Hindawi
Journal of Sensors
Volume 2021, Article ID 5051863, 13 pages
https://doi.org/10.1155/2021/5051863

Research Article

Adaptive Chaotic Ant Colony Optimization for Energy Optimization in Smart Sensor Networks

Wenxian Jia,[1] **Menghan Liu**,[1] **and Jie Zhou**[1,2]

[1]*College of Information Science and Technology, Shihezi University, Shihezi 832000, China*
[2]*Xinjiang Tianfu Information Technology Co., Ltd., China*

Correspondence should be addressed to Jie Zhou; jiezhou@shzu.edu.cn

Received 14 April 2021; Revised 8 June 2021; Accepted 18 June 2021; Published 5 July 2021

Academic Editor: Omprakash Kaiwartya

Smart sensor network has the characteristics of low cost, low power consumption, real time, strong adaptability, etc., and it has a wide range of application prospects in the agricultural field. However, the smart sensor node is limited by its own energy; it also faces many bottlenecks in agricultural applications. Therefore, balancing the energy consumption of nodes and extending the life of the network are important considerations in the design of efficient routing for smart sensor networks. Aiming at the problem of energy constraints, this paper proposes an intelligent sensor network clustering algorithm based on adaptive chaotic ant colony optimization (ACACO). ACACO introduces logical chaotic mapping to interfere with the pheromone on the initial path and uses the adaptive strategy to improve the transition probability formula. After selecting the best next hop node, the advancing ants are released to update the local pheromone, and the current pheromone content is adjusted by the chaos factor. When the ants determine the path, they release subsequent ants to update the global pheromone. The simulation results show that ACACO has obvious advantages over genetic algorithm (GA) and particle swarm optimization (PSO).

1. Introduction

Smart sensor networks use smart sensors to collect environmental information in the monitored area, which have changed the way of interaction between humans and nature, which greatly expanded human perception. And smart sensor networks are widely used, such as realizing the monitoring of forest factors such as temperature, humidity, and light in forest environmental protection. In terms of security, the monitoring of late arrivals is realized by deploying sensor nodes in public places [1], implementing campaign tactical reconnaissance against enemy targets in the military field to monitor the enemy's real-time dynamics, and, in terms of wildlife protection, the deployment of sensor nodes to monitor the activities of wild animal groups, and so on.

Many key areas of smart sensor networks are worth studying, such as energy management [2, 3], data privacy protection, node location monitoring, and network routing settings. Although the application prospect is very impressive, many problems are still exposed. For example, the cluster head node of the traditional network is arbitrarily selected, without considering factors such as transmission distance. In addition, smart sensor nodes are generally deployed in unmanned areas with harsh conditions, and the access of nodes to the network increases the difficulty of network maintenance. In addition, power replacement under centralized management is impractical and difficult to achieve. Therefore, the irreplaceability of node power makes the energy consumption problem particularly important compared to other key technologies of smart sensor networks. Without affecting performance, designing an effective energy consumption control strategy has become a core issue in smart sensor networks.

It is worth mentioning that the cluster head node of the traditional network is arbitrarily selected, without considering factors such as transmission distance, which will cause excessive power consumption of public nodes [4–6]. In addition, some large-scale and vulgar mobile smart sensor networks have complex structures and changeable topologies. At the same time, the communication distance between sensor nodes is also limited. Therefore, how to select cluster head nodes for clustering in smart sensor networks and

design an effective energy consumption control strategy while ensuring the completion of the detection task has become the core issue in smart sensor networks [7–9].

Taking energy optimization as the starting point, this paper studies and designs a clustering algorithm based on ACACO to reduce the energy consumption of smart sensor single-round communication as much as possible. To verify the effectiveness of the algorithm, we compare it with two heuristic artificial intelligence algorithms, which are GA [10, 11] and PSO [12]. The contributions of this research are as follows:

(1) We propose a new smart sensor clustering model with randomly distributed nodes. We also define the energy consumption formula for network transceivers and calculate the total energy consumption of the network

(2) Different from the traditional ant colony optimization (ACO) [13, 14] to solve the cluster optimization problem, this paper proposes a new intelligent ACACO. It uses chaotic mapping to perturb the pheromone update and then uses an adaptive path selection strategy. This improves the usability of the algorithm and avoids falling into local optima. What is more important, ACACO balances the energy consumption of nodes and prolongs the life of the network, thereby solving the problem of energy constraints, enabling effective use of resources and reducing industrial costs

The structure of the paper can be expressed as follows. In Section 2, the related work is discussed. Then, in Section 3, the sensor clustering model and the evaluation of the energy consumption of smart sensor networks are introduced. In Section 4, ACACO based on ant colony optimization is proposed for minimizing the energy consumption of smart sensor networks. Section 5 introduces and discusses the performance of the proposed model and algorithm through simulation experiments. Finally, the conclusion part is given in Section 6.

2. Related Work

Compared with other traditional networks, smart sensor networks not only meet the high-quality service requirements of high throughput or low transmission delay but also pay attention to energy utilization and extend the lifespan of the network. In practical applications, smart sensors are usually deployed randomly at one time, and power replacement under centralized management becomes impractical. However, smart sensor nodes are powered by limited memory and batteries, and smart sensor networks consume a lot of energy in practical applications. Therefore, the energy efficiency of smart sensor nodes basically determines the life cycle of smart sensor networks, which is crucial to the overall network life. In order to extend the service life, smart sensor networks can save a lot of energy for the network through clustering. The correct choice of cluster head is one of the solutions to this problem. In the work of selecting cluster heads, the commonly used methods are as follows:

(1) Use improved artificial intelligence algorithms when optimizing cluster head selection

(2) Improve the objective function to balance the energy consumption of nodes

In paper [15], a subtractive clustering algorithm is proposed. The solution relies on subtractive clustering to generate cluster head nodes in densely populated areas. The algorithm solves the problem of the ownership of noncluster head nodes so that the consumption of the entire network is evenly distributed and reduces the energy consumption of a part of the network. However, the algorithm converges slowly and its run time is long.

Paper [16] proposes an improved PSO-based fuzzy clustering algorithm. It designs a new objective function by optimizing the movement of particles and specifies a suitable cluster head. That solution overcomes the problems of hot spots and energy holes, but in actual operation, when the number of iterations increases, it is easy to cause premature convergence.

