frac{num_{\max} - num_{\min}}{k} \tag{26}$$

$$Th_{\min} = num_{ave} - \frac{num_{\max} - num_{\min}}{k} \tag{27}$$

$$f_4 = (\frac{num_{\max} - num_{ave}}{num_{\max}})\frac{num_h - num_u}{k} \tag{28}$$

where num_{ave} is the average number of members in each cluster, num_{max} and num_{min} are the number of members in the largest and smallest clusters, num_h is the number of clusters with more members than Th_{max}, num_u is the number of clusters with less members than Th_{min}.

The fitness function is a standard to evaluate the quality of solutions. The above four fitness functions are normalized by the way of weighted sum, so that the multi-objective optimization can be transformed into a single objective optimization, as shown in equation (29)

$$f = \alpha f_1 + \beta f_2 + \lambda f_3 + \mu f_4 \tag{29}$$

where α, β, λ, μ are weighting factors, and $\alpha+\beta+\lambda+\mu = 1$.

Because the fitness value of CGTABC2 is inversely proportional to the quality of the solution, that is, the smaller the fitness value is, the better the quality of this solution. Therefore, referring to the selection probability of onlooker bees in CGTABC1, the selection probability of onlooker bees in CGTABC2 is designed as

$$P_{CGTABC2(i)} = \cos(\frac{fit_i - fit_{\min}}{fit_{\max} - fit_{\min}}) \tag{30}$$

where fit_i represents the fitness value of the i-th solution, fit_{max} and fit_{min} represent the fitness values of the current optimal solution and the worst solution, respectively, and $P_{CGABC2(i)}$ represents the probability that the i-th nectar source is selected by the onlooker bee. It can be known from equation (30) that the independent variable takes a value between [0,1], the cosine function is constant greater than zero and monotonically decreasing in this interval. It is ensured that the greater the fitness value of a nectar source, the greater the probability of the nectar source being selected by the onlooker bee. The proposed probability selection model effectively enhances the convergence speed and optimization ability of the algorithm.

The pseudo code of selecting cluster heads by CGTABC2 algorithm is shown in Algorithm 2

D. MULTI-HOP TRANSMISSION PATH BASED ON ANT COLONY OPTIMIZATION

According to the energy consumption model, the energy consumption of nodes is exponentially related to the transmission distance. If the cluster head communicates directly with the base station, a large amount of energy will be consumed. Especially the cluster head which is far away from the base station will die prematurely due to too much communication energy consumption [44]. In order to reduce the energy consumption of cluster heads and balance the load between clusters, an improved ant colony optimization algorithm is

Algorithm 2 Selecting Cluster Heads by CGTABC2 Algorithm

1:Parameter initialization: Both the number of employed bees and onlooker bees are SN, the maximum number of times a nectar source can be mined repeatedly $Limit$, the maximum number of iterations $maxCycle$, the cross coefficient cr
2:Initialize the population, randomly generate a population containing SN individuals, the dimension of the individual vector is determined by the optimal number of cluster heads.
3:Calculate the fitness function value of all individuals according to equation (29), and remember the optimal solution
for iteration=1 to $maxCycle$
  Employed bee
  for $i = 1$ to SN
    Employed bee search
    A new nectar source is obtained by cross operation between the nectar source searched by employed bee and the iterative optimal nectar source
    Ensure the new nectar source is within the scope of optimized search
    The fitness value of the new nectar source is calculated by equation (29), and the better nectar source is retained according to the greedy strategy
  end
  for $i = 1$ to SN
    Calculate the probability $P_{CGTABC2(i)}$ that the onlooker bee chooses the nectar source i according to equation (30)
  end
  Onlooker bee
  for $i = 1$ to SN
    The onlooker bee choose which employed bee to follow according to the probability $P_{CGTABC2(i)}$
    Onlooker bee becomes employed bee and perform operations corresponding to employed bees
  end
  If a nectar source meets the conditions of being abandoned, put
  it in the tabu list
  Scout bee
    The scout generates a new nectar source
    Ensure that this new nectar source is available and replace the abandoned nectar source
  Remember the current optimal nectar source
end
The global optimal solution is the optimum cluster heads selected for the current round.

used to construct efficient inter-cluster routing, that is, cluster heads send data to the base station in a multi-hop approach.

Based on the above analysis, at time t, forward ant a is located at cluster head i, and it will select cluster head j as the next hop according to (31).

$$P_{ij}^{a}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha_{ant}}(t) \times \eta_{ij}^{\beta_{ant}}(t)}{\sum_{s \in allowed_a} \left[\tau_{is}^{\alpha_{ant}}(t) \times \eta_{is}^{\beta_{ant}}(t)\right]}, & s \in allowed_a \\ 0, & s \notin allowed_a \end{cases} \tag{31}$$

where τ_{ij} is the pheromone concentration between cluster head i and cluster head j, α_{ant} is pheromone inspired factor, η_{ij} is the inspiring factor for selecting the next-hop cluster head, β_{ant} is the weight factor of the heuristic, and $allowed_a$ is the next-hop cluster head set that cluster head a can choose.

