Research Article

A Chaotic Elite Niche Evolutionary Algorithm for Low-Power Clustering in Environment Monitoring Wireless Sensor Networks

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In recent years, as people's demand for environmental quality has increased, it has become inevitable to monitor sensitive parameters such as temperature and oxygen content. Environmental monitoring wireless sensor networks (EMWSNs) have become a research hotspot because of their flexibility and high monitoring accuracy. This paper proposes a chaotic elite niche evolutionary algorithm (CENEA) for low-power clustering in EMWSNs. To verify the performance of CENEA, simulation experiments are carried out in this paper. Through simulation experiments, CENEA was compared with shuffled frog leaping algorithm (SFLA), differential evolution algorithm (DE), and genetic algorithm (GA) in the same conditional parameters. The results show that CENEA balances node energy and improved node energy usage efficiency. CENEA's network energy consumption is reduced by 8.3% compared to SFLA, 3.9% lower than DE, and 4.6% lower than GA. Moreover, CENEA improves the precision and minimizes the computation time.

1. Introduction

The development of human society is inseparable from the support of various resources, but in the process of continuous development of human society, due to the continuous deepening of industrialization, the problem of environmental pollution has become increasingly serious. The human ecological environment has been damaged to varying degrees.

Wireless sensor networks (WSNs) have the disadvantages of short network life and high environmental impact. One of the protocols of WSNs is LEACH, which uses a probability model to determine the cluster head, thereby prolonging the life of the network in a complex environment. In the LEACH protocol, the nodes in the WSNs are divided into multiple clusters. Each cluster is composed of a cluster node and many ordinary nodes. The ordinary nodes collect data and then transmit them to the cluster head nodes of the respective clusters. The node fusion compresses the received data and transmits it to the base station [1].

A widely used energy-saving mechanism in WSNs is the duty cycle scheme to reduce energy waste caused by idle monitoring. However, to coordinate the sleep/wake cycle of sensor nodes, the duty cycle scheme requires more control packages to achieve specific application goals. Under different network mechanisms, the duty cycle of sensor nodes needs to be adjusted as network conditions change during operation to achieve the desired delay and energy efficiency. The sender node and the receiver node need to wake up at the same time during the transmission process to complete the data transmission. If a synchronization mechanism is used for data transmission between nodes, to ensure that the clocks between nodes in the network remain constant, more control packets are required in the process of synchronizing the clocks. If the asynchronous mechanism is used for data transmission of the node, the sending node needs to first send a data packet to inform the receiving node of the length of time that it needs to wake up during the data transmission process and then need to retransmit the data packet to complete the data transmission [2].

EMWSNs provide a fast and convenient optional monitoring program for environmental protection due to their advantages of convenient and flexible deployment. However,

due to the limited energy of nodes, the development and application of EMWSNs are hindered. Wireless sensor nodes are generally deployed in unmanned areas with poor conditions. Node access to the network will increase the difficulty of network maintenance. Most of the node batteries will not be replaced, resulting in a limited lifespan of the node in reality. Clustering in EMWSNs divides the nodes in the network into cluster heads and ordinary monitoring nodes. The cluster head contacts other ordinary nodes covered by it to obtain data and then sends the data to the terminal [3–5]. How to use reasonable clustering to conserve the power usage of the EMWSNs while completing the perception task has attracted more and more attention from researchers. Consequently, it is very urgent to create a new EMWSN clustering algorithm to minimize the power usage in the system, increase the efficiency of data transmission, and extend the living period of the system. The CENEA proposed in this paper can greatly improve the performance of EMWSNs.

Within the traditional clustering algorithm, the choice associated with the cluster head will be arbitrary during the establishment phase regarding the cluster [6–8]. The influence factors such as the point transmission distance are not considered, resulting in an improper selection of the cluster head as well as excessive power usage of the common nodes in EMWSNs. In the stage of cluster establishment, CENEA introduces parameters such as node transmission distance to select cluster head nodes to minimize EMWSNs power usage. With the rapid development of EMWSNs, the research of clustering algorithm technology in the network has also achieved outstanding results. The focus of research on clustering algorithms is to optimize the choice of cluster head nodes and the establishment associated with clusters as well as decrease the power usage of nodes in the system [9–11]. Some scholars have proposed new clustering and routing schemes, which provide excellent ideas for improving the life cycle of networks [12–17]. With these years of research and development, the swarm intelligence majorization model has been well utilized in the clustering technology of EMWSNs. Many scholars have optimized the traditional clustering algorithm to increase efficiency, decrease complexity, and improve the algorithm [18]. SFLA, DE, and GA are currently a research focus of clustering algorithms. Using optimization algorithms can quickly discover the optimum way for data transmission as well as extend the life of the network.

For some EMWSNs, researchers are more concerned about the single-round power usage of the EMWSNs after clustering. It is hoped that the energy consumption of sensors per unit time is minimal to reduce the cost. Assuming that EMWSNs are made up of a huge quantity of sensing nodes, a small number of cluster head nodes, and a single gateway node. The gateway node usually has strong signal transceiving capabilities and a fixed location. How to select a small quantity of cluster head nodes from a huge quantity of EMWSN nodes to minimize the power usage of a data collection on the entire network is an important issue in practical applications.

El Alami et al. [19] proposed an improved routing protocol, which can greatly improve the performance of mobile nodes in WSNs, improve network life and energy efficiency, and reduce packet loss to a large extent. Lee et al. [20] proposed an improved clustering protocol, which has an excellent performance in mobile sensor networks. Even during the movement of the node, the packet loss rate can be kept at a low level. El Alami et al. [21] proposed a new clustering hierarchy algorithm to save network energy by changing the sleep and working time of nodes. It has an excellent performance in homogeneous and heterogeneous networks. Lee et al. [22] proposed an improved clustering protocol. This protocol can effectively increase the lifetime of the network and has a good performance in large-scale WSNs.