In the paper [17], the chaotic monkey algorithm was used to establish a problem model for the low-energy clustering problem. Simulation experiments show that there is indeed higher energy efficiency in large-scale wireless sensor networks, but it falls into local convergence in smart sensor networks.

In addition to optimizing artificial intelligence algorithms, there are also ways to extend the life of the network by optimizing energy budgets. For example, in data collection or surveillance, unmanned aerial vehicles (UAV) are used to create a more flexible data collection platform, and then, the optimal cluster head selection strategy is proposed. As shown in paper [18], it installs sensors for each UAV and then uses the average remaining energy of the sensor nodes, channel conditions, and Euclidean distance to select cluster head nodes. Although the lifespan of the network has increased compared with the traditional solution, the algorithm complexity is too high to accept.

3. System Model

First of all, the following assumptions are given for the network model.

Assumption 1. The monitoring environment of smart sensor networks is a regular shape, and the sensor nodes are randomly and discretely distributed in the monitoring area.

Assumption 2. All sensor nodes have the same initial energy, and it consumes information when sending, fusing and transmitting. With the same power, the data communication capability is the same, the energy of the base station is not limited, and it is always in a normal working state. Other nodes have limited energy, and they are judged as dead nodes after the energy is zero.

Assumption 3. According to the distance between nodes, the transmission power of each node can be flexibly selected, and the communication between nodes is not restricted.

3.1. Topological Structure Model. Based on the above-mentioned hypothetical network model, the types of smart sensor nodes can be divided into cluster head nodes, gateway nodes, and perception nodes. Among them, the perception node merges the data it monitors and sends it to the cluster head node in a single hop. After that, the cluster head node receives the data from the perception node, then performs data fusion, and finally sends it to its corresponding gateway node. Then, the gateway node aggregates the data and gives it to the cluster head node. The user does further analysis and processing. Then, the user sends the monitoring task to the gateway node and distributes the monitoring target in the network. In the initial state, all nodes with the same state evolve into nodes with the above-mentioned different functions based on the routing protocol and form the topology as shown in Figure 1.

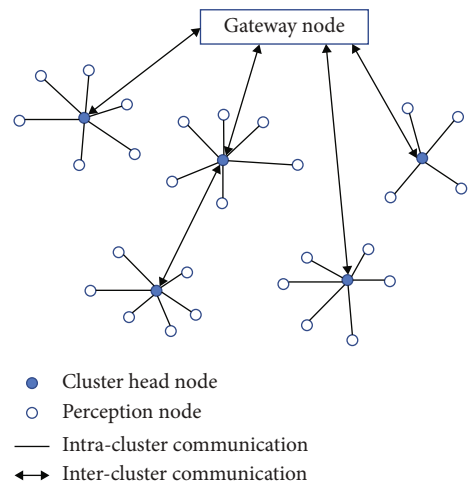


Figure 1: ACACO cluster structure.

3.2. Energy Consumption Model. This part adopts the energy consumption model in LEACH protocol, that is, different models are adopted according to different distances. To reduce the energy consumption of the network while being restricted by the communication distance of nodes, smart sensor networks must develop efficient clustering schemes for reasonable clustering. The energy consumption of smart sensor networks is mainly composed of communication energy consumption, perception energy consumption, and microprocessing energy consumption. Research shows communication energy consumption such as sending and receiving accounts for more than half of the energy consumption of smart sensor networks. At the same time, the perceived energy consumption and microprocessing energy consumption are relatively fixed, and it is not easy to optimize and reduce them. This part mainly focuses on how to reduce the communication energy consumption of smart sensor networks through reasonable clustering.

The energy consumption formula for sending bit data is shown in

$$\text{cost}_s(k, d) = \begin{cases} E_{\text{elec}}k + \varepsilon_{\text{fs}}kd^2, d < d_0, \\ E_{\text{elec}}k + \varepsilon_{\text{amp}}kd^4, d > d_0, \end{cases} \quad (1)$$

where $\text{cost}_s(k, d)$ is the energy consumed by the sending node to send k bits of data to the receiving node with a distance of d. E_{elec} is the electronics energy parameter, ε_{amp} is the power amplification parameter in the multipath fading channel model, and d is the transmission distance between the sending node and the perception node. Among them, ε_{fs} is the power amplification parameter in the free space propagation model.

When the distance between the sending node and the perception node is less than d_0, the free space propagation model (power loss is proportional to d^2) is used. Otherwise, the multipath fading channel model is used (power loss is proportional to d^4).

The energy consumption of the perception node to receive k bits data can be obtained by

$$\text{cost}_r(k) = E_{\text{elec}}k, \quad (2)$$

where $\text{cost}_r(k)$ is the energy consumed by the perception node to receive k bits data.

4. ACACO for Energy Consumption in Smart Sensor Networks

The traditional clustering routing protocol adopts a random selection method in the election of cluster head nodes, and the possibility of obtaining the optimal clustering is low, which leads to uneven distribution of nodes and high energy consumption for communication within the cluster. To solve this problem, the cluster head node set is selected from the candidate cluster head node set to complete the initialization of the cluster head node, and ACACO is used to optimize the cluster head node set.

4.1. Population Initialization. We use binary individual coding to cluster. First, we number the Q sensor nodes in the area except the gateway node with natural numbers. The binary code of an individual can be represented by a vector. The number "1" means that the sensor at the corresponding position on the vector is a cluster head node, and the number "0" means that the sensor node at the corresponding position on the vector is a perception node. For example, if there are a total of 8 nodes in smart sensor networks and the individual code is "00101011", it means that nodes 3, 5, 7, and 8 are cluster head nodes, and the remaining nodes are perception nodes. The perception node only clusters with the nearest cluster head node, so no coding is required.