The heuristic value for cluster head i to next-hop cluster head j can be defined as

$$\eta_{ij} = \frac{1}{2}\left(k_1 \times C_{ij} + k_2 \times \frac{1}{2 - \cos\theta}\right) \tag{32}$$

where C_{ij} is the energy-distance factor of the heuristic function, which can be defined by equation (33). θ is the angle formed by the connection between cluster head i and the base station and the connection between cluster head i and cluster head j, as shown in Fig. 4. k_1 and k_2 are weighting factors.

$$C_{ij} = \sum\nolimits_{j \in allowed_a} \frac{E_{can}(j)}{\overline{E}_{can}} \log_a \frac{\frac{E_{can}(j)}{\overline{E}_{can}}}{\frac{d(i,j)}{d_{max}}} \tag{33}$$

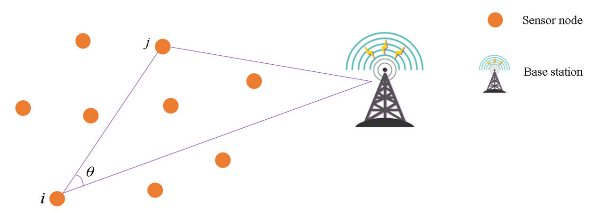

FIGURE 4. Schematic diagram of angle factor.

Where E_{can} is the residual energy of the next-hop cluster head to be selected, and $\overline{E}_{can}$ is the average residual energy of all candidate next-hop cluster heads, $d(i, j)$ is the Euclid distance from cluster head i to next-hop intermediate cluster head j, d_{max} is the maximum distance between the current cluster head and all optional next-hops. The improved heuristic function comprehensively considers factors such as energy, distance, angle, etc., so that the selection of the next-hop is more targeted.

The traditional ant colony optimization algorithm only considers the length of the path when updating pheromone, but ignores some other factors which have great influence on the path [45]. Therefore, we optimized the pheromone update method. In addition, in order to improve the global activity of the network and enhance the global optimum, so as to establish more efficient inter-cluster routing, the pheromone update adopts a combination of local update and global update.

The pheromone update model is as follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}(t) \tag{34}$$

where ρ represents the pheromone volatility coefficient and $\Delta\tau_{ij}(t)$ is the increment of pheromone.

The forward ant moves from cluster head i to cluster head j, and calculates local pheromone increment according to (35).

$$\Delta\tau_{ij}^{a}(t) = Q_{local}\frac{E_{can}(j)}{d(i,j)+num_j} \tag{35}$$

where Q_{local} is the local pheromone concentration and num_j is the number of members in the cluster to which cluster head j belongs. It can be seen from the formula that the proposed local pheromone update method comprehensively considers the energy, load, geographic location and other factors of the nodes. The higher the residual energy of the candidate cluster head, the smaller the load, and the closer to the current cluster head, the larger the local pheromone increment between the two cluster heads.

Forward ants automatically disappear when they reach the base station, and the corresponding backward ants are generated. Backward ants return to the source node and update the global pheromone according to the following rules.

$$\Delta\tau_{ij}^{a}(t) = Q_{global}\frac{E_{\min}}{v_c \times L_{ant}^{a}} \tag{36}$$

where Q_{local} is the global pheromone concentration, E_{min} is the minimum energy value of all nodes in the path, L_{ant}^{a} is the length of the path that the m-th ant traverses, v_c is the coefficient of variation, which is used to measure the energy balance degree of nodes in the path [46], and is calculated according to (37).

$$v_c = \frac{E_\sigma}{E_\mu} \tag{37}$$

where E_σ and E_μ are the standard deviation and mean of energy of all nodes in the path.

It can be seen from the formula that the proposed global pheromone update method comprehensively considers the energy of bottleneck node in the path, the path length and the energy balance degree of all nodes in the path, which meets the energy requirements of the path, and ensures the communication distance, which can effectively improve the efficiency of inter-cluster routing. To better understand the operation of the proposed routing algorithm, Fig.5 provides a flowchart showing the operation of the routing algorithm.

