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Multi-factor Clustering Routing Algorithm for Wireless Sensor Networks based on Improved Butterfly Optimization Algorithm

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Abstract. *The main part of network energy consumption is data transmission in wireless sensor networks. The key to extending network lifespan is to improve clustering routing algorithms based on energy constraints and optimize network energy. This study combines the wireless sensor networks and particle swarm optimization algorithm, introduces Circle mapping and convergence factor to perfect the butterfly optimization algorithm. Finally, based on the improved algorithm, a clustering routing algorithm is designed to gain the optimal cluster head. The test results show that the first node death time of IBA-LEach algorithm is 3.96%, 15.6% and 24.3% longer than that of GWO-LEACH, EHO-LEACH and IGA-LEACH algorithm, respectively. The death times for all nodes in the four algorithms are as follows: 1423, 1238, 1197, and 9561 rounds, respectively. The improved algorithm has a higher number of rounds in which node energy is depleted, indicating that the performance of the designed algorithm is greater. The constructed algorithm for energy optimization in wireless sensors can efficiently identify the optimal cluster head, prolong the lifespan of nodes, and offer specific benefits in reducing energy loss and extending the network's lifespan.*
Keywords:BOA; PSO; Wireless sensor network; Clustering routing algorithm; Cluster head

1. **Introduction.** The expansion of information technology and wireless networks has resulted in a rise in data acquisition, processing, and analysis demand, as well as an increased demand for sensor technology. Wireless Sensor Networks (WSN) collect, process, analyze, and transmit surrounding data by controlling sensor nodes to connect network space and the external world [1, 2]. WSN has dramatically altered the way in which individuals obtain data and interpret reality. Traditional WSN consists of sensor nodes and base stations forming a self-organizing network with the ability to receive and send data [3]. However, traditional WSN nodes have limited battery carrying capacity, are unable to adapt to complex and ever-changing network environments, and cannot be recycled [4]. Saving energy and optimizing energy are key factors in enhancing traditional WSN. Extending the network life cycle and reducing the energy usage of sensor nodes are the focus of energy optimization, and it is also the goal of multi factor clustering routing algorithms [5]. The Clustering Routing Algorithm (CRA) mainly considers two factors: node energy

and distance in WSN, but the dynamic changes of the network increase the difficulty of CRA [6]. To optimize network energy, CRA is improved based on the principles of intelligent algorithms. Under this background, this manuscript designs an improved Butterfly Optimization Algorithm (I-BOA) built on the Particle Swarm Optimization (PSO), and then applies the I-BOA to WSN multi-factor CRA to obtain the optimal cluster head, optimize node energy consumption (EnC), and extend the network lifecycle.

This study is divided into four parts. The second part provides a review of the current research status of WSN multi-factor CRA and I-BOA. The third part proposes CRA design based on I-BOA, which has three sections. The first section explains the working principle of WSN, the second section improves BOA using PSO, and the third section applies the I-BOA to the CRA design. The fourth part conducts experimental verification on the I-BOA and CRA, and analyzes the experimental results.

2. **Related Work.** WSN is distributed with plenty of spatially distributed sensor nodes, users, and base stations. The two main issues with WSN are energy usage and the remaining lifespan of the network. Hu et al. regarded energy efficiency as a key factor affecting WSN performance, and proposed a novel energy-saving routing protocol based on the hybrid improvement optimization algorithm of whale artificial ecosystem. The protocol selected both the cluster header and other nodes by evaluating multiple fitness functions of the WSN. Experimental results showed that this protocol improved the energy efficiency of WSN and had been used to select other forwarding nodes [7]. Ashween et al. designed an energy optimized embedded routing protocol for mobile nodes. The protocol used different types of routing structures to reduce the update of sink locations, and received and identified information through Fuzzy clustering. This protocol could reduce information latency and maximize network lifespan [8]. A new three-factor authentication protocol for the sensitive data transmission of WAS was proposed by Wu et al. The security of this protocol was validated by formal and nonformal analysis, Burross-Abadii-Needham (BAN) logic, and ProVerif tools. The experimental results showed that the protocol had high security and low computational overhead. By comparing security and performance, it was proved that the protocol had high security, could resist key leakage fake attacks and known specific session temporary information attacks, and the computational cost was low [9].

To enhance WSNCRA, researchers have proposed various intelligent optimization algorithms to find the optimal cluster head and extend the network's lifespan. Heidari et al. proposed a new CRA- genetic algorithm (GA) and equilibrium optimization. Firstly, WSN nodes were clustered to select the optimal cluster head, and then the information collected by the nodes was passed into the cluster head. Then the head used a balanced optimization algorithm to send the collected data into the basestation using a multi-hop optimized routing algorithm. This new CRA had significant advantages over other algorithms in terms of network lifecycle and EnC [10]. To extend the network life, Dwivedi et al. proposed a hierarchical energy-saving routing algorithm based on grey wolf optimization (LBR-GWO) algorithm. The entire region of the sensor deployment node within the WSN was divided into four layers, with the first layer being selected as the cluster head. When there were more than two nodes in the first layer, the cluster heads were selected based on the game theory model. Otherwise, the decision was made based on the remaining energy of the nodes. The test showed that the proposed algorithm was easy to apply in clustered sensor networks compared to other algorithms [11]. Pattnaik and Sahu proposed an improved Elephant Herd Optimization (EHO) greedy algorithm with base stations as the main consideration. This method introduced mobile sinks to extend the network life cycle, used the Fuzzy clustering method to find the optimal cluster head, and finally used the improved EHO greedy algorithm to transmit WSN routing data. The improved algorithm had significant advantages in improving energy utilization and extending the network lifecycle [12]. Radhika and Sivakumar proposed a WSN (IGA-LEACH) method based on energy optimized microGA. This method combined the IGA algorithm and LEACH protocol to enhance the acquisition of cluster heads and decrease the WSN's consumption. The experimental comparison with existing routing algorithms, e. g. LEACH, LEACH-C, and LEACH GAGADA under different packet sizes and initial energy showed that the IGA-LEACH algorithm had a significant effect on improving network lifespan and reducing EnC [13].