In smart sensor networks with Q sensors, as the number of individuals in the population is N and the cluster heads

number is M, the population coding and constraint conditions can be expressed as the matrix form shown in

$$F = \begin{bmatrix} f_{1,1} & f_{1,2} & \cdots & f_{1,Q-1} & f_{1,Q} \\ f_{2,1} & f_{2,2} & \cdots & f_{2,Q-1} & f_{2,Q} \\ \vdots & \vdots & f_{n,q} & \vdots & \vdots \\ f_{N-1,1} & f_{N-1,2} & \cdots & f_{N-1,Q-1} & f_{N-1,Q} \\ f_{N,1} & f_{N,2} & \cdots & \mathrm{f}_{N,Q-1} & f_{N,Q} \end{bmatrix} = \begin{bmatrix} F_1 \\ \vdots \\ F_n \\ \vdots \\ F_N \end{bmatrix}, \tag{3}$$

$$\sum_{q=1}^{Q} f_{n,q} = M, \ (n\epsilon\{1, 2, \cdots, N\}). \tag{4}$$

In formula (3), $f_{n,q} = 1$ means that the qth sensor in the nth individual is a cluster head node. If it is 0, it is a perception node. Formula (4) constrains the cluster head node number in each individual in smart sensor networks to a fixed value M.

4.2. Fitness Value. In the clustering scheme of smart sensor networks for the purpose of optimizing the energy consumption of a single round of transmission, the ACACO objective function can be expressed in the form shown in

$$\mathrm{fit}(F_n) = \mathrm{cost}_s(k, d) + \mathrm{cost}_r(k). \tag{5}$$

Formula (5) indicates that the communication energy consumption of a single round is the sum of the perception energy consumption and the sending energy consumption in formulas (1) and (2).

4.3. Initial Pheromone Improvement. To ensure that the ACACO can search for multiple transmission paths in the initial stage, this chapter designs and improves the initial state path pheromone. ACACO introduces a chaotic mapping mechanism and replaces the traditional ACO with a chaotic operator to optimize the solution. The reciprocal distance is used to represent the initial pheromone concentration, thereby jumping out of the limitation of the suboptimal path solution. The initial pheromone is obtained by using logistic mapping of the typical nonlinear chaotic sequence in chaos theory, which is defined as

$$\tau_{ij}(t+1) = \mu\tau_{ij}(t)\left(1 - \tau_{ij}(t)\right) \quad \tau_{ij} \in (0, 1), \tag{6}$$

where $\tau_{ij}(t)$ represents the pheromone concentration on the initial path from cluster node i to perception node j in the $(t+1)^{\text{th}}$ iteration and μ is the logistic parameter.

4.4. Transition Probability Formula. In ACACO, a binary route of an ant can be generated according to the pheromone intensity and visibility to update the current optimal solution. The ant's movement rules and transition probability can be shown in

$$P_{ij}^{k}(t) = \frac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{j\epsilon \mathrm{allowed}_k} \tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}. \tag{7}$$

Among them, $\eta_{ij}^{\beta}(t)$ represents the path enlightenment information from node i to node j. α is the pheromone track intensity, and β is the path visibility. $\mathrm{allowed}_k$ represents the set of perception nodes that ant k has not visited and is stored in the taboo table.

$\eta_{ij}^{\beta}(t)$ is calculated as formula (8). When the energy consumption from the current cluster head node i to the perception node j is less than the original energy consumption, the path enlightenment information is the distance. In this model, the nodes selected by the ants are the cluster heads in smart sensor networks. In order to evenly distribute the cluster heads in the monitoring area to reduce energy consumption, instead of clustering them together, we tentatively determine that the larger the distance between the cluster heads, the better. As the number of iterations increases, the optimal solution will be selected according to the termination condition.

$$\eta_{ij}^{\beta}(t) = \begin{cases} d_{ij}, \text{ if } \mathrm{fit}'(j) < \mathrm{fit}(j), \\ 0, \text{ otherwise}, \end{cases} \tag{8}$$

where $\mathrm{fit}(j)$ is the original fitness value and $\mathrm{fit}'(j)$ is the current fitness value.

4.5. Pheromone Update Strategy. Ants release pheromone during the path search. To prevent the accumulation of too much pheromone and cause the algorithm to stagnate, a pheromone volatilization mechanism is introduced. The pheromone update operation is performed after a complete access path. The specific calculation formula is shown as

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t), \quad \rho \in (0, 1), \tag{9}$$

where $(1-\rho)\tau_{ij}(t)$ represents the pheromone volatilization process and ρ is the pheromone volatilization rate. $\Delta\tau_{ij}(t)$ is the pheromone increase mechanism and the calculation method is as follows:

$$\Delta\tau_{ij}(t) = \begin{cases} \sum_{k=1}^{m} \frac{Q}{L_k} & \text{, if the } k^{\text{th}} \text{ ant passes through the path } (i, j) \text{ in this cycle\#}, \\ 0, \text{ otherwise} \end{cases} \tag{10}$$