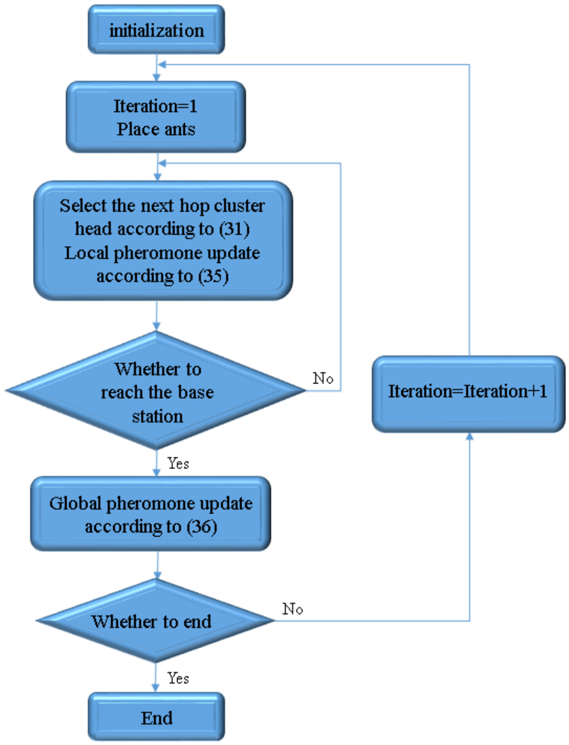

FIGURE 5. **Flowchart of the proposed ACO-based routing algorithm.**

E. IMPROVED INTRA-CLUSTER COMMUNICATION MECHANISM

In existing clustering routing algorithms of WSN, the intra-cluster communication mechanism generally adopts TDMA (Time Division Multiple Access). After the cluster heads are selected, the cluster heads use CSMA mechanism to broadcast the information that they become cluster heads to the entire network. After the ordinary nodes receive the signal, they select the cluster head with the largest signal strength and join the cluster, and use CSMA mechanism to send the information of request to enter the cluster to the cluster head. The cluster head creates a TDMA time slot table according to the number of nodes in the cluster. Each node sends the monitored data to the cluster head in its own time slot, and the rest of the time is dormant to reduce energy consumption. If the sensor node has no data to send in its own time slot, it will have a free time slot and energy will be wasted. To solve this problem, we introduce a polling control mechanism based on busy/idle nodes [47]. After the cluster heads are selected, the members send information to the cluster head requesting to enter the cluster. The cluster head establishes a polling table based on the number of members. The corresponding relationship between node ID, polling order and free busy status is recorded in the polling table. In the polling table, the free and busy status ID value of the member node with data to be sent is set to 1, and the free and busy status ID value of the node without data to be sent is set to 0. Before each polling cycle, the free and busy status of all nodes is updated. After the polling table is established, the cluster head polls the nodes whose free and busy status identification value is 1 in turn according to the query order in the polling table, and receives the monitoring data sent from them. When a node runs out of energy, is in sleep, or leaves its cluster, the cluster head deletes the node from the polling table. If a node does not detect effective data in a period of time, its free and busy status identification value will always be 0, and the cluster head does not query the node, which effectively improves the energy utilization rate, and can effectively avoid the energy loss caused by collision when sending packets in common protocols. The model of polling control mechanism based on busy/idle nodes is shown in Fig. 6.

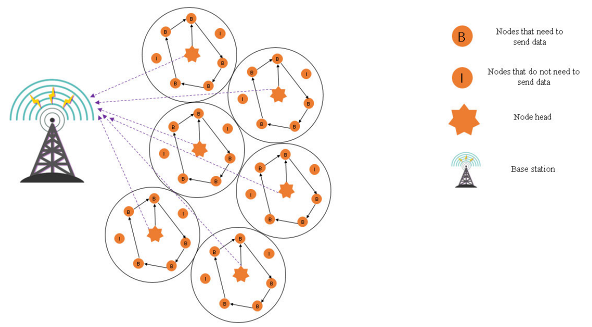

FIGURE 6. Model of polling control mechanism based on busy/idle nodes.

After the cluster head completes a polling cycle, the collected data is fused and sent to the base station using the CSMA mechanism.

VI. SIMULATION RESULTS AND PERFORMANCE EVALUATION

In this section, we present the performance evaluation results of the proposed protocol, and Matlab is used to write our simulation code. We first describe our simulation environment, and then introduce the metrics used to evaluate the performance of the protocol. Finally, we compare the proposed protocol with LEACH-C [16], FIGWO [18], ABC-SD [19] and PSO [20].

A. SET SIMULATION PARAMETERS

The number of nodes, the location of the base station and network size are the three main parameters that affect the network lifetime [reference]. Considering these factors, we set up several scenarios of different sizes, as shown in Table 1, and simulate the proposed algorithm in these scenarios. The parameters of CGTABC are set as follows: the population size is 30, the maximum number of iterations *maxCycle* is 200, and the cross coefficient *cr* is 0.6. Table 2 shows the parameters of CGTABC2 and ACO-based routing algorithm. The specific parameters used in the simulation experiment are shown in Table 3.