In summary, to attempt to address the matters of WSN's fast EnC, uneven distribution of node, premature node death, and short network lifespan, this manuscript constructs a routing algorithm on the ground of energy optimization. To find the optimal cluster head, extend network lifespan, and optimize energy, WSNCRA is designed based on intelligent optimization algorithms. This study improves BOA based on PSO in intelligent optimization algorithms, resulting in I-BOA, and then designs WSN-CRA based on I-BOA. Finally, the designed algorithm is taken to search the optimal cluster-head, optimize WSN, and extend the network lifecycle.

3. **Design of WSN multi-factor CRA based on I-BOA.** Firstly, the structure and composition of WSN paths are introduced, and sensor nodes, energy supply methods, and cluster heads are analyzed. Secondly, the principles of PSO and BOA algorithms are explained, and PSO is used to improve BOA. The I-BOA introduces Circle mapping and convergence factor, and finally designs WSN-CRA in combination with I-BOA.

3.1. **Wireless sensor networks.** WSN is a distributed sensor network, and its main body is composed of sensor nodes, task management nodes, and base stations. WSN has three functions: data collection, processing, and transmission [14]. Figure 1 is the diagram of the WSN architecture.

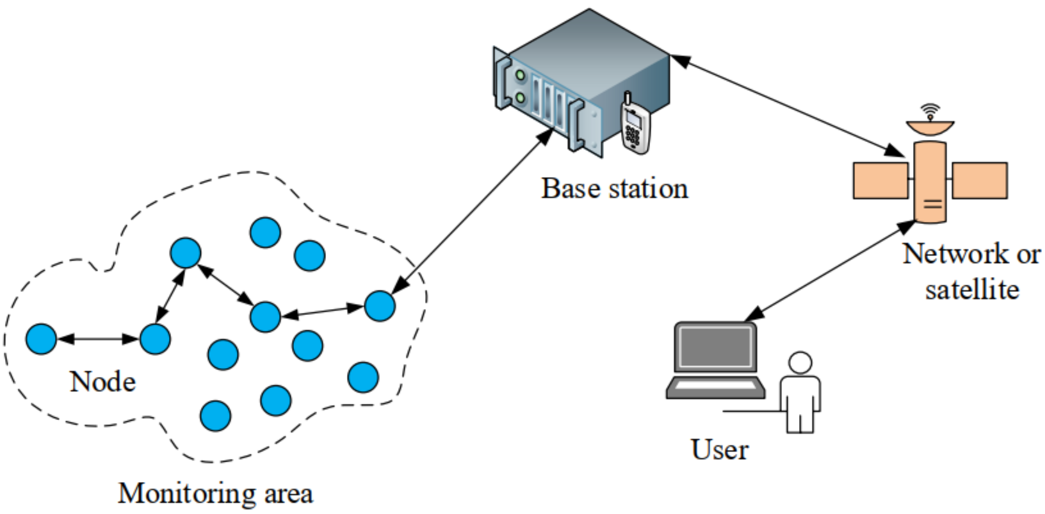

Figure 1. WSN network topology

From Figure 1, the middle layer of WSN is the base station, which can receive information from monitoring area nodes and also publish monitoring tasks from task nodes. Users, also known as task nodes, are mainly responsible for coordinating and configuring WSN, analyzing and managing data. There are a lot of sensor nodes in the monitoring area of WSN, which have sensing, signal processing, and wireless communication functions [15]. Sensor nodes are both the initiator and forwarder of information packets. The positions of the nodes are randomly and densely distributed. Figure 2 shows the sensor node architecture.

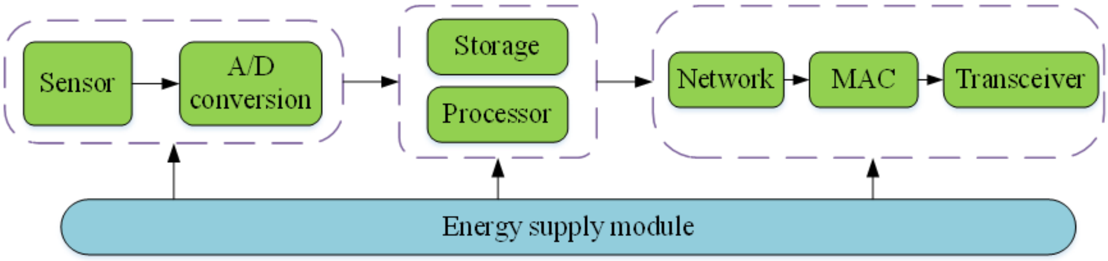

Figure 2. Sensor node architecture

From Figure 2, the sensor node consists of four modules: sensor, processor, wireless communication, and energy. The data acquisition and A/D conversion unit are the main functional unit of the sensor module. A/D conversion mainly converts collected data from analog signals to digital signals. The data acquisition unit directly affects the EnC of the sensor. The energy module provides energy to other modules to ensure the normal operation of the sensor. The wireless communication module is responsible for information exchange between sensor nodes and is the module that consumes the most energy. Improving router algorithms and optimizing data transmission paths is the key to energy optimization in WSN.