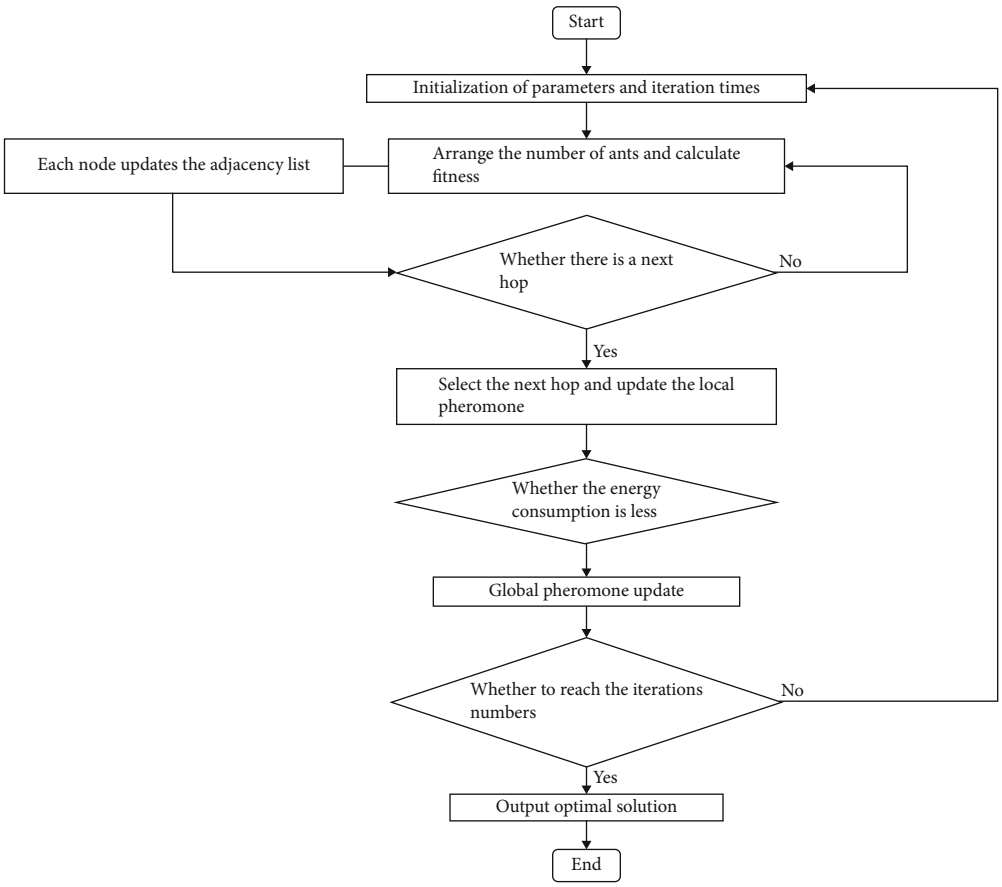


Figure 2: Steps of ACACO.

Table 1: Parameters of the simulation.

Parameter	Parameter symbol	Value
Electronics energy parameter	E_{elec}	50 nJ/bit
Power amplification parameter in the multipath fading channel model	ε_{fs}	10 PJ/(bit × m^2)
Power amplification parameter in the free space propagation model	ε_{amp}	0.013 PJ/(bit × m^4)

where Q is the pheromone constant and L_k is the total length of road by the kth ant in this cycle.

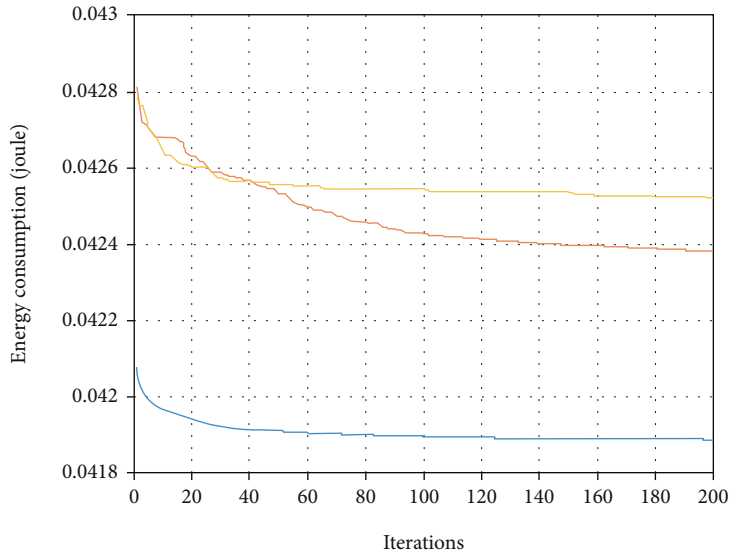
4.6. Adaptive Selection Strategy of Ant Enlightenment Information. After all the ants in the ant colony have moved, the enlightenment information of the ants needs to be updated according to the optimal solution of the previous iteration. In order to collect node and path information in the search process and give positive feedback to the final complete path information, ACACO designs an elite selection strategy.

Set to the t generation, $a(t)$ in the population is the best individual. Assume that $a(t+1)$ is a new generation population. If there is no better individual than $a(t)$ in $a(t+1)$, add $a(t)$ to $a(t+1)$. $a(t)$ will be the nth individual of $a(t+1)$. Here, n is the size of the population. In order to maintain a certain population size, if elite individuals are added to the new population, the individual with the smallest fitness value in the new population needs to be removed.

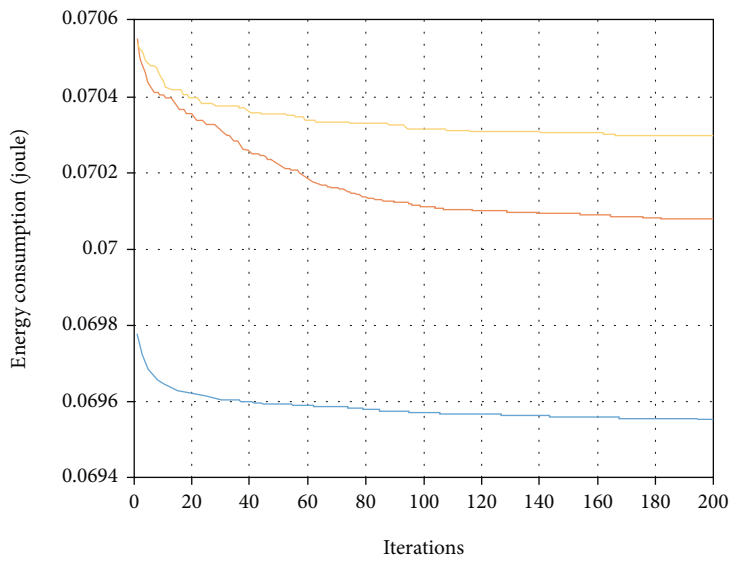
Table 2: Parameters of the ACACO.

	α	β	ρ	Q	μ
ACACO	2	3	0.9	20	0.5

It can be seen from formula (8) that the distance between nodes in this cycle of ants has been selected by elites. Nodes with small path distances are eliminated directly, leaving large distances and increasing the proportion of large path distances. Therefore, the possibility of selecting a node with a large distance to become the cluster head increases, thereby reducing the energy consumption between the cluster head node and the sensing node. Therefore, the elite selection node

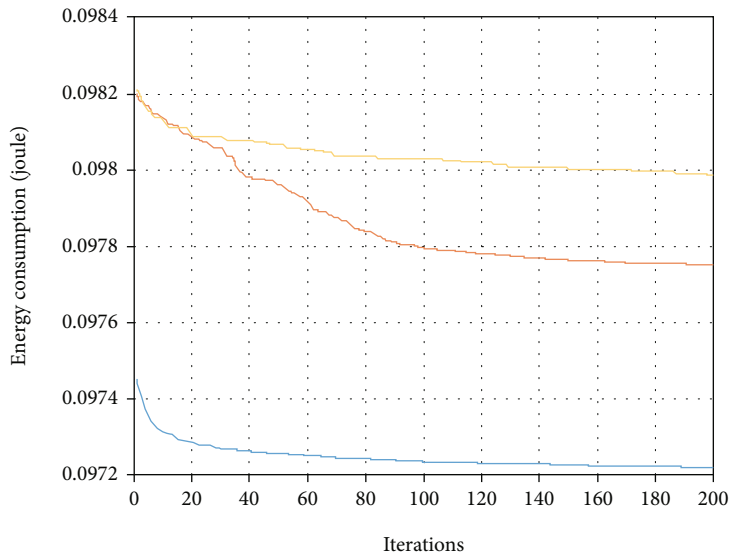


(a)