Liu et al. [23] proposed a model of cluster head selection and path planning based on DE. Improve the performance of each part of the algorithm by reducing the amount of calculation and unifying system energy consumption. In [24], the neural network algorithm is applied to the WSN data fusion process, and the algorithm significantly improves the data processing efficiency. Fattoum et al. [25] use GA to establish a routing mechanism between cluster heads, which reduces energy consumption between clusters.

However, DE, GA, and neural network algorithms cannot dynamically adjust the crossover and mutation probabilities according to the fitness of individuals and populations and tend to fall into premature convergence, resulting in higher energy consumption for the final clustering scheme.

Islam et al. [26] proposed the idea of the main cluster head and a below cluster head. A below cluster head is selected in a cluster to share the energy consumption of the major cluster head nodes and avoid the main cluster head nodes through perishing because of excessive energy consumption. Huamei et al. [27] proposed a cluster head election mechanism based on SFLA, which allows the cluster heads to be reelected after the previous round of cluster heads meet certain conditions, reducing the energy consumption caused by each round of cluster head selection.

However, the operations of these two algorithms are too complicated, and the change of the cluster head does not take into account the complex environment in the actual situation, so the reliability of the algorithm is poor.

Wang et al. [28] proposed a multihop routing protocol, which allows the distant node to choose a node closest to itself for data forwarding, reducing the distance of direct communication with the terminal. In [29], after the nodes are divided into clusters, they have grouped again in each cluster according to the distance and data similarity between the nodes, and a representative node is selected again in each group to deliver the information to the cluster head nodes.

However, once the power of the inner sensor nodes is tired, the outer sensor nodes with a large amount of energy remaining will not be able to work normally because of the too-long transmission distance because it cannot be relayed. It takes a long time to set up a cluster, has a long delay, and consumes a lot of node energy. Also, multiple detection steps before transmitting data packets will increase the delay of data transmission, so it is not appropriate for EMWSNs that require great live performance.

Majeed et al. [30] combine energy and node location to introduce a cost function and uses GA to perform cluster

head election. So that nodes with higher energy and better locations are elected as cluster heads, making the tasks of each node more reasonable. Ghahramani and Laakdashti [31] proposed a routing protocol based on the DE in WSN to minimize power usage as well as extend the system living cycle.

However, the quality of the cost function will determine the efficiency of the way, and the capabilities of the cost function will be poor in a complex environment. Each time the algorithm needs to send a data packet, the source node will discover and establish a cluster. Therefore, it takes a certain time to establish the corresponding cluster, and the cluster will be removed after a certain time. A lot of node energy will be spent in the process of cluster establishment.

The computational time of the cluster head selection problem increases exponentially with the increment of cluster head nodes. To reduce the network power usage rate, we present a CENEA. An objective function is formulated to maximize the reduced network energy consumption rate under multiple constraints. This paper also gives advanced operators by employing elite operators and chaotic map operators in each iteration of the evolutionary procedure. The CENEA combines the merits of the elite evolution and chaotic map. CENEA is a kind of swarm algorithm, which has a strong global search capacity. To denote the advantages of CENEA, experiments are conducted for the cluster head selection problem and performance comparisons are made with SFLA, DE, and GA. Simulation simulations reveal the superior performance of the presented CENEA in both the reduced network energy consumption rate and fast convergence.

The main contributions of this paper are as follows.

(1) This paper proposes a new clustering algorithm. CENEA can reduce the energy consumption of EMWSNs and improve network performance. CENEA has less time complexity and can complete the selection of EMWSN cluster heads and cluster coverage in a short time

(2) This paper designs a new clustering model of EMWSNs. The model coding adopts the real number coding scheme of sensor position information. In EMWSNs, sensors are randomly placed in the environmental monitoring area to simulate complex situations in reality, so it is closer to the situation of environmental monitoring in reality

(3) This paper verifies the excellent performance of CENEA in EMWSNs through simulation experiments. CENEA can improve the viability of EMWSNs and propose a new clustering scheme for the development of EMWSNs

The structure of this paper is as follows. Section 2 introduces the clustering model of EMWSNs and the selection mechanism of cluster heads. Section 3 uses CENEA to optimize the clustering algorithm. Section 4 gives the results of simulation experiments and discusses the performance of CENEA. Then, Section 5 concludes.

2. EMWSN Clustering Model

The distribution of cluster head nodes in EMWSNs determines the energy consumption of network communication. This section will introduce the network clustering model. The network distribution area studied in this paper is a square, and a certain number of sensor nodes are aimlessly dispersed in the square region. The typical network structure is as follows.

As shown in Figure 1, EMWSNs usually adopt a clustered structure. The sensing nodes are divided into multiple clusters within the monitoring range, and each cluster has a cluster head [32]. In the uplink transmission phase, the sensing nodes randomly distributed within the monitoring range complete the sensing of the monitoring target and gather the sensing outcomes to the head of the cluster. The cluster head node collects relevant information from the sensing nodes in the cluster and uploads the information to the gateway node within a direct or multihop manner [33]. The gateway node summarizes the information through every cluster head and transmits it to the user for further analysis and processing. In the downlink transmission stage, the user releases monitoring tasks in the downlink through the gateway node and uniformly allocates monitoring targets and various resources in the network. The gateway node distributes the monitoring task to the sensing nodes in the cluster through the cluster head node and completes the downlink distribution process of the monitoring task.