Due to the different application scopes of WSN, the topology structure also changes accordingly. According to the topology, routing algorithms can be segmented into planar routing algorithms and CRA. Although it is easy to maintain, the network structure of the former option is relatively simple, making it unsuitable for large-scale WSNs due to its high economic costs and lack of a central node [16]. CRA utilizes local and global information to construct a network topology, and adopts a two-layer communication mechanism to effectively avoid data conflicts. Therefore, this study selects CRA with good performance, as shown in Figure 3.

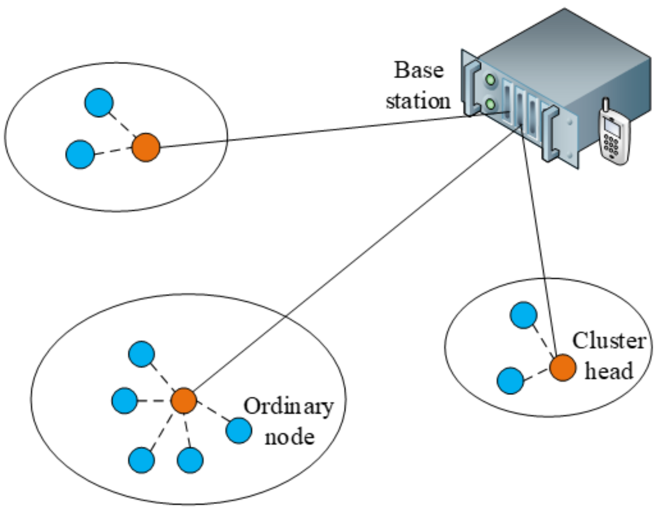

Figure 3. A diagram of the subcluster router algorithm

In Figure 3, the CRA cluster comprises WSN partitions, with the highest level designated as the cluster head. It receives data from other members of the cluster, processes it, and transmits it to the basestation. The selection of cluster heads is a particularly important step in energy optimization, and the distance and energy of sensor nodes are two important factors for selecting cluster heads. Sensor nodes are ordinary nodes in a cluster, usually far away from the base station with low capacity, responsible for sending and obtaining information.

3.2. **The improved butterfly optimization algorithm.** Excellent CRA can extend the service life of WSN and affect its energy efficiency. Cluster head selection and data transmission improvement are important steps in improving CRA. Randomly selecting unsuitable cluster heads can lead to the problem of some cluster heads having low capacity, overload, and premature death [17].

To solve this problem, the method of selecting cluster heads in this study is to use swarm intelligence optimization algorithms (IOA). This method is a commonly used intelligent algorithm in computers, and its basic theory is to simulate the behavior of animal populations such as bird swarms, bee swarms, and wolf swarms in nature. It utilizes information exchange and cooperation between groups to achieve optimization through individual interaction [18, 19]. BOA is an excellent swarm IOA designed to simulate the behavior of butterflies in nature. Each butterfly has the ability to perceive and emit fragrance [20]. The formula for calculating fragrance concentration is Equation (1).

$$f = sI^{\alpha} \tag{1}$$

In Equation (1), α represents the intensity index. I represents the stimulus intensity, and α can change f according to changes in stimulus intensity. f represents the aroma concentration perceived by the butterfly, and s represents the sensory mode. Due to the different odors of each butterfly, the s is introduced, as Equation (2).

$$s = 0.001 + \frac{0.025}{0.1 \times T_{\max}} \tag{2}$$

In Equation (2), $T_{\max}$ is the max-iterations. The probability of BOA seeking the optimal solution will increase due to the search behavior of butterflies. The formula for random initialization of butterfly populations is shown in Equation (3).

$$X = lb + rand\,(N, d) \times (ub - lb) \tag{3}$$

In Equation (3), ub is the upper limit of the search space. lb refers to the lower limit, and d represents the dimension of the space. X represents the butterfly population, denoted as $X = (X_1, X_2, \ldots, X_N)$. The d dimension vector of butterfly i is $X_i = (X_{i1}, X_{i2}, \ldots, X_{id})$.

When the random number r is greater than or equal to the conversion probability P, the BOA algorithm performs a global search, and the butterfly migrates to the most advantageous position among all positions. The expression formula is Equation (4).

$$X_i^{t+1} = X_i^t + (r^2 \times g^* - X_i^t) \times f_i \tag{4}$$

In Equation (4), g^* represents the most advantageous position among all positions. X_i^t and X_i^{t+1} are the location of the i-th butterfly in t iteration and $t+1$ iteration. i means the butterfly in the population, and r represents a random number. When $r \geq p$ is reached, a local search is carried out using the search method shown in Equation (5).

$$X_i^{t+1} = X_i^t + \left(r^2 \times X_j^t - X_k^t\right) \times f_i \tag{5}$$

In Equation (5), X_t^j and X_t^k represent the position of the t-th iteration of the random j-th and k-th butterfly. The optimal position obtained by the BOA iteration is the optimal solution of the fitness function. Although the BOA has strong global search capacity, it is prone to falling into the local optimal dilemma. PSO is a swarm intelligence algorithm that simulates the search for food by mobile bird groups in nature [20]. The particle position velocity is an important factor affecting particle search for the optimum solution in PSO. To maintain the inertia of particle movement, linear weight coefficients are introduced into the PSO algorithm. The random initialization of particle populations is Equation (6).

$$\begin{cases} V_i^{t+1} = \omega \cdot V + c_1 \cdot rand_1 \times \left(p_{best} - X_i^t\right) + c_2 \cdot rand_2 \times \left(g_{best} - X_i^t\right) \\ X_i^{t+1} = X_i^t + V_i^{t+1} \end{cases} \tag{6}$$