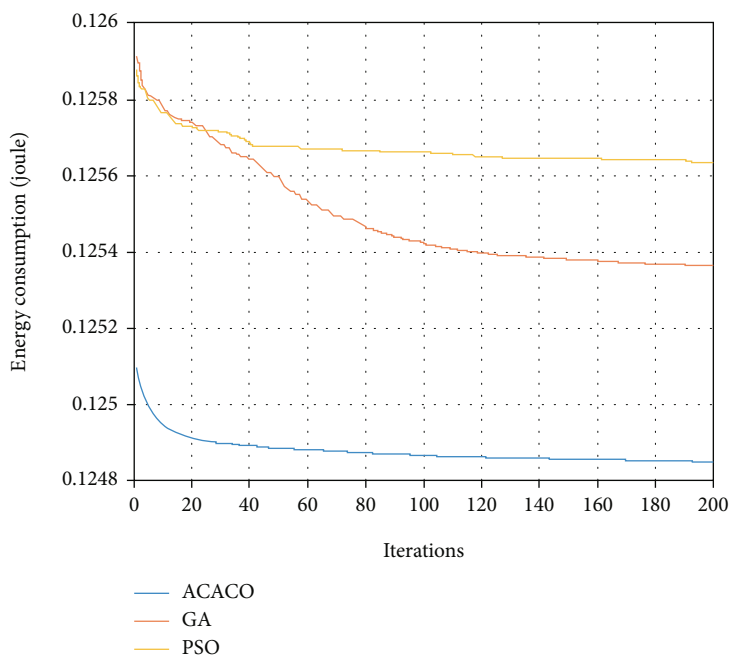


(b)

Figure 3: Continued.



(c)



(d)

Figure 3: The energy consumption of the three algorithms under different numbers of nodes: (a) 150 node number, (b) 250 node number, (c) 350 node number, and (d) 450 node numbers.

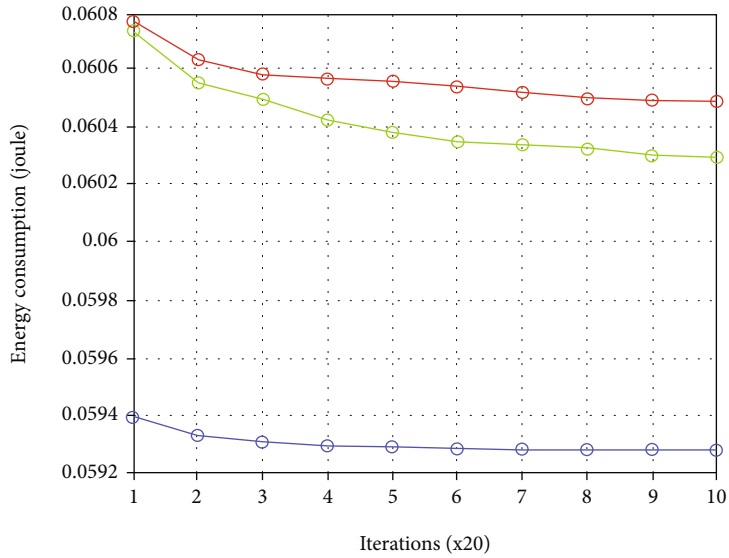
strategy can effectively improve the fitness of weakened ants, thereby improving the overall fitness of the ant colony.

4.7. Termination Condition. The termination condition is the criterion by which ACACO decides whether to continue operation or stop. In the process of repeating the iterative loop, until the solution of the predetermined iterations number is reached. When the target value reaches a certain threshold, ACACO will terminate according to the iteration number. After the maximum iteration number, the process is terminated, and the individual with the lowest network energy consumption in the community is the final solution.

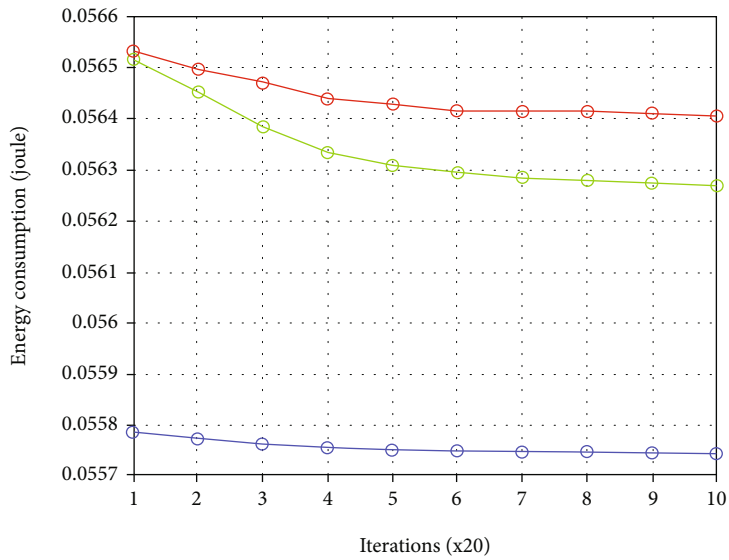
4.8. The Steps of ACACO. The specific steps of ACACO are as follows.

Step 1. The initial ant colony is generated by logistic chaotic mapping, and the parameter initialization includes parameters such as initialization pheromone and various heuristic factors; at the same time, update the number of iterations.

Step 2. Deploy m ants on the original cluster head node and calculate fitness.