The power usage of EMWSNs primarily arrives through delivering data, getting data, and transmission paths. The node has receiving consumption and sending consumption and part of the energy consumption from the amplifier. This part of the energy consumption is closely related to the transmitting range. If a is under a offered parameter a_{set}, the sending amplifier uses the energy of free space. When a is greater than a_{set}, the transmitting amplifier adopts the energy consumption model of multipath attenuation. When the data of n bit needs to be sent and the distance from the sender to the destination is a, the energy consumption of the sender is

$$
\begin{aligned}
L_{Tx}(n, a) &= L_{(Tx-elec)}(n) + L_{(Tx-amp)}(n, a) \\
&= \begin{cases} n \times L_{elec} + n \times \beta_{fs} \times a^2, a < a_{set}, \\ n \times L_{elec} + n \times \beta_{amp} \times a^4, a \geq a_{set}. \end{cases}
\end{aligned} \tag{1}
$$

In equations (1), a is the data transmission distance on the path, L_{elec} is the power consumed through the transmitting signal, β_{fs} and β_{amp} correspond to different energy transmission models, β_{fs} corresponds to the energy transmission model of free space, and β_{amp} corresponds to the energy transmission model of multipath attenuation, where a_{set} determines which energy transmission model the sender adopts, as shown in

$$
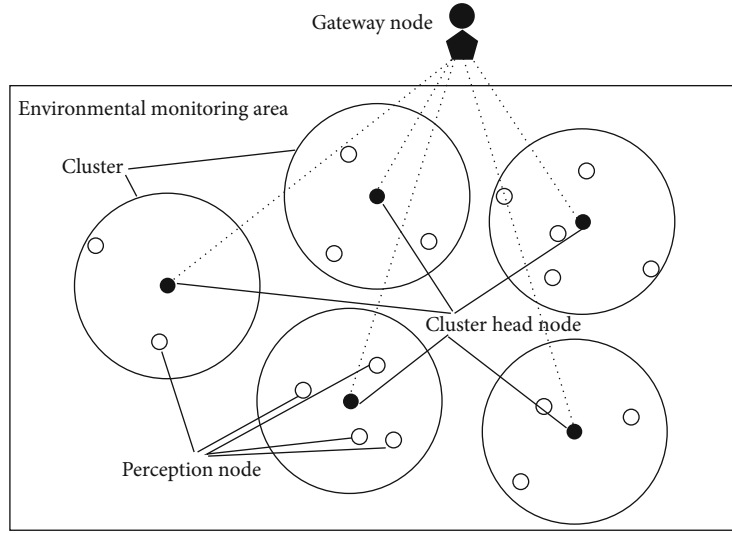a_{set} = \sqrt{\frac{\beta_{fs}}{\beta_{amp}}}. \tag{2}
$$

FIGURE 1: EMWSN cluster structure.

The amount of energy consumed by data transmission on the path is represented by

$$L(n, a) = L_{Tx}(n, a) + L_{Rx}(n). \tag{3}$$

In equations (3), $L_{Tx}(n, d)$ represents the power ingested through the node to deliver information. $L_{Rx}(n)$ represents the power taken through the node to obtain information. Power usage is mainly composed of two parts, the signal energy consumption $L_{T-\text{elec}}(n)$ and the transmission amplifier circuit energy consumption $L_{T-\text{amp}}(n, a)$. The size of $L_{Tx}(n, d)$ is shown in

$$L_{Tx}(n, d) = L_{T-\text{elec}}(n) + L_{T-\text{amp}}(n, a). \tag{4}$$

The receiver is different from the sender, and the energy consumption of the receiver has nothing to do with the distance. Therefore, the energy required to receive the data of n bit can be obtained as

$$L_{Rx}(n) = n \times L_{\text{elec}}. \tag{5}$$

3. CENEA for Reducing Network Energy Consumption in EMWSNs

In this work, our CENEA follows the framework of the conventional stochastic methodology. Two novel programs were produced, namely, chaos mapping and elite programs. In the cluster head selection problem of EMWSNs, elite technology can be used to find feasible solutions close to the ideal solution. These procedures are effective strategies, easy to understand and to implement, extensively utilized in the optimizing of cluster head node distributions. The novel procedures of the CENEA are qualified to create a feasible solution for EMWSNs in a computationally acceptable time.

Compared to conventional optimization algorithms like calculus-based techniques as well as exhaustive techniques,

CENEA can effectively deal with some complex problems that are not able to be resolved through conventional methods. The standard technique to resolve the optimization issue is to design an objective function so that the objective function can be modeled reasonably while combining various constraints and then transform the optimization problem into finding the maximum value. CENEA simulates the natural biological evolution model, using real number coding to obtain the initial population, cross mutation operation, and group iteration based on the greed criterion to realize the function of search and optimization. Real number coding is more universal in the type of problem solving than binary coding. The greedy selection criterion will retain the best solution individual in the current search space and will not stop until the preset number of iterations is reached. For the problem to be solved, a fitness function is designed, and then the fitness function was taken as the evaluation objective. Retain elite individuals with better fitness values in the iterative process to induce the final solution to approach a better direction. This process makes CENEA have better dynamic tracking. The many advantages of CENEA make it unnecessary to make use of the feature info of the issue to a certain extent, effectively solving the optimization problem in the complex environment.

CENEA is mainly used to solve global optimization problems of continuous variables. It is an intelligent evolutionary algorithm with dynamic tracking and random search. CENEA is aimed at denoting good chromosomes through this evolutionary process. The CENEA utilizes various simple procedures to simulate evolution. The main steps are as follows:

(Step 1) In the initialization stage, the initial population is generated by the chaotic map operator and generally satisfies the condition that it can cover the whole search space

(Step 2) In the mutation stage, a certain number of individuals are selected from the population to produce mutant individuals

(Step 3) In the crossover stage, the target individual and the variant individual are mixed concerning the crossover probability criterion to obtain the test individually

(Step 4) In the individual evaluation stage, the result function value of this offspring is evaluated

(Step 5) In the selection stage, determine the superior new iteration using the greedy method and save elite individuals

(Step 6) In the final stage of the iteration, judge the stop criteria; if termination criterion is attained, then stop the procedure

The flow chart of CENEA is shown in Figure 2.