TABLE 1. Parameters of scenarios.

Parameter	Scenario 1	Scenario 2	Scenario 3
Area	$100\times100\text{m}^2$	$200\times200\text{m}^2$	$300\times300\text{m}^2$
Base station location	(50, 50)	(0, 0)	(300, 450)
Number of sensors	100, 200, 300	100, 200, 300	500

B. PERFORMANCE METRICS

In this paper, we mainly carry out simulation experiments from the aspects of network lifetime, network total residual energy, network stability period and network throughput, and compare the proposed algorithm with LEACH-C, FIGWO, PSO and ABC-SD under the same simulation parameters to prove the feasibility and superiority of the proposed algorithm.

1) Network lifetime: We consider the network lifetime as the number of rounds until 75% of the nodes die.
2) The total remaining energy of the network: The sum of the current remaining energy of all nodes participating in data transmission in the network.
3) Network stability period: The time that all sensor nodes can collect data normally is defined as the network stability period, that is, the number of rounds until the first node dies.
4) Network throughput: The total number of data packets received by the base station is defined as the network throughput.

TABLE 2. Parameters of CGTABC2 and ACO-based routing algorithm.

Parameter	Value
ω_1	3/5
ω_2	2/5
α	1/3
β	1/3
λ	1/6
μ	1/6
α_{ant}	1
β_{ant}	5
k_1	1/2
k_2	1/2
ρ	1/2

TABLE 3. Simulation experiment parameters.

Parameter	Value
Data packet size	4000 bits
Control packet size	200 bits
Initial energy	0.5 J
Percentage of cluster heads	5 %
E_{elec}	50 nJ/bit
E_{DA}	5 nJ/bit/packet
ε_{fs}	10 pJ/bit/m^2
ε_{mp}	0.0013 pJ/bit/m^4

C. COMPARISON RESULTS

In scenario 1, five protocols are simulated, and the network lifetime metrics is shown in Fig.7. In terms of network lifetime, the proposed protocol performs better than compared protocols. In scenario 1 with 100 sensors, 200 sensors and 300 sensors, the proposed algorithm has a longer lifetime. The scale of scenario 1 is small, and the base station is located in the center of the area, and the distance between the member

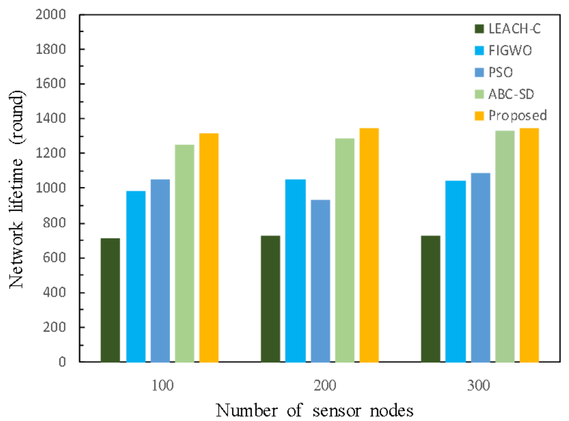

FIGURE 7. Lifetime metrics of scenario 1.

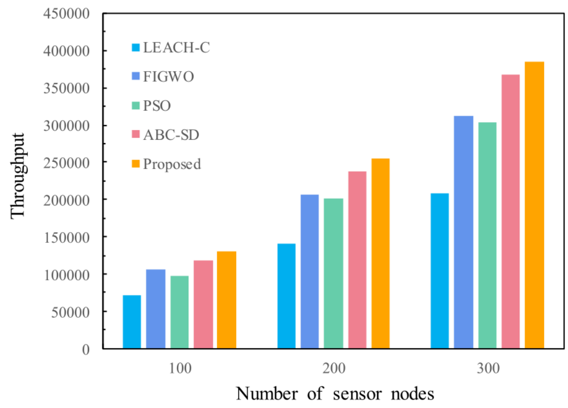

FIGURE 9. Throughput metrics of scenario 1.

nodes to their respective cluster heads and the distance from the cluster heads to the base station is relatively close. In this case, the main factor affecting the performance of the protocol is the clustering effect. Based on the above analysis, the main reason for the proposed protocol to have a better network lifetime is to select cluster heads reasonably and optimize clustering.

Fig. 8 shows the network stabilization time metrics of scenario 1. As shown in the figure, in scenario 1 with different node density, the network stability metrics of the proposed protocol is better than that of the other four protocols, because the proposed protocol can well balance the network energy consumption. It also shows that compared with the other four protocols, the proposed protocol is more suitable for scenarios with high reliability requirements.