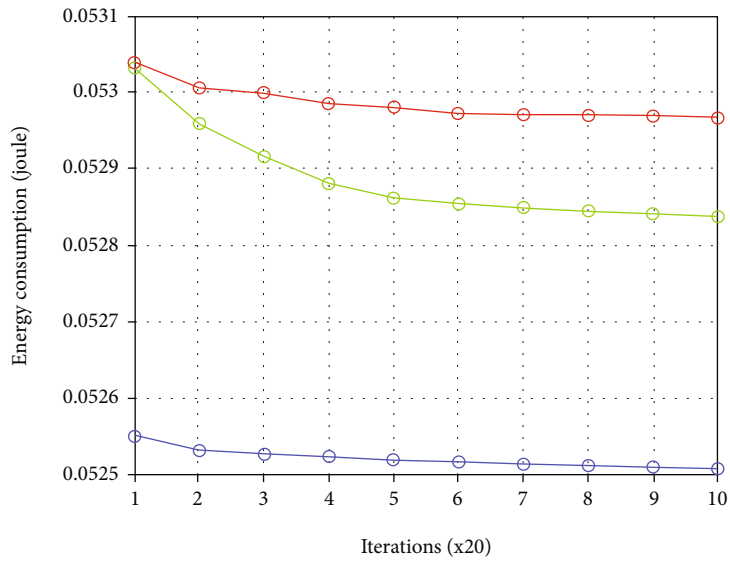


(a)

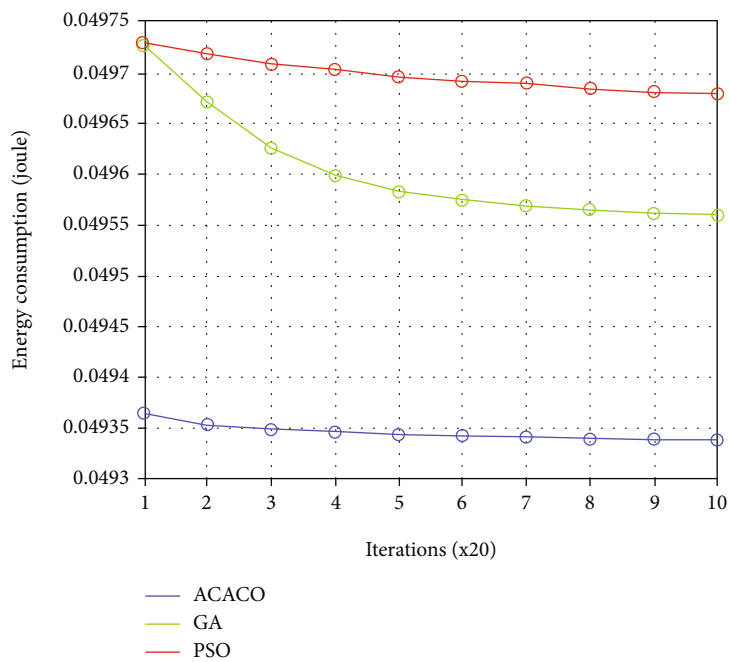


(b)

Figure 4: Continued.



(c)



(d)

Figure 4: The energy consumption of the three algorithms under different cluster head probabilities. (a) The cluster head probability is 5%. (b) The cluster head probability is 10%. (c) The cluster head probability is 15%. (d) The cluster head probability is 20%.

Step 3. Measure the specific position of each ant and update the adjacency list.

Step 4. Check whether there is a next-hop node to be selected in the adjacency list; if it does not exist, expand the search radius and update the adjacency list; if it exists, go to Step 5.

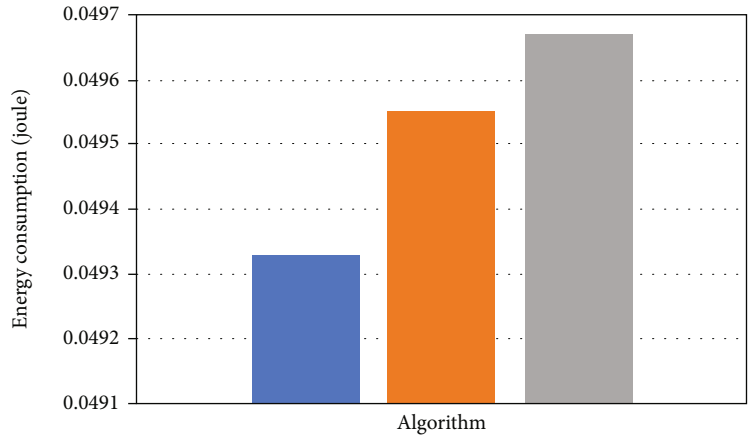
Step 5. According to the transition probability formula, select the next hop node.

Step 6. Record and update node and path information, and perform local pheromone update operations.

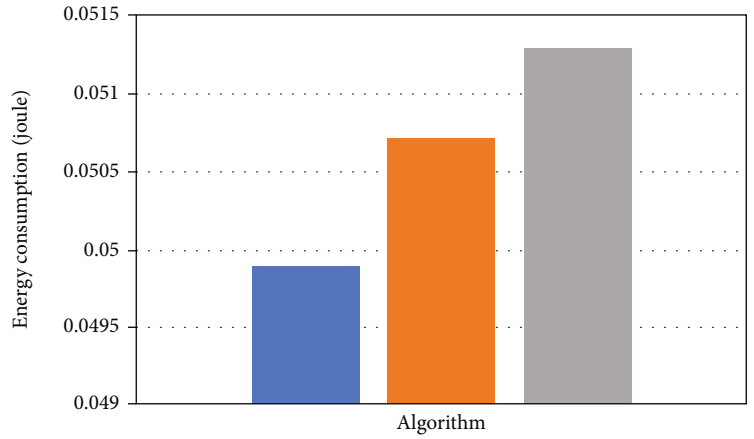
Step 7. Determine whether the energy consumption of m ants is less than the previous one; if yes, execute the elite selection strategy and update the global pheromone; if not, release the ants again.

Step 8. Determine whether the number of iterations of the algorithm is met; if the conditions are not met, continue to iteratively execute Steps 3–7, and terminate the algorithm if the conditions are met and output the result.

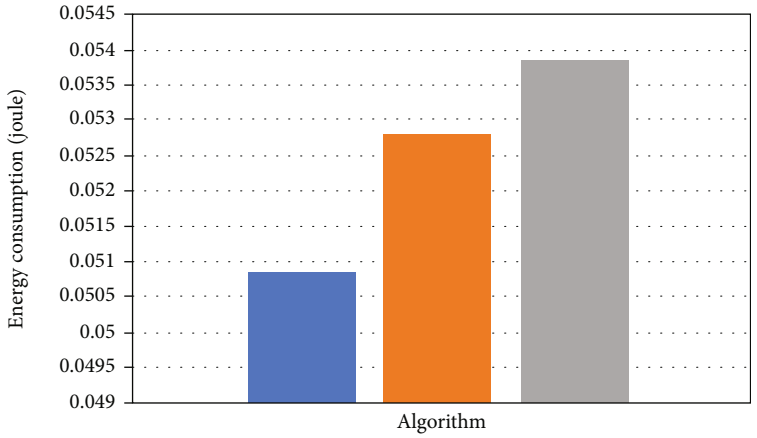
The concrete simulation flowchart is shown in Figure 2.