3.1. Population Initialization Operation of CENEA.

The first step of the CENEA is to establish a proper chromosome representation. To utilize a CENEA to match the cluster head node distribution to the EMWSNS, it is necessary to produce an effective encoding scheme and a result function, which will allow the algorithm to choose the fittest solutions. The individual code of CENEA is a string of limited length and limited precision that is usually indicated like $P_k = [p_1, p_2, \cdots, p_M]$ mathematically. K is the quantity of populations, P_k is called a chromosome, M is called the number of genes on the chromosome, and p_M is called a gene on the chromosome. y_m signifies the cluster head node of the m_{th} cluster in the chromosome. In CENEA, each solution is referred to chromosome. Every chromosome represents a feasible solution of cluster head node distribution for the cluster head selection problem. In the d generation, the entire population can be expressed by

$$
P(d) = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,M-1} & y_{1,M} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,M-1} & y_{2,M} \\ \vdots & \vdots & y_{z,j} & \vdots & \vdots \\ y_{K-1,1} & y_{K-1,2} & \cdots & y_{K-1,M-1} & y_{K-1,M} \\ y_{K,1} & y_{K,2} & \cdots & y_{K,M-1} & y_{K,M} \end{bmatrix}
$$
$$
= \begin{bmatrix} P_1(d) \\ P_2(d) \\ \vdots \\ P_{K-1}(d) \\ P_K(d) \end{bmatrix}.
$$

$$(6)$$

3.2. Chaotic Map Operation of CENEA.

The chaotic map operator is used to generate K initial population combinations of length M. The length of the chromosome is the same as the quantity of cluster head nodes within EMWSMs,

which means that each value of the final optimized individual maps the selection of each cluster head node.

Chaotic motion is a common nonlinear random phenomenon. It looks complicated and chaotic on the outside. But in reality, it contains exquisite laws, which have good randomness, ergodicity, and regularity. The randomness and ergodicity of chaotic motion can traverse all states within a certain range without repetition. It is these characteristics of chaotic that provide a broad new idea for optimization calculations and various optimization algorithms. Highly sensitive to initial conditions, boundedness, randomness, and ergodicity are the four most distinctive characteristics of chaotic. The chaotic map used in this paper is the sinusoidal map. The chaotic map iteration is

$$s_{x+1} = \theta s_x{}^2 \sin(\pi s_x). \tag{7}$$

In equation (7), x is the number of iterations. When the θ value is 2.3 and the s_1 value is 0.7, it can be expressed as

$$s_{x+1} = \sin(\pi s_x). \tag{8}$$

The value range of the chaotic value jumps out of the special limitation of the sine function range of [-1,1], and its value range becomes (0,1).

3.3. Fitness Calculation of CENEA.

In the EMWSM clustering scheme for optimizing the power usage of a solitary circular transmission, the major consideration is how to decrease the power consumption of a single round of communication through clustering. At the same period, the Euclidean length via the common sensor node to the corresponding cluster head node is considered. Assigning a common node to the nearest cluster head node helps sensor nodes consume less energy when communicating with cluster head nodes. Therefore, the common nodes are assigned to their corresponding cluster head nodes; the average length T from the sensor node to the cluster head node is

$$T = \frac{1}{G} \sum_{g=1}^{G} F_g. \tag{9}$$

In equation (9), G represents the overall number of ordinary common nodes distributed in EMWSNs, and F_g represents the length through the sensor node to its corresponding cluster head node.

The smaller the average distance, the better the clustering scheme. The fitness function of CENEA can be expressed as

$$H(P) = \delta \times T. \tag{10}$$

In equation (10), δ is the proportional coefficient. Without loss of generality, set the value of δ to 1.

3.4. Mutation Operation of CENEA.

To keep the number of cluster heads constant and introduce randomness, the mutation operation uses a certain mutation probability Q to replace a random bit of the individual with other nonduplicate nodes.
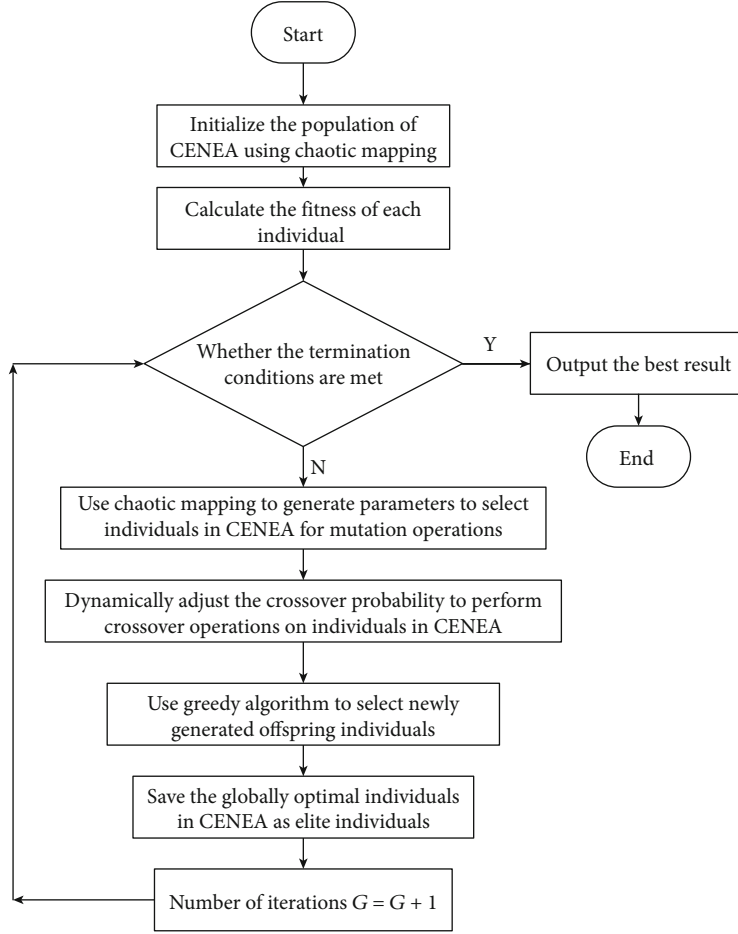
Figure 2: Process of the CENEA.

The newly selected sensor node is regarded as the cluster head node. For a single individual, a random number Q_r is generated according to the chaotic mapping. Then, the operation is performed in

$$y_{z,j} = \begin{cases} y_{z,j}, & Q_r > Q, \\ y_{new}, & Q_r < Q. \end{cases} \quad (11)$$

In equation (11), y_{new} represents the newly generated cluster head node, and y_{new} does not overlap with the existing cluster head node in the individual.