In Equation (6), V_t^i and V_{t+1}^i are the velocities of the i-th particle in the t-th and $t+1$-th iterations. g_{best} and p_{best} represent the global optimal and the initial position of the particle. c_1 and c_2 are generally set to 2. c_1 represents the local optimal adjustment step size, and c_2 represents the global optimal adjustment step size. ω represents the weight coefficient, while ω may have different optimization results. ω adaptively helps particles break out of the local optimal limit, as shown in Equation (7).

$$\omega\left(t\right) = \omega_{\max} - \frac{t}{t_{\max}}\left(\omega_{\max} - \omega_{\min}\right) \tag{7}$$

In Equation (7), $\omega_{\min}$ represents the minimum weight coefficient and $\omega_{\max}$ represents the maximum weight coefficient. The PSO has better global search ability and can search the better solution in the solution space. By simulating the foraging behavior of butterflies, the BOA also has a strong global search ability. Combining the two can further improve the effect of the global search, and help to find a better solution. At the same time, both the PSO and the BOA have a fast convergence speed, and can quickly find the best solution. The combination of these two can accelerate the convergence process of the algorithm, improve the quality of the solution and the efficiency of the algorithm. The PSO is easy to fall into the local optimal solution, while the BOA can maintain the diversity of the population through the foraging behavior of the butterfly. The combination of the two can avoid falling into the local optimal solution. Based on the advantages and disadvantages of both approaches, as well as their working principles, the combination of BOA and PSO can lead to improved search performance in the form of the I-BOA. I-BOA combines the advantages of BOA and PSO to improve the global search ability, local search ability, convergence speed and diversity maintenance ability of the algorithm, so as to achieve better optimization effect. The nonlinear dynamic convergence factor and Circle mapping improvement algorithm are introduced [22]. The Circle mapping is defined as Equation (8).

$$x_{d+1} = \operatorname{mod}\left(x_d + 0.2 - \left(0.5/2\pi\right)\sin\left(2\pi x_d\right), 1\right) \tag{8}$$

In Equation (8), the introduction of Circle mapping makes the initial position distribution of the population more uniform. To dynamically adjust the optimization ability and control the Rate of convergence and accuracy, the I-BOA also introduces a nonlinear dynamic convergence factor, whose formula is Equation (9).

$$\beta\left(t\right) = \beta_c \times \exp\left(-\left(4 \times t/T_{\max}\right)\right) \tag{9}$$

In Equation (9), β represents the nonlinear dynamic convergence factor, and β_c represents the initial value of the convergence factor. When $r \leq p$, the I-BOA performs a global search, as shown in Equation (10).

$$\begin{cases} X_i^t = \omega X_i^{t-1} + \left(r^2 \times X_i^k - \omega X_i^{t-1}\right) \times f_i \\ X_i^{t+1} = X_i^t + c_1 \cdot r_1 \times \left(p_{best} - X_i^t\right) + c_2 \cdot r_2 \times \left(g_{best} - X_i^t\right) \end{cases} \tag{10}$$

When $r > p$, the I-BOA performs local search, as shown in Equation (11).

$$\begin{cases} X_i^t = \beta\omega X_i^{t-1} + \left(r^2 \times g_{best} - \omega X_j^{t-1}\right) \times f_i \\ X_i^{t+1} = X_i^t + c_1 \cdot r_1 \times \left(p_{best} - X_i^t\right) + c_2 \cdot r_2 \times \left(g_{best} - X_i^t\right) \end{cases} \tag{11}$$

Based on the above formula, the I-BOA structure is Figure 4.

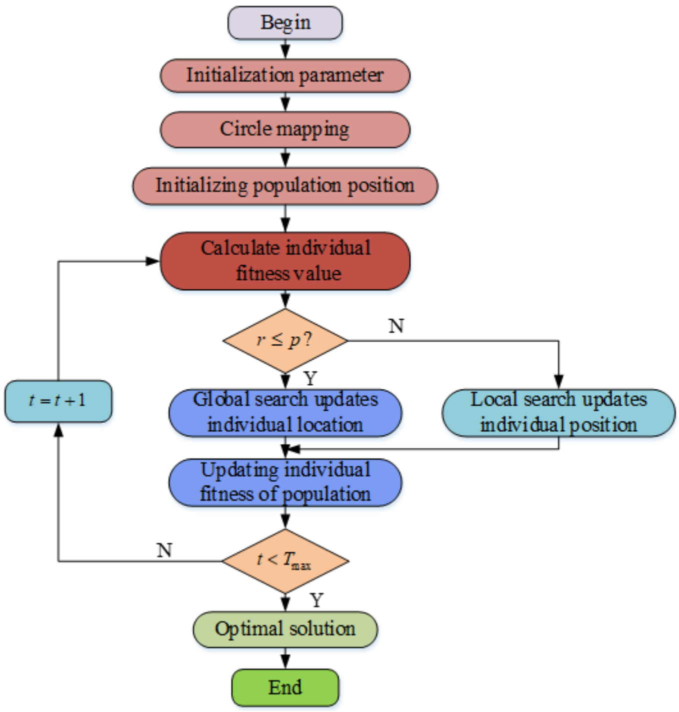

Figure 4. Flow chart of the I-BOA

From Figure 4, the I-BOA introduces a Circle mapping to initialize the population position, making the population more evenly spread in the search space. Individual fitness is calculated using Equation (1). When $r \leq p$, performing a global search to update the individual position according to Equation (10), otherwise performing a local search.