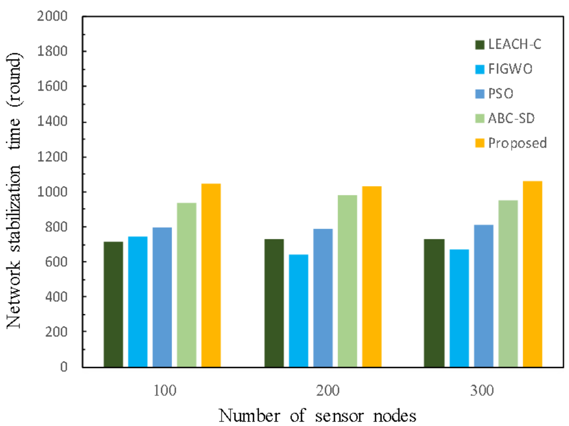

FIGURE 8. Stabilization time metrics of scenario 1.

Fig. 9 shows the network throughput metrics for scenario 1. It can be seen from the figure that during the working time of the network, the base station receives more data packets, because the proposed protocol has a longer network lifetime, and the polling control mechanism based on busy/idle nodes is introduced in the intra-cluster communication phase, which makes full use of the time slot and improves the network throughput.

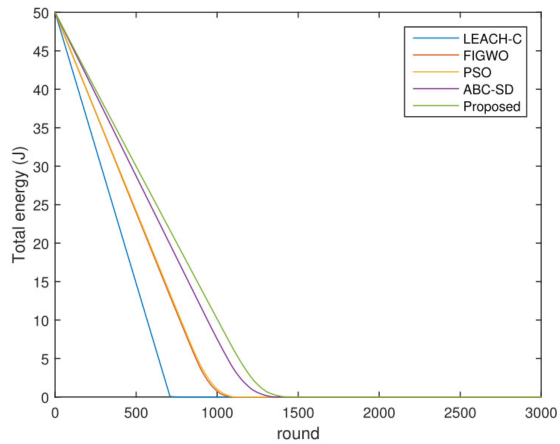

FIGURE 10. Total energy for scenario 1 with 100 sensors.

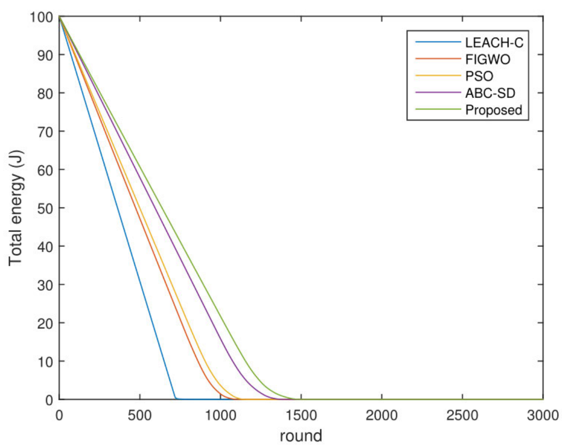

FIGURE 11. Total energy for scenario 1 with 200 sensors.

Figs. 10, 11 and 12 show the total energy per round of scenario 1 with 100 sensors, 200 sensors and 300 sensors, respectively. It can be clearly seen from the figure that in

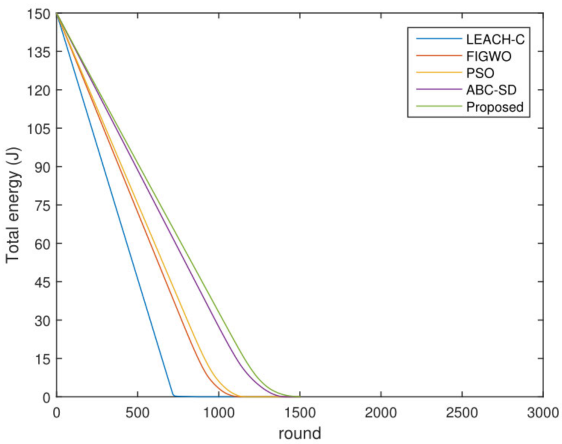

FIGURE 12. Total energy for scenario 1 with 300 sensors.

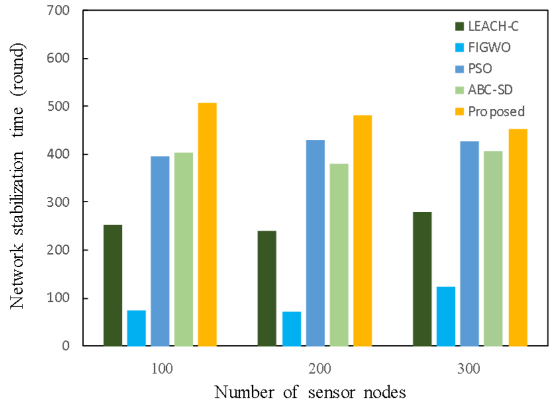

FIGURE 14. Stabilization time metrics of scenario 2.

scenario 1 with three different node densities, the total residual energy of the proposed algorithm is always higher than compared protocols. This proves that the proposed protocol can effectively balance network energy consumption and improve energy efficiency.