3.5. Crossover Operation of CENEA. First, perform a logical AND operation on two individuals to get an intermediate individual P'. Secondly, perform the logical XOR operation on the two individuals to obtain another intermediate individual P''. Finally, the cluster head node position in the intermediate individual P'' obtained by the exclusive OR operation is allocated to the new cross individual P''' by the crossover probability C. The fresh individual P_{new} obtained after the crossover could be indicated as

$$P_{new} = P' + P'''. \quad (12)$$

The crossover probability has an excellent impact on the searchability and convergence efficiency of the formula. In this paper, the relative value depending on the individual fitness benefit of the parent and the average fitness benefit of the group is used for adjustment. The next-generation crossover probability set update strategy is shown in

$$C_k^{d+1} = \begin{cases} C_k^d, & H(P_k)^d < H_m^d, \\ C_k^d(\mu_2 + (\mu_2 - \mu_1)), & H(P_k)^d > H_m^d. \end{cases} \quad (13)$$

In equation (13), C_k^{d+1} is the crossover probability of the kth individual in the next generation. $H(P_k)^d$ symbolize the fitness value of the present k_{th} individual and H_m^d represent the average fitness value. When the fitness benefit of the current individual is better than the average fitness benefit, the crossover probability of the next-generation individual remains unchanged. Otherwise, the crossover probability will change with a certain coefficient until the fitness benefit of the next generation chromosome is better. μ_1 and μ_2 are the higher and lesser limitations of the crossover probability. When the fitness value of the current individual is higher than the average fitness value, their constituent coefficients affect the

change of the crossover probability of the next generation of individuals.

3.6. Selection Operation of CENEA. The selection operation determines which of the target individual and the newly generated individual will survive to the next generation. Use the greed principle to determine whether the newly generated individual replaces the old individual. The operation rule is shown in

$$P_k = \begin{cases} P_k, & H(P_k)^d < H(P_k)^{d-1}, \\ P_{\text{new}}, & H(P_k)^d > H(P_k)^{d-1}. \end{cases} \quad (14)$$

In equation (14), $H(P_k)^d$ represents the fitness of the k_{th} individual in the d generation. $H(P_k)^{d-1}$ represents the fitness of the k_{th} individual in the $d-1$ generation.

3.7. Elite Operation of CENEA. A global variable is set in CENEA to store the optimal individual in the iterative process. The global variable is the elite individual. After the selection operation is performed, CENEA judges whether the fitness of the optimal individual in the population is lower than the fitness of the elite individual. Corresponding operations were performed according to different results, and the operation rules are as in

$$P_{\text{best}} = \begin{cases} P_{\text{best}}, & H\left(P_t^d\right) > H(P_{\text{best}}), \\ P_t^d, & H\left(P_t^d\right) < H(P_{\text{best}}). \end{cases} \quad (15)$$

In equation (15), P_{best} represents an elite individual, and P_t^d represents the best individual in the d generation. $H(P_{\text{best}})$ represents the fitness of elite individuals, and $H(P_t^d)$ represents the fitness of the best individuals in the population. If the fitness of the elite individual is smaller than the fitness of the best individual in the population, the elite individual is retained; otherwise, the best individual replaces the elite individual. To make the CENEA iterative process always update the population positively, it is necessary to save the elite individuals in the population. The operation of saving elite individuals is as in

$$P_i^{\text{d}} = P_{\text{best}}. \quad (16)$$

In equation (16), P_i^d represents the i_{th} individual in the d generation population. The value of i is generated by the chaotic map.

3.8. Niche Algorithm of CENEA. The niche algorithm means that in CENEA, the population is divided into several subpopulations, and each subpopulation completes the evolution independently. In every few generations, the best individuals will be exchanged among subpopulations. The niche algorithm can effectively enhance the performance of the formula and prevent the formula from falling into local optimum.

TABLE 1: Simulation experiment parameter settings.

Parameter	Value
L_{elec}	50 nJ/bit
β_{fs}	$10 \, \text{pJ}/(\text{bit} \times \text{m}^2)$
β_{amp}	$0.0013 \, \text{pJ}/(\text{bit} \times \text{m}^4)$
a_{set}	87 m
n	3072 bits

4. Results and Discussion

To verify whether the CENEA optimized clustering formula could efficiently save the power usage of EMWSNs in the cluster head selection problem. The simulation software is implemented in this section, and the CENEA optimized routing clustering algorithm is compared with SFLA, GA, and DE, optimization algorithms for comparison and analysis. In the simulation experiment, this paper compared CENEA, SFLA, GA, and DE. In this paper, a simulation experiment is carried out on the MATLAB R2018b software and Intel Core i7 processor platform. After several simulation experiments, the optimal values of the parameters were taken. The environmental parameters of the EMWSNs experiment are shown in Table 1.

The simulation adopted the clustering method based on CENEA, SFLA, GA, and DE. The setting area is 400 m × 400 m. In CENEA, the number of algorithm iterations is 100, and the number of individuals in the population is 100. In SFLA for comparison, the total number of frogs is 100, the population is 20, and the number of frogs in each population is 5. The maximum step size is 40 m. In GA, the population numbers are 100. The roulette method is used for selection, the crossover operation is a single point crossover, and the mutation probability is 0.1. In DE, the population numbers are 100. The crossover factor is 0.3, and the scaling factor is 1.

The cluster head ratio is set to 0.05. The simulation result is shown in Figures 3(a)–3(d), respectively, representing the cases where the number of sensor nodes is 100, 200, 300, and 400.