3.3. **CRA design based on I-BOA.** To obtain the optimal cluster head, a CRA based on the I-BOA (I-BOA-LEACH) is designed to select the optimal cluster head for WSN. Appropriate parameters are introduced in the I-BOA-LEACH to adjust the selection ability of the objective function. The remaining energy status of candidate cluster heads (CCH) is represented by the reciprocal sum of CCH, and the calculation formula for the reciprocal sum is shown in Equation (12).

$$f_1 = \sum\nolimits_{i=1}^{m} \frac{1}{E_i} \tag{12}$$

In Equation (12), f_1 represents the reciprocal sum of CCHs within the cluster head. m represents the quantity of CCHs, and E_i represents the rest of energy of the i-th node. The higher the remaining energy and the smaller f_1, the better the selected cluster head. During data transmission, the closer the cluster head node is to the basestation, the lower the transmission EnC. The calculation formula for the distance between the node and the basestation is Equation (13).

$$f_2 = \sum\nolimits_{i=1}^{m} \frac{d_i - d_{\min}}{d_{\max} - d_{\min}} \tag{13}$$

In Equation (13), f_2 is the distance from the candidate group node to the basestation, and d_i means the distance from i to the basestation. $d_{\min}$ and $d_{\max}$ are the min and max distance from the node to the basestation. The distance from the node to the CCH is used to represent the intra cluster compactness, as shown in Equation (14).

$$f_3 = \sum\nolimits_{hi=1}^{m} \left(\frac{\sum_{i=1}^{n_{hi}} d\left(i, hi\right)}{n_{hi}} \right) \tag{14}$$

In Equation (14), h_i represents the i-th node in the CCH group. n_{h_i} represents neighboring node numbers within the range of CCH group R. $d(i, h_i)$ represents the distance between the i-th node within the R range and the CCH group. The shorter $d(i, h_i)$, the more important and compact the position of this node is. The three factors of f_1, f_2, f_3 are multiplied by the corresponding weight values, and finally adding them together to obtain the single objective function. The calculation formula is Equation (15).

$$\begin{cases} f = \varphi_1 f_1 + \varphi_2 f_2 + \varphi_3 f_3 \\ \varphi_1 + \varphi_2 + \varphi_3 = 1 \end{cases} \tag{15}$$

In Equation (15), $\varphi_1, \varphi_2, \varphi_3$ represent the weights of f_1, f_2, f_3, the values are 0.291, 0.327, and 0.382, respectively. Set the $\varphi_1 > \varphi_3, \varphi_2 > \varphi_3$. The smaller the f, the greater the cluster head group, the better the rest of energy, and the more appropriate distance between clusters. The selected excellent cluster heads are clustered into cluster head groups. For example, cluster head group $HI = \{3, 9, 22\}$ represents the selection of ordinary sensor node ID numbers P_3, P_9, and P_{22} to form a cluster head group. The I-BOA-LEACH algorithm is utilized to adopt the optimum cluster head group, as shown in Figure 5.

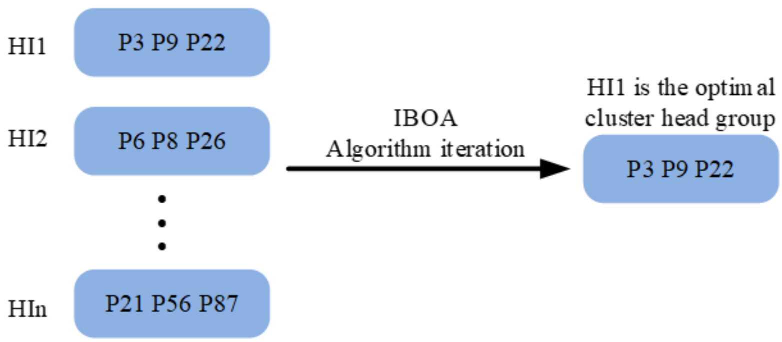

Figure 5. Schematic diagram of cluster head selected by I-BOA-CRA algorithm

From Figure 5, cluster head groups $HI1, HI2$, and HIn are iteratively operated using the I-BOA. Finally, $HI1 = \{3, 9, 22\}$ is selected as the optimal cluster head group.

4. **Analysis of experimental data and performance analysis.** This section first verifies the I-BOA performance and compares it with other algorithms through experiments. Furthermore, to confirm the implementation of I-BOA on the network operation status in WSN, the experiment evaluates two aspects: energy and lifespan.

4.1. **Algorithm performance analysis.** In the method design, the I-BOA introduces nonlinear dynamic convergence factors and improves the drawbacks of the Circle mapping algorithm. The study uses Circle mapping to initialize the individual butterfly position. Firstly, the variables are mapped to the chaotic variable space using the Circle mapping relationship, and then the produced chaotic variables are mapped to the solution space that needs to be optimized through linear transformation. The experimental comparison results of Circle mapping population initialization and population random initialization are shown in Figure 6.

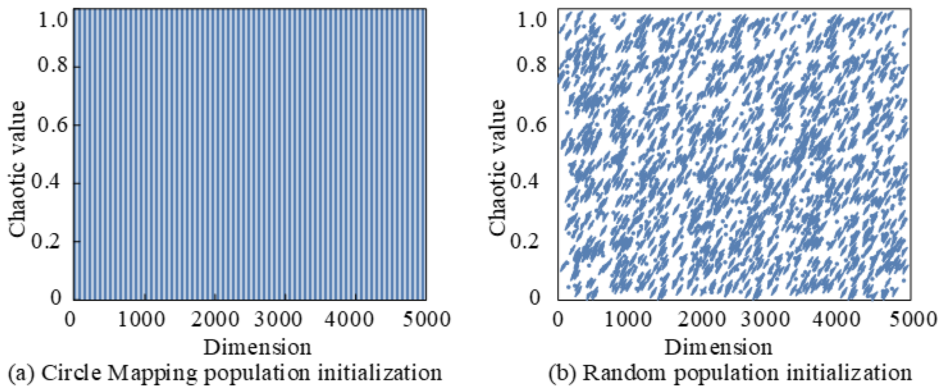

Figure 6. Circle Mapping the population initialized contrast plot

The (a) in Figure 6 shows the initialization positions of the population after introducing the Circle map, and the (b) shows the initialization positions of the random population. Comparing the two figures, (a) has a more uniform distribution of population initialization positions than (b). The more uniform the population distribution is, the higher the Rate of convergence and the wider the search range are. The convergence factor also has different effects on the optimization process, and the comparative results is Figure 7.