(a)

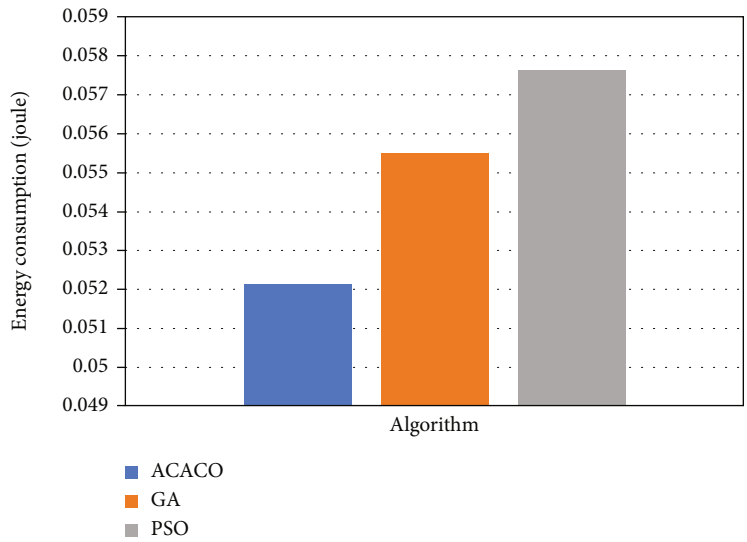


(b)



(c)

Figure 5: Continued.



(d)

Figure 5: The energy consumption of the three algorithms under different monitoring areas. (a) The monitoring area is 100 × 100 m. (b) The monitoring area is 200 × 200 m. (c) The monitoring area is 300 × 300 m. (d) The monitoring area is 400 × 400 m.

5. Results and Discussion

This paper uses MATLAB R2018a environment to carry out simulation experiments of three algorithms. To ensure the accuracy of the experimental data, the simulation experiment is run 50 times and the average value is taken as the experimental result. In this section, we compare how different node numbers, cluster head ratios, and monitoring area affect the energy consumption of smart sensor networks.

We uniformly define the parameters for calculating sensor energy consumption in smart sensor networks, to compare these three algorithms under the same experimental conditions. The iteration number is set to 200 generations, the population size is 40, and the coordinates of the nodes are randomly generated in this area. The specific parameters of ACACO are in Table 1.

The key to affecting the behavior and performance of genetic algorithms is the possibility of crossover and mutation. Therefore, in this simulation calculation, as a comparison algorithm, the crossover probability of GA is set to 0.9, and the mutation probability is 0.05. Besides, in PSO, the maximum speed determines the maximum moving distance of the particles in a cycle, which is set to 4. Both cognitive and social parameters are set to 2, namely, $c_1 = c_2$. And the specific simulation parameters of ACACO are set in Table 2. In actual data transmission, packet drop is inevitable, so the packet drop rate from the sensing node to the cluster head is set to 1% in the simulation. Correspondingly, the packet drop rate from the cluster head to the gateway is also 1%. Then, the overall packet drop rate is 98.01%.

Figure 3 shows the energy optimization in smart sensor networks based on ACACO, GA, and PSO when the sensor cluster head ratio is 0.1. In order to determine the energy consumption of the algorithm under different numbers of sensors, in the four subgraphs, the number of sensors is set to 150, 250, 350, and 450, respectively. And the monitoring area is 100 × 100 m.

It can be seen from the simulation results in Figures 3(a)–3(d) that the energy consumption value based on PSO decreases slowly with the increase of the number of iterations of the algorithm. Compared with the ACACO which dynamically adjusts the pheromone, the fixed parameters of GA are more difficult to introduce new genes, which make it difficult to reduce energy consumption. The energy consumption reduction based on PSO is relatively stable, but due to the fixed coding method, it is easy to fall into a stagnant state in the later stage of the algorithm operation. The ants in ACACO use chaotic mapping to dynamically adjust the pheromone concentration and introduce the elite selection strategy to select the next node, avoiding the phenomenon of premature convergence and evolutionary stagnation caused by the deterministic state.

Figure 4 shows the variation of the average communication energy consumption of smart sensor nodes with the ratio of sensor cluster heads when smart sensor nodes move within the monitoring area. The proportions of cluster heads for Figures 4(a)–4(d) are 5%, 10%, 15%, and 20%, respectively. The number of sensors is 200. And the monitoring area is 100 × 100 m.

It can also be seen from Figure 4(a) that when the proportion of cluster heads is 5%, the downward trend of the energy consumption of the three algorithms is not very obvious. However, the advantages of reducing communication energy consumption based on ACACO's simulated evolutionary calculation are obvious compared with the other two algorithms. When the proportion of cluster heads is 10%, 15%, and 20%, as the proportion of sensor cluster heads increases, the energy consumption of GA drops rapidly, and the evolution speed of PSO is slow.

Figure 4(b) shows that when the cluster head ratio is 10%, the PSO-based clustering method has relatively stable

performance during operation, and the energy consumption is not significantly reduced. Based on the GA-based solution for cluster head selection, the energy consumption has dropped significantly. However, compared with the fixed parameters of GA and PSO, ACACO has introduced a global update strategy. The best path obtained after the end of each generation cycle is rewarded for the pheromone content on the path with a positive feedback mechanism. This way means that at the beginning of each generation cycle, the pheromone content has been dynamically changed, the probability of selecting the best path is greatly increased, and the probability of retaining the previous generation of low-power solutions is also increased. Therefore, after the iterative cycle, the network using ACACO has the better performance in terms of energy consumption. In Figures 4(c) and 4(d), the single-round energy consumption decline trends of PSO and ACACO are similar, but ACACO converges faster.