Figure 3 shows the complete network communication power ingested through all sensor nodes in CENEA, SFLA, GA, and DE when the cluster head ratio is 5% and the quantity of sensor nodes varies with the number of algorithm iterations. From the simulation outcomes, it could be observed which SFLA has a certain decline in the initial stage of algorithm iteration, but after the number of iterations reaches a certain number, it repeatedly falls into evolutionary stagnation, and the finally obtained clustering scheme has a large network communication energy consumption. GA and DE have a relatively stable performance during operation, but fail to dynamically adjust the algorithm parameters during the evolution process, resulting in slower algorithm evolution. The final clustering scheme has a higher network communication energy consumption than CENEA's clustering scheme. CENEA's clustering scheme uses the calculation of the fitness of the individual to be crossed, the fitness of the
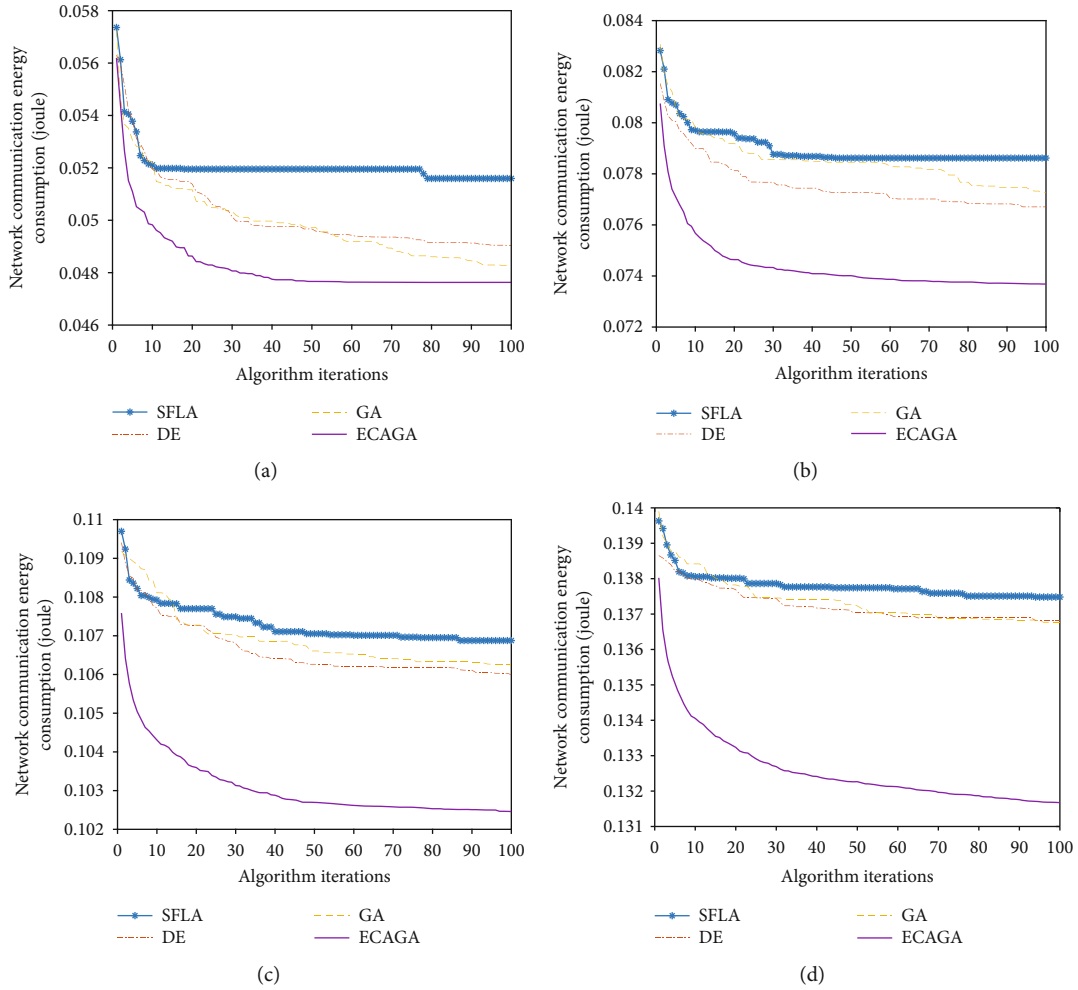
FIGURE 3: Changes in network communication energy consumption with the number of sensor nodes: (a) 100 sensors; (b) 200 sensors; (c) 300 sensors; (d) 400 sensors.

individual to be mutated, and the average fitness of the population as inputs to avoid the algorithm from falling into the local optimum. The chaotic map is used to obtain random numbers during initialization and selection operations, which ensures the global efficiency of the CENEA. Simultaneously, due to the adoption of the niche method, the crossover and mutation probabilities are dynamically adjusted during operation. CENEA's clustering scheme avoids evolutionary stagnation and premature convergence caused by fixed algorithm parameters. It can be seen from Figure 3 that under the condition of different sensor nodes, the total power usage of EMWSN communication required by CENEA is reduced by 4.1% to 8.3% compared to SFLA and 1.3% to 4.6% compared to GA. DE has dropped by 2.9% to 3.9%, which means that the energy efficiency is higher when the amount of data transmitted is the same.

Figure 4 shows the changes in network communication energy consumption when 400 sensor nodes are within the monitoring area of different area sizes. The cluster head ratio is 5%. Figures 4(a)–4(d), respectively, represent the area sizes which are $100 \, \text{m} \times 100 \, \text{m}$, $200 \, \text{m} \times 200 \, \text{m}$, $300 \, \text{m} \times 300 \, \text{m}$, and $400 \, \text{m} \times 400 \, \text{m}$.

Figure 4 shows that CENEA has greater performance advantages than SFLA, GA, and DE in both small and large areas. In EMWSNs, the area of environmental monitoring is uncertain. Compared with SFLA, GA, and DE, CENEA has stronger adaptability when EMWSNs change the size of the monitoring area. This is the ability to quickly configure EMWSN cluster heads under different environmental conditions. CENEA optimization is faster. It can be seen that when the number of iterations is 20, the network energy consumption is close to the optimal result. CENEA can use the least time to get the best results. The running time of the CENEA is shown in Table 2.

Table 2 shows that the running time of CENEA's algorithm is much shorter than SFLA and smaller than DE and GA. The final result of algorithm optimization is shown in Figure 5.