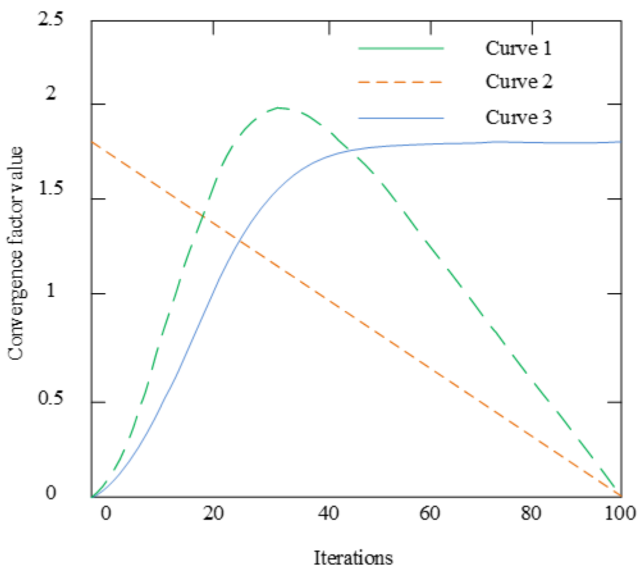

Figure 7. The convergence factor curve is compared to Fig

In Figure 7, curve 1 represents the linear curve of the weight coefficient ω. Curve 2 represents the curve of nonlinear dynamic convergence factor β. Curve 3 represents the product curve of the combination of ω and β. Among the three curves in Figure 7, curves 2 and 3 are superior to curve 1. Curve 2 has a smaller β during the initial iteration of the I-BOA.

As the iteration grows, the speed of β changes accelerates to improve the algorithm's search speed. In the later iteration stage, the growth rate of β value slows down and converges to the maximum to lift the convergence accuracy of the algorithm.

To verify the I-BOA performance, Matlab was selected as the simulation tool in this study to conduct simulation tests on I-BOA, BOA, POA, and the FPSOEE algorithm in reference [19]. The convergence accuracy and stability were evaluated using standard test functions. Four commonly used functions were taken for capability comparison, namely: Sphere, Ackley, Ratrigrin and Rosenbrock function. Although the value ranges of the four functions were different, their global minimum values were all the same, taking a value of 0. Let the Sphere, Ratrigrin, Rosenbrock, and Ackley functions be F1, F2, F3, and F4, respectively. Set all the algorithms' population sizes to 50, the max-iteration to 1000, and run the test function independently 20 times. The search accuracy was represented by the experimental mean, and the stability was on the behalf of the experimental standard deviation (SD). Table 1 shows the results.

Table 1. Simulation Test Results of The Four Algorithms.

/	**BOA**		**POA**		**FPSOEE**		**I-BOA**	
	Mean value	Standard deviation	Mean value	Standard deviation	Mean value	Standard deviation	Mean value	Standard deviation
F1	8.15*10-10	2.46*10-10	1.16*10-114	1.36*10-116	0	0	0	0
F2	3.25*10-1	2.31*10-1	1.86*10-9	5.79*10-10	2.69*10-14	5.71*10-14	0	0
F3	28.68	1.48*10-2	28.91	1.38*10-2	28.68	7.12*10-3	28.82	3.27*10-3
F4	6.38*10-5	2.27*10-6	0	0	0	0	0	0

From Table 1, the Sphere and Ackley functions of the I-BOA algorithm have relatively low SDs for F1 and F2 functions. From the perspective of function F4, the mean and SD of the I-BOA are both 0, and the mean and SD are relatively optimal, resulting in improved algorithm accuracy. The function convergence of the above algorithms are compared, and the results are shown in Figure 8.

The Ratrigrin function in Figure 8(a) shows that the optimal values of the test functions for I-BOA, FPSOEE, POA, and BOA were obtained around 50, 162, 812, and 937 iterations, respectively. The Rosenbrock function in (c) of Figure 8 shows that there was a small gap in the Rate of convergence between the I-BOA and the POA and the FPSOEE at the early phase of the iteration. However, in the later phase, several algorithms differed greatly, and I-BOA had the fastest Rate of convergence. In Sphere, Ackley and Rosenbrock, the Rate of convergence of I-BOA was obviously higher than other three algorithms. The I-BOA reduced the number of invalid iterations when solving the standard test function, and the Rate of convergence of the algorithm was significantly accelerated. The I-BOA outperformed the other three algorithms in terms of search accuracy and stability.

4.2. **Analysis of simulation results.** The CRA based on I-BOA was applied to WSN to evaluate the network performance. This study evaluated both energy and lifecycle aspects. The EnC of all nodes in WSN could be used to determine the energy changes of the network. The amounts of remaining nodes were positively correlated with the network lifespan for the same number of rounds. In the network life cycle, half of the node death time (NDT), the first NDT, and all NDT were commonly used evaluation indicators. If the sensor node energy was depleted, it was considered a dead node. In the simulation experiment, the network lifecycle changed based on I-BOA-LEACH, GWO-LEACH in reference [11], EHO-LEACH in reference [12], and IGA-LEACH algorithm in reference [13] are shown in Figure 9.