Figure 5 better shows the energy efficiency of these three algorithms in different monitoring areas. In Figures 5(a)–5(d), we set the size of the monitoring area of smart sensor networks to 100×100 m, 200×200 m, 300×300 m, and 400×400 m in turn. The number of sensors is 200, and the cluster head ratio is 0.2.

The histogram in Figure 5 has the same trend. It can be seen that the clustering method based on ACACO calculation requires less average communication energy consumption of nodes, which can effectively improve energy utilization efficiency.

6. Conclusions

We propose a clustering algorithm based on ACACO, which uses heuristic simulation evolution calculation method to dynamically select the number and location of cluster heads to reduce the energy consumption of smart sensor networks. In the iterative process, the algorithm dynamically changes the algorithm parameters through chaotic mapping, avoiding premature convergence, and at the same time, the convergence speed is faster. We also dynamically update the global pheromone content and adopt an adaptive strategy to select the best individual. The simulation results show that compared with the other two schemes, the proposed clustering scheme based on ACACO calculation can effectively reduce the single-round communication energy consumption of smart sensor networks. This paper only considers a single case where there is only one base station in the scenario. When there is a many-to-many relationship between the optional base station and the cluster head node, how to effectively allocate transmission tasks to optimize the network lifespan needs to be considered from multiple perspectives in the future.

Data Availability

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

Disclosure

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

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgments

This paper was funded by the Corps Innovative Talents Plan, grant number 2020CB001; the Project of Youth and Middle-Aged Scientific and Technological Innovation Leading Talents Program of the Corps, grant number 2018CB006; the China Postdoctoral Science Foundation, grant number 220531; the Funding Project for High-Level Talents Research in Shihezi University, grant number RCZK2018C38; and the Project of Shihezi University, grant number ZZZC201915B.

References

[1] P. K. Kashyap, S. Kumar, A. Jaiswal, M. Prasad, and A. H. Gandomi, "Towards precision agriculture: IoT-enabled intelligent irrigation systems using deep learning neural network," *IEEE Sensors Journal*, p. 1, 2021.

[2] S. K. Aanchal, O. Kaiwartya, and A. H. Abdullah, "Green computing for wireless sensor networks: optimization and Huffman coding approach," *Peer-to-Peer Networking and Applications*, vol. 10, no. 3, pp. 592–609, 2017.

[3] S. Kumar, O. Kaiwartya, M. Rathee, N. Kumar, and J. Lloret, "Toward energy-oriented optimization for green communication in sensor enabled IoT environments," *IEEE Systems Journal*, vol. 14, no. 4, pp. 4663–4673, 2020.

[4] F. Lin, W. Dai, W. Li, Z. Xu, and L. Yuan, "A framework of priority-aware packet transmission scheduling in cluster-based industrial wireless sensor networks," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 8, pp. 5596–5606, 2020.

[5] Y. Cao and Z. Wang, "Combinatorial optimization-based clustering algorithm for wireless sensor networks," *Mathematical Problems in Engineering*, vol. 2020, 13 pages, 2020.

[6] A. Pathak, "A proficient bee colony-clustering protocol to prolong lifetime of wireless sensor networks," *Journal of Computer Networks and Communications*, vol. 2020, Article ID 1236187, 9 pages, 2020.

[7] L. Chen, W. Liu, D. Gong, and Y. Chen, "Clustering and routing optimization algorithm for heterogeneous wireless sensor networks," in *International wireless communications and Mobile computing (IWCMC)*, pp. 407–411, Limassol, Cyprus, 2020.

[8] H. L. Wang, G. B. Zhou, L. Bhatia, Z. C. Zhu, W. Li, and J. A. McCann, "Energy-neutral and QoS-aware protocol in wireless sensor networks for health monitoring of hoisting systems," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 8, pp. 5543–5553, 2020.

[9] F. Sanhaji, H. Satori, and K. Satori, "Cluster head selection based on neural networks in wireless sensor networks," in *2019 International Conference on Wireless Technologies, Embedded and Intelligent Systems (WITS)*, pp. 1–5, Fez, Morocco, 2019.

[10] P. K. Kashyap and S. Kumar, "Genetic-fuzzy based load balanced protocol for WSNs," *International Journal of Electrical & Computer Engineering*, vol. 9, no. 2, pp. 1168–1183, 2019.

[11] S. H. Sackey, J. Chen, A. J. Henry, and X. Zhang, "A clustering approach based on genetic algorithm for wireless sensor network localization," in *2019 15th international conference on computational intelligence and security (CIS)*, pp. 54–58, Macao, China, 2019.

[12] S. Kumar and S. Mehfuz, "A PSO based malicious node detection and energy efficient clustering in wireless sensor network," in *2019 6th International Conference on Signal Processing and Integrated Networks (SPIN)*, pp. 859–863, Noida, India, 2019.

[13] P. S. Lakshmi and M. G. Jibukumar, "Energy efficient MAC protocol for lifetime maximization in wireless sensor networks," in *2018 IEEE 13th international conference on industrial and information systems (ICIIS)*, pp. 191–195, Rupnagar, India, 2018.

[14] M. Abdelhafidh, M. Fourati, L. C. Fourati, A. B. Mnaouer, and M. Zid, "Linear WSN lifetime maximization for pipeline monitoring using hybrid K-means ACO clustering algorithm," in *2018 Wireless Days (WD)*, pp. 178–180, Dubai, United Arab Emirates, 2018.

[15] L. Chen, W. Liu, D. Gong, and Y. Chen, "Cluster-based routing algorithm for WSN based on subtractive clustering," in *2020 International Wireless Communications and Mobile Computing (IWCMC)*, pp. 403–406, Limassol, Cyprus, 2020.

[16] G. Kadiravan and P. Sujatha, "PSO based clustering approach for mobile wireless sensor network," in *2019 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN)*, pp. 1–5, Pondicherry, India, 2019.

[17] Y. Lu, J. Zhou, and M. Xu, "A biologically inspired low energy clustering method for large scale wireless sensor networks," in *2019 IEEE International Conference of Intelligent Applied Systems on Engineering (ICIASE)*, pp. 20–23, Fuzhou, China, 2019.

[18] S. K. Haider, M. A. Jamshed, A. Jiang, H. Pervaiz, and Q. Ni, "UAV-assisted cluster-head selection mechanism for wireless sensor network applications," in *2019 UK/ China Emerging Technologies (UCET)*, pp. 1-2, Glasgow, UK, 2019.