Figure 5 shows that the last optimization outcomes of CENEA are optimal compared to SFLA, GA, and DE under different area size conditions. Simultaneously, the CENEA has the shortest running time. It means that CENEA can get the best EMWSN cluster head solution in the shortest time in a complex environment.
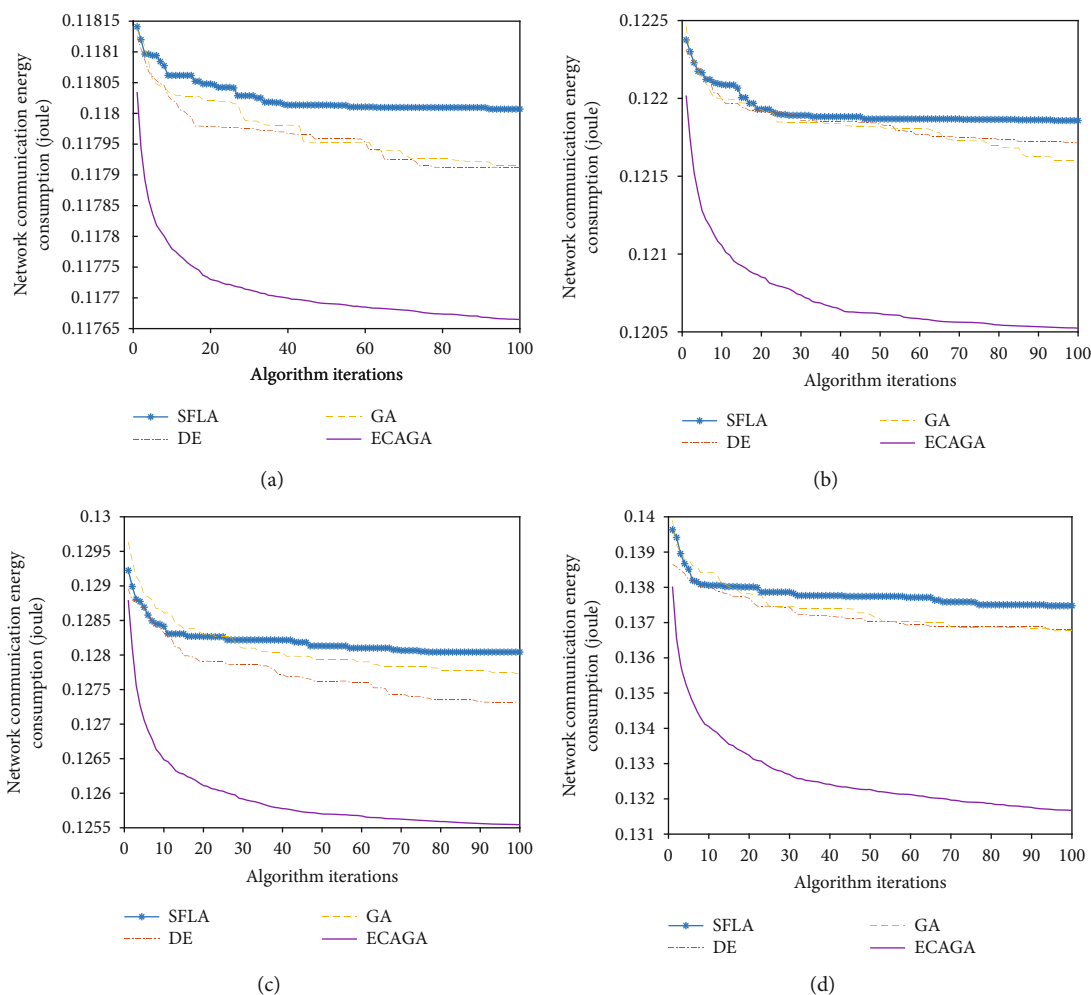
Figure 4: Changes in network communication energy consumption with the following area sizes: (a) 100 m × 100 m; (b) 200 m × 200 m; (c) 300 m × 300 m; (d) 400 m × 400 m.

Table 2: Algorithm running time.

	100 m × 100 m	200 m × 200 m	300 m × 300 m	400 m × 400 m
CENEA	17.3 s	23.2 s	17.8 s	18.8 s
SFLA	207.0 s	275.2 s	205.8 s	214.0 s
GA	17.7 s	24.6 s	19.2 s	19.3 s
DE	30.6 s	46.0 s	33.1 s	34.1 s

Figure 6 shows that when the cluster head ratios in EMWSN are different and the clustering methods of CENEA, SFLA, GA, and DE are used, respectively, the values of SFLA, GA, and DE are more than the overall power usage of the EMWSN communication. The number of sensor nodes is 400, and the area size is 400 m × 400 m. Figures 6(a)–6(d), respectively, represent the proportion of cluster heads is 5%, 10%, 15%, and 20%.

