

CM-OOA: An Energy-Efficient Clustering Algorithm for Wireless Sensor Networks Using Chaotic Mapping and Osprey Optimization

Songhao Jia, Wenqian Shao*, Cai Yang, Shuya Jia, Yaohui Yuan, Huiyuan Chen and Haiyu Zhang
School of Artificial Intelligence and Software Engineering, Nanyang Normal University, Nanyang, Henan, 473061, China

E-mail: shaowenqian2023@163.com

*Corresponding author

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A wireless sensor network (WSN) represents a promising approach for establishing self-organizing wireless networks comprising a substantial number of wireless sensors, with the objective of facilitating communication in regions where the existing communication infrastructure has been severely disrupted. In order to address the issue of excessive energy consumption by cluster heads and central nodes in emergency communication networks of wireless sensor networks, this paper proposes an emergency communication algorithm for wireless sensor networks based on chaos mapping and osprey optimization. Firstly, an optimization algorithm based on chaos theory is used to select the virtual position of the initial population of the Osprey optimization algorithm. This is achieved by simulating the randomness and unpredictability of chaotic systems. Secondly, the osprey optimization algorithm and the improved fitness function are used to select the optimal cluster head combination. In the selection process, six factors, such as the energy level of network nodes, the distance between cluster heads, the distance between cluster heads and base stations, the distance between cluster heads and ordinary nodes, the variance of the distance between cluster heads and base stations and the variance of the distance between cluster heads, are comprehensively considered. Finally, the heuristic function of FA-star algorithm is used to select the next hop node to transmit the message. The results of the simulation demonstrate that the residual energy of the CM-OOA algorithm is 14% higher than that of the CGWOA algorithm following the transmission of 1000 data rounds. This figure is 54% higher than that observed for the PSO-C algorithm. The findings demonstrate that the CM-OOA algorithm effectively extends the network lifetime and preserves a favorable load balance in diverse network settings.

Povzetek: CM-OOA algoritem s kaotičnim preslikovanjem in optimizacijo osprejev natančno izbere optimalna vozlišča, zmanjšuje energijsko porabo in podaljšuje življenjsko dobo WSN, kar je ključnega pomena za nujne komunikacijske sisteme.

1 Introduction

In recent years, with the gradual warming of the global climate, after earthquakes, floods, strong tropical storms or other disasters, fixed communication network facilities may be completely destroyed or most of them may not work normally. Communication is extremely important for emergency rescue and disaster relief [1]. At this time, we need an emergency network that can be quickly deployed without relying on any fixed network facilities. A wireless sensor network is a network composed of a large number of randomly distributed nodes that are capable of self-organization. The primary function of the system is to monitor and obtain data from the target area and subsequently transmit it to the base station. A plethora of potential applications can be envisaged in the context of the Internet of Things, including those in the military, aerospace, ocean and agricultural sectors,

among others. Due to its low cost and ease of use, it is capable of functioning in a multitude of challenging environments. In areas inaccessible to humans, unmanned aerial vehicles (UAVs) can be deployed to establish wireless communication networks [2]. It can be reasonably proposed that wireless sensor networks represent a potential method for emergency communication. However, the considerable number of sensor nodes, coupled with the limited energy capacity and relatively short operational lifespan, present significant challenges. Nevertheless, the length of time that emergency communication networks based on wireless sensors can remain operational is a significant challenge. One promising avenue for further research is to enhance the energy efficiency of these networks, thereby prolonging their operational lifespan. Aiming at the energy consumption problem of WSNs in data transmission, it is an effective method to prolong the

life of wireless sensor networks by selecting cluster heads for network nodes and data fusion [3]. At present, cluster head selection algorithm usually uses two technologies, one is to randomly select cluster heads through thresholds, and the other is to design appropriate fitness function to select cluster heads by using swarm intelligence technology. Some scholars have also proposed to solve the problem of rapid death of central nodes by using non-uniform clustering algorithm.

Firstly, scholar Wendi Rabiner Heinzelman proposed LEACH protocol, which randomly rotates cluster heads with a certain threshold, and reduces energy consumption and prolongs network life cycle by clustering nodes to cluster heads [4]. Saxena Madhvi scholars enhanced the original LEACH protocol by introducing new algorithms CHME-LEACH and CHP-LEACH, reducing communication energy consumption and prolonging network life [5]. Jonnalagadda Suman scholars put forward an energy-aware routing protocol MAX LEACH, which is suitable for heterogeneous networks and homogeneous networks, to minimize the energy consumption of nodes and extend the network life [6]. These scholars employ data fusion techniques with the objective of reducing network energy consumption and extending network lifetime.

Secondly, with the continuous development of intelligent algorithms, intelligent algorithms have broad application prospects in selecting cluster heads in wireless sensor networks. The selection of cluster heads in wireless sensor networks is very similar to swarm intelligence algorithm. Therefore, Gülbaş, Gülşah scholars introduced simulated annealing algorithm to propose LEACH-SA algorithm, and introduced simulated annealing algorithm to select cluster heads to extend the network life [7]. Mishra Rashmi scholars select the optimal number of cluster heads among dense network nodes by introducing butterfly optimization algorithm, and select the next hop node by introducing ant colony optimization algorithm in the data transmission stage [8]. Nurul muazzah abdul latiff scholar proposed PSO-C protocol by introducing particle swarm optimization algorithm, which reduced network energy consumption and extended network life [9]. Bejjam Komuraiah scholar put forward at the 14th International Conference on Computing Communication and Networking Technologies in 2023 that genetic algorithm is introduced into wireless sensor networks, which makes the network balance load and optimize, and increases the better results in lower cycle [10]. Muntather Almusawi scholars proposed the CGWOA protocol by introducing chaos algorithm and grey wolf optimization algorithm, which reduced energy consumption by reducing the transmission distance