In Figure 9, the quantity of rounds in which the first dead node appears in I-BOA-LEACH, GWO-LEACH, EHO-LEACH, and IGA-LEACH algorithms is 598, 43208362, respectively. The I-BOA-LEACH algorithm appears later, and the death rate of the entire WSN node is relatively slow. As the WSN number running rounds increases, the number of dead nodes for the four algorithms also increases. The network period of

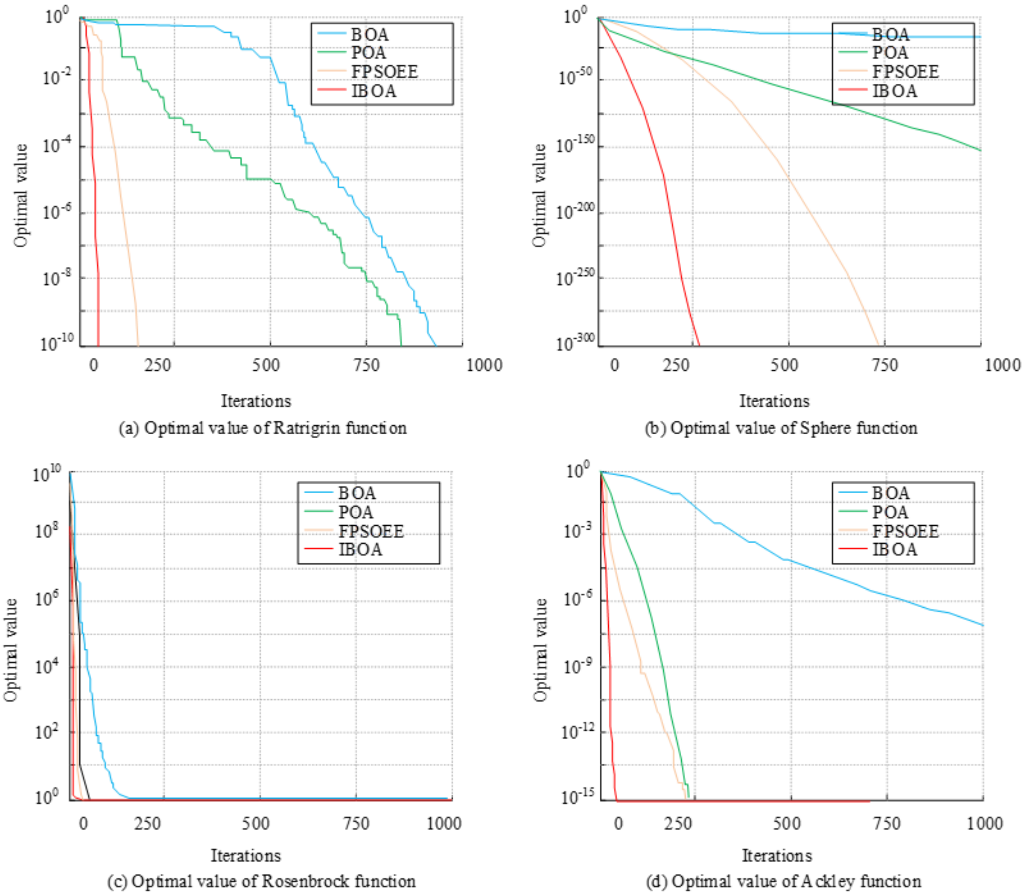

Figure 8. Graph of the functional convergence of the different algorithms

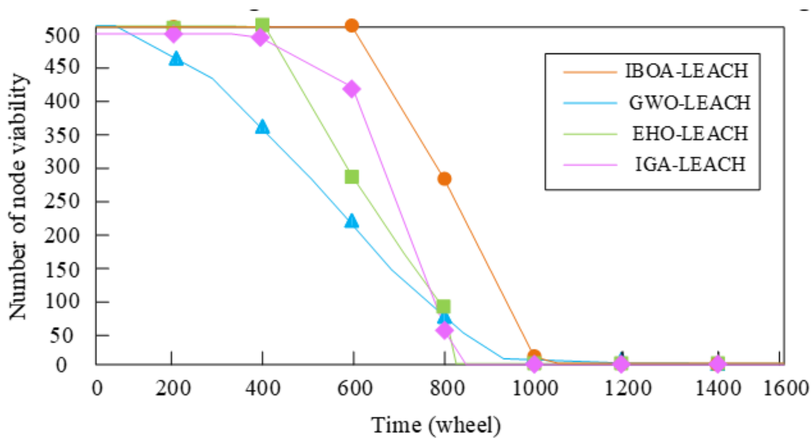

Figure 9. Comparison of the network life cycle of the four algorithms

I-BOA-LEACH algorithm is significantly longer than the other three algorithms. The node EnC of the algorithm is slow, and the network lifetime is long. The dead time of four algorithm nodes, I-BOA-LEACH, GWO-LEACH, EHO-LEACH, and IGA-LEACH, is shown in Figure 10.