It could be observed from Figure 6 that the CENEA-based clustering technique effectively reduces network communication energy consumption compared to SFLA, GA, and DE. When the proportion of cluster heads is 5%, the advantage of CENEA communication energy reduction is very large compared with other algorithms. When the proportion of cluster heads is 10%, 15%, and 20%, the greater the number of sensor nodes is. Compared with the other three algorithms, the reduction in network communication energy consumption by CENEA is also obvious. The main reason is that SFLA, GA, and DE did not dynamically adjust their parameters in the iterative process, resulting in slow evolution. In the process of evolution, CENEA can dynamically adjust its mutation probability through the fuzzy controller. Use elite operators to ensure the optimization trend, and improve the evolution speed of the algorithm. Like the
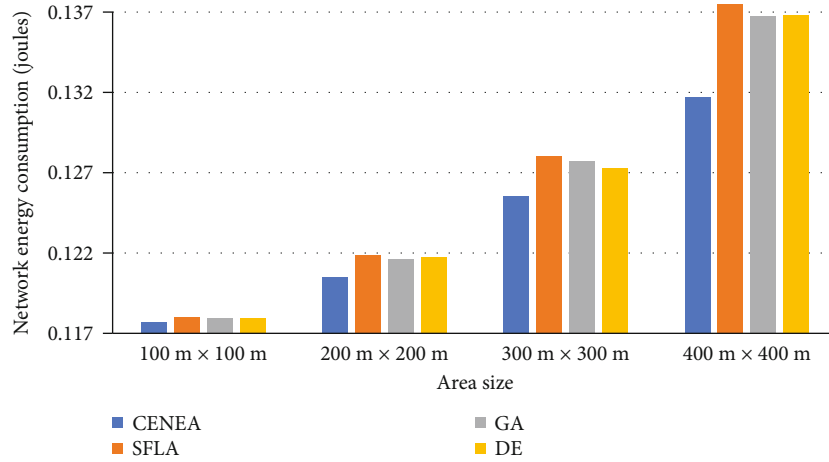
FIGURE 5: The final optimization results of the algorithm in different area sizes.
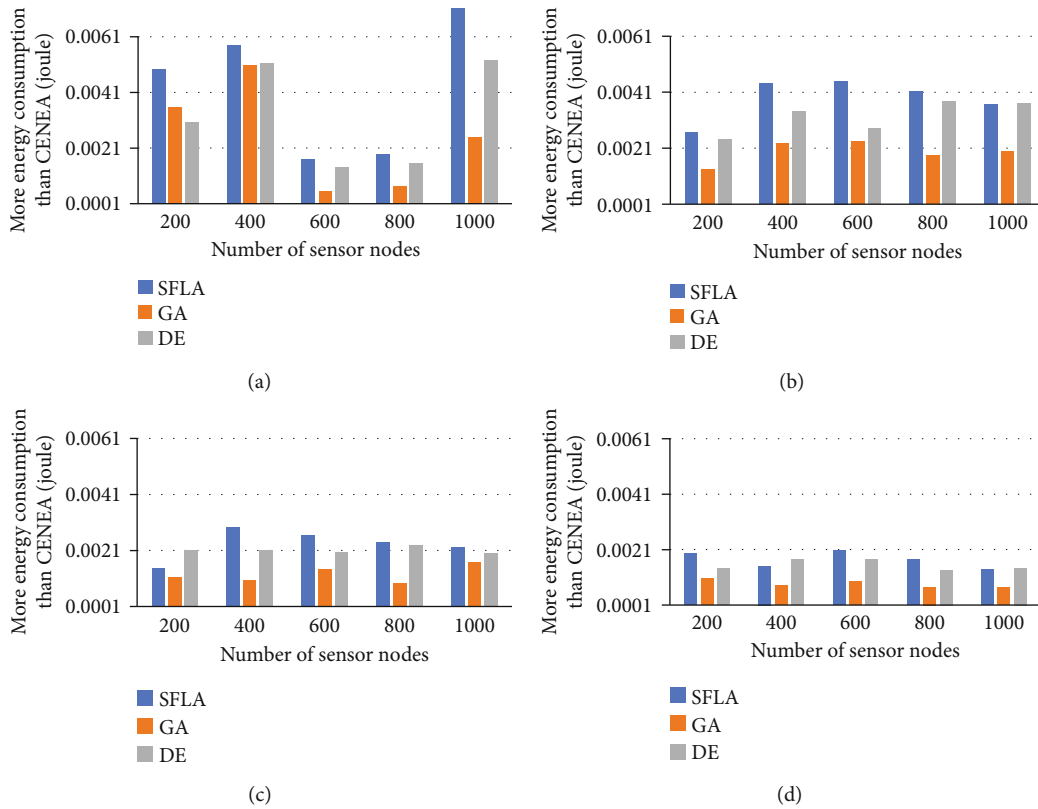

FIGURE 6: The values of SFLA, GA, and DE are more than the total energy consumption of CENEA network communication: (a) the proportion of cluster heads is 5%; (b) the proportion of cluster heads is 10%; (c) the proportion of cluster heads is 15%; (d) the proportion of cluster heads is 20%.

quantity of sensor nodes raising, the complexity of the problem increases exponentially, and CENEA still has a great performance advantage over the other three algorithms.

5. Conclusion

This paper proposes a CENEA clustering scheme for EMWSNs, which uses a heuristic algorithm to dynamically select the location of the cluster head to decrease the power usage of EMWSNs. The CENEA avoids premature convergence by dynamically changing the algorithm parameters in the iterative process and, at the same time, has a faster convergence speed. The simulation outcomes display that, compared with the other three schemes, the proposed CENEA clustering plan in EMWSNs could efficiently decrease the power usage of a single round of network communication.

Comparing CENEA with SFLA, GA, and DE through simulation, it is verified that CENEA effectively reduces network energy consumption in a small-scale environment (100 m × 100 m) and a large-scale environment (400 m × 400 m). The performance advantage of CENEA means that it can propose more excellent cluster head selection schemes in environmental monitoring. CENEA can meet the actual needs of EMWSNs.

Although the energy-efficient clustering algorithm proposed in this paper has proved its superior performance through simulation, it still has some shortcomings due to the limitation of research ability and environmental conditions. Although the computation overhead of CENEA is greatly reduced compared to SFLA, DE, and GA. However, CENEA still cannot avoid a certain computational overhead, especially when facing large-scale wireless sensor networks or running on low-performance hardware. In this paper, the sensor nodes in EMWSNs are statically and randomly distributed in the monitoring area, but some application scenarios require the sensor nodes to be distributed as mobile monitoring data. Although it was verified and implemented under computer simulation conditions, it did not consider the impact of environmental factors on the communication between EMWSN nodes. The application scenario of CENEA is EMWSNs with homogeneous nodes, and the nodes are randomly distributed in a two-dimensional area, without considering the actual three-dimensional environment. In the future, it will be studied to distribute sensor nodes as mobile monitoring data in certain application scenarios. To improve the practicability and adaptability of the algorithm, the next step of research can place the network in a three-dimensional scene and be heterogeneous. In the future, the impact of noise, temperature, obstacles, and other environmental factors on data transmission between EMWSN nodes will be considered, and it will be close to the actual monitoring site.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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