In scenario 2, five protocols are simulated. Compared with scenario 1, the base station in scenario 2 is placed in the corner of the field, and the scale of the area becomes larger. As for the number of sensor nodes, we still consider we still consider 100 sensors, 200 sensors and 300 sensors. Fig. 13 shows lifetime metrics for scenario 2. As can be seen from the figure, compared with the other four protocols, the proposed protocol has a better network lifetime. This is because the proposed protocol can reasonably select cluster heads and make the location of the cluster heads more disperse, and then the proposed ACO-based routing algorithm carefully finds the path between each cluster head and the base station.

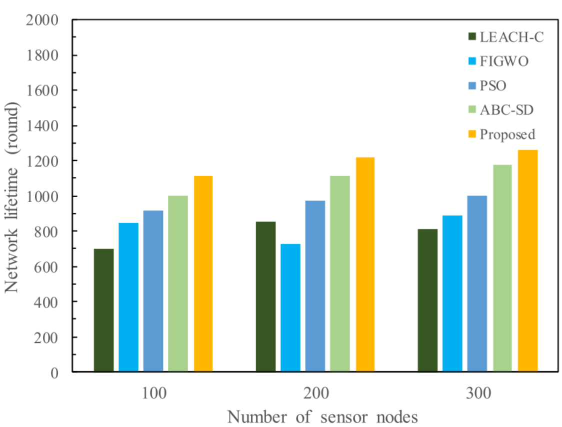

FIGURE 13. Lifetime metrics of scenario 2.

Fig. 14 shows the network stabilization time metrics for scenario 2. As can be seen from the figure, the proposed protocol has a better network stabilization time. This is because the proposed protocol successfully selects the relatively optimal cluster heads and finds the optimal path from each cluster head to the base station. This also shows that compared with the other four protocols, the proposed protocol can prolong the stable working time of the network, and is more suitable for scenarios with high reliability requirements.

Fig. 15 shows the network throughput metrics for scenario 2. As can be seen from the figure, the proposed protocol has a better network throughput. There are two main reasons why the proposed protocol performs better than compared protocols in network throughput metrics. The first reason is that the proposed protocol has a longer network lifetime, so the base station receives more data packets, and the second reason is that the polling mechanism is introduced in the intra-cluster communication phase, which makes full use of the time slot and further improves the network throughput.

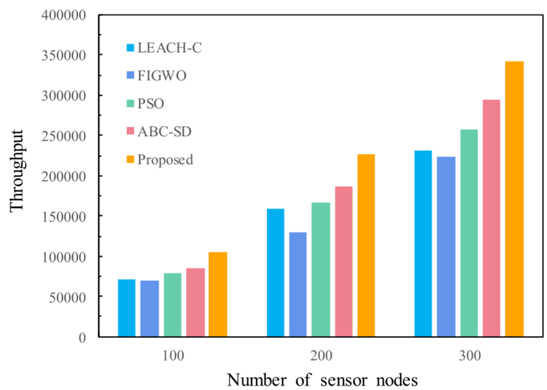

FIGURE 15. Throughput metrics of scenario 2.

Figs. 16, 17 and 18 show the total energy per round of scenario 2 with 100 sensors, 200 sensors and 300 sensors, respectively. As can be seen from the figure, the proposed protocol performs well in the total remaining energy metrics. This is because the proposed clustering algorithm and ACO-based routing algorithm take into account the energy factor when looking for the optimal solution, so it finds the

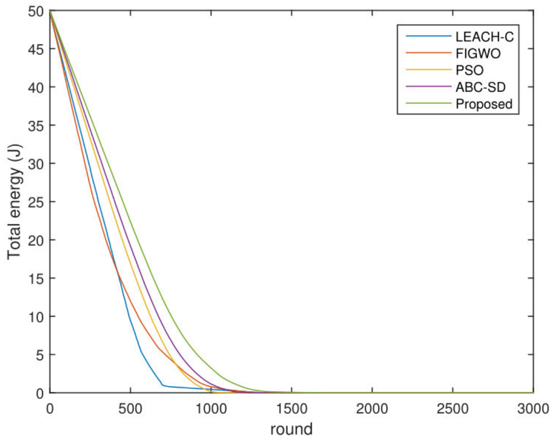

FIGURE 16. Total energy for scenario 2 with 100 sensors.

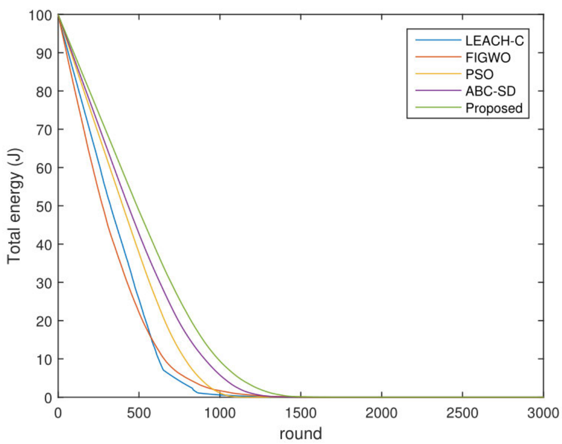

FIGURE 17. Total energy for scenario 2 with 200 sensors.

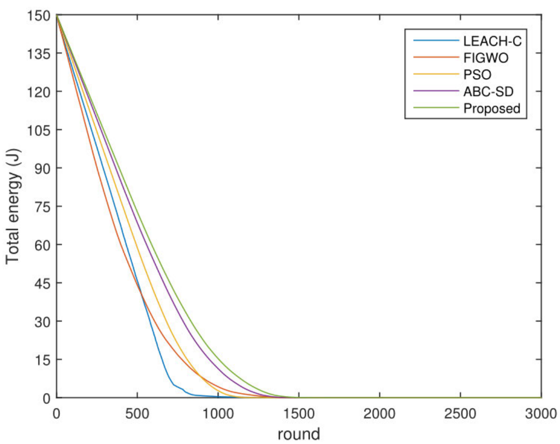

FIGURE 18. Total energy for scenario 2 with 300 sensors.

optimal solution in terms of energy consumption and energy balance.

In scenario 3, the network area becomes larger, the number of sensor nodes is increased to 500, and the base station is located outside the wireless sensor network area. We test the

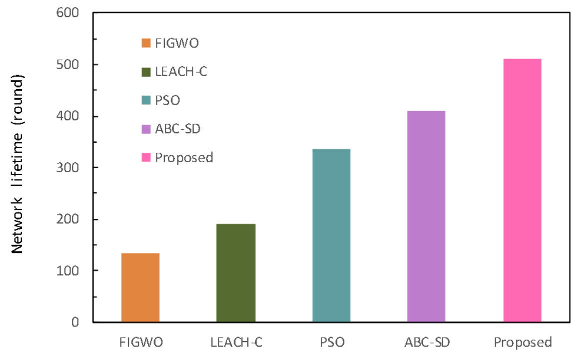

FIGURE 19. Lifetime metrics of scenario 3.

scalability of the protocols in this scenario. Fig. 19 shows lifetime metrics for scenario 3. As can be seen from the figure, in large-scale WSN, the proposed protocol performed better than compared protocols in network lifetime metrics. This is mainly due to the fact that the proposed ACO-based routing algorithm can build efficient inter-cluster routing, and the cluster head sends data to the base station through the optimal path, which avoids the excessive energy consumption of the cluster heads far away from the base station.

Fig. 20 shows lifetime metrics for large-scale WSN. The proposed protocol constructs efficient inter-cluster routing and avoids excessive energy consumption of cluster heads far away from the base station, thus greatly expanding the network stabilization time. This enables the proposed protocol to collect more comprehensive data information and is more suitable for large-scale WSN with high reliability requirements.

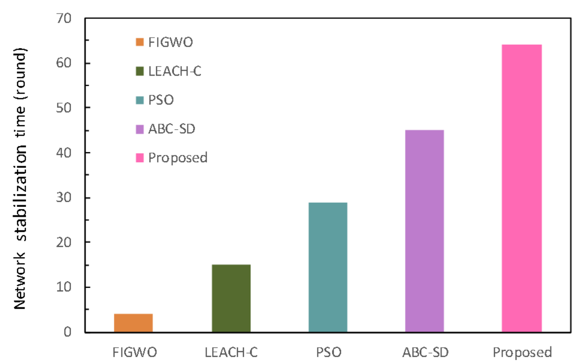

FIGURE 20. Stabilization time metrics of scenario 3.

Fig. 21 shows the network throughput metrics for scenario 3. It can be seen from the figure that the network throughput of the proposed protocol is much higher than compared protocols, that is to say, the base station collects more data information during the working time of the network. Longer network lifetime and the introduction of polling mechanism are the main reasons for the best performance of the proposed protocol in terms of throughput.

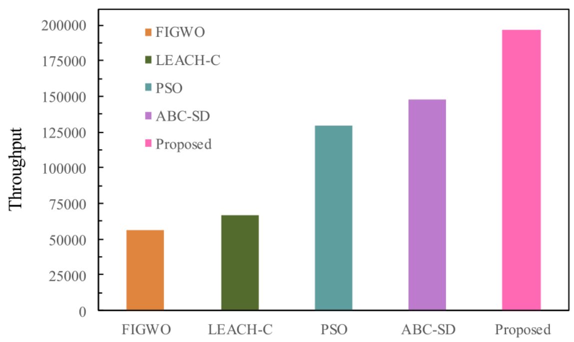

FIGURE 21. Throughput metrics of scenario 3.

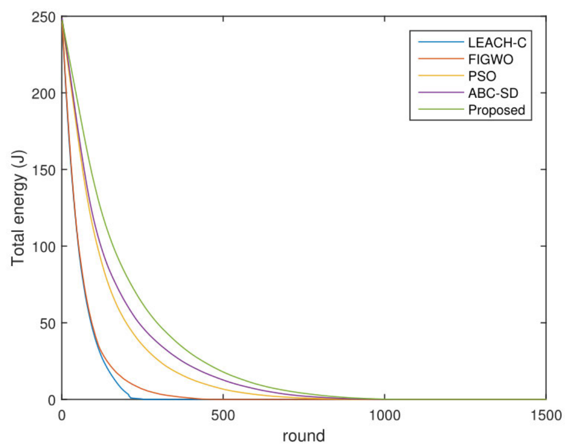

FIGURE 22. Total energy for scenario 3.

Fig. 22 shows the total remaining energy per round of the five protocols in scenario 3. It can be seen intuitively from the figure that the total remaining energy of the proposed protocols is always higher than compared protocols. The proposed clustering algorithm can solve the optimal clustering problem very well, and the proposed routing algorithm can find the optimal path from each cluster head to the base station, which are the two main reasons why the proposed protocol performs well in this metrics.

VII. CONCLUSION

With the progress of science and technology and the advent of the IoT era, WSN has been pushed to a new height in large-scale application due to its advantages such as no wiring, strong invulnerability, timely information dissemination and low power consumption. However, the characteristic of no wiring also leads to the energy can not be supplied directly to sensor nodes, only the battery with limited energy can provide energy to the nodes. Therefore, it is of great significance to design an energy-efficient routing protocol for WSNs. In this paper, the problem of minimizing the energy consumption of WSNs is studied. and an energy efficient routing protocol based on improved artificial bee colony algorithm is proposed. The goal of the proposed algorithm is to balance the energy consumption and improve the energy efficiency under the constraint of the limited power of the sensor nodes, thereby extending the network lifetime. In order to select the reasonable cluster heads in the first round, this paper uses the improved ABC algorithm to optimize the fuzzy C-means clustering, cluster the network nodes, and select the optimum cluster heads when all nodes have the same energy levels. In the stable transmission phase, this paper introduces a polling control access mechanism based on busy/idle nodes, instead of the TDMA mechanism used by common protocols, which saves energy and improves network throughput. The simulation results show that the proposed algorithm has good performance in energy consumption balance, energy efficiency, network life, network stability period and network throughput. Because this work is carried out under the premise of fixed network, which makes the proposed algorithm have some limitations, we plan to extend the research on energy-efficient routing protocols for WSNs to mobile networks in future work.

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ZONGSHAN WANG (Member, IEEE) was born in 1995. He is currently pursuing the M.E. degree with the School of Information Science and Engineering, Yunnan University, Kunming, China. His research interests include energy-efficient routing protocol design for wireless sensor networks based on swarm intelligence algorithms, smart city, and polling multiple access communication theory.

HONGWEI DING (Member, IEEE) was born in 1964. He is currently a Professor and a Ph.D. Supervisor with Yunnan University. His main research interests include wireless sensor networks, communication and information systems, network and communication engineering, polling multiple access communication theory, and random multiple access communication systems.

BO LI (Member, IEEE) was born in 1976. He is currently a Professor and a Master Tutor with Yunnan University. His main research interests include wireless sensor networks, edge computing, communication and information systems, network and communication engineering theory, and random multiple access communication systems.

LIYONG BAO (Member, IEEE) received the Ph.D. degree from the School of Information Science and Engineering, Yunnan University. He is currently an Associate Professor with Yunnan University. His main research interests include wireless sensor networks, information systems, and polling multiple access communication theory.

ZHIJUN YANG (Member, IEEE) received the Ph.D. degree from the School of Information Science and Engineering, Yunnan University. He is currently a Senior Fellow with the Yunnan Education Department, Yunnan. His research interests include wireless sensor networks, information systems, and polling multiple access communication systems.