In Figure 10, under the same WSN setting conditions, the first dead node occurrence times of I-BOA-LEACH, EHO-LEACH, GWO-LEACH, and IGA-LEACH algorithms are 123611871043936 rounds, respectively. Compared with EHO-LEACH, GWO-LEACH,

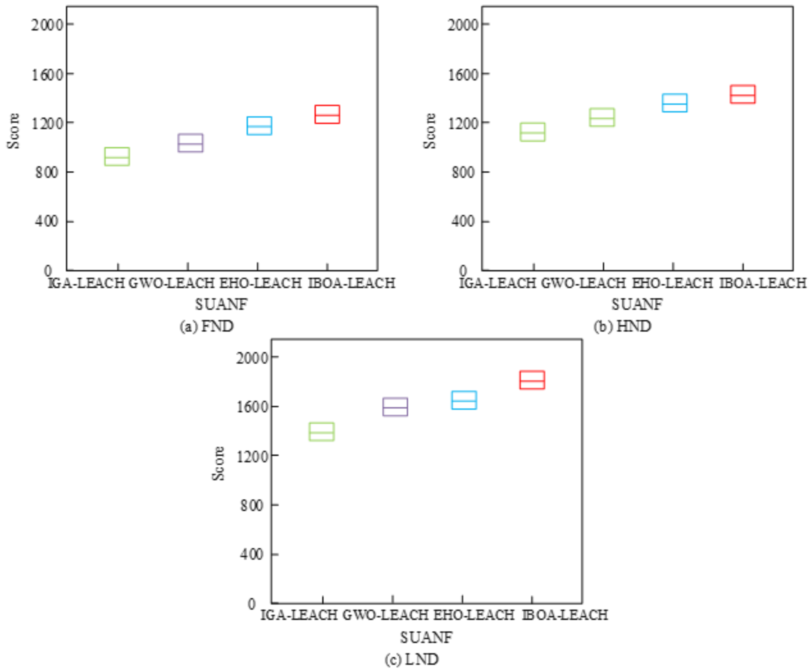

Figure 10. Comparison of FND, HND and LND of the four algorithms

and IGA-LEACH algorithms, I-BOA-LEACH has extended the FND time by 3.96%, 15.6%, and 24.3%, respectively. The four algorithms for the number of Breaking wheel of half the nodes in WSN are 1446135412051089. The number of Breaking wheel of all nodes in the WSN I-BOA-LEACH is 843, which is longer than other algorithms. Overall, the NDT of the I-BOA-LEACH is greater than that of other algorithms. The remaining energy of the four algorithms, I-BOA-LEACH, GWO-LEACH, EHO-LEACH, and IGA-LEACH, is shown in Figure 11.

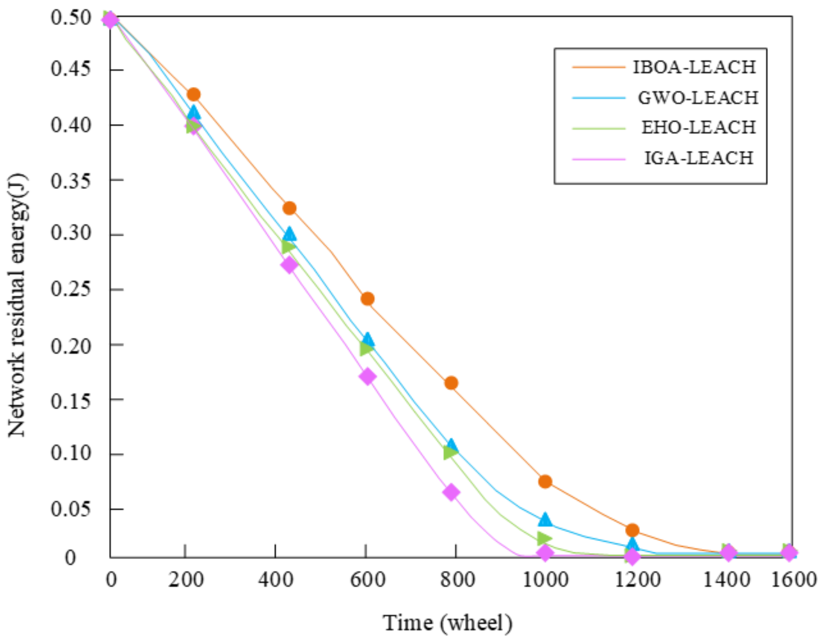

Figure 11. Comparison of the network residual energy of the four algorithms

In Figure 11, as the network amount runs increases, the remaining energy of the network decreases, but the downward trend of the algorithm is different. In terms of the total NDT, the I-BOA-LEACH, GWO-LEACH, EHO-LEACH, and IGA-LEACH algorithms are 1423123811979561 rounds, respectively. In the I-BOA-LEACH algorithm, the number of rounds in which the node energy is depleted is higher. From the perspective of remaining energy, the I-BOA-LEACH algorithm performs better.

5. **Conclusion.** In response to the high EnC and short lifespan of WSN, this study designed an I-BOA based WSN-CRA design to optimize network energy. The experimental results showed that the LND of I-BOA-LEACH, GWO-LEACH, EHO-LEACH, and IGA-LEACH algorithms were 1423123811979561 rounds, respectively. The four algorithms' FND appeared in 123611871043936 rounds. The four algorithms' HND in WSN appeared in 1446135412051089 rounds. Compared to GWO-LEACH, EHO-LEACH, and IGA-LEACH algorithms, the I-BOA-LEACH had a higher number of rounds in which the EnC of nodes was exhausted. Compared with other algorithms, when using the I-BOA-LEACH algorithm to test the objective function value, the function curve had the steepest descent rate, the fastest descent rate. The best convergence was appeared when the curve was flatter at the end. This indicated that the WSN-CRA designed based on I-BOA effectively solved the problems of high EnC and short lifespan of WSN, optimized network energy and prolonged network lifespan, which was beneficial for network operation. Finally, the shortcomings of this study lie in the fact that the weight values of the designed algorithm for selecting cluster heads still need to be analyzed, and the weight values will be further compared and optimized in the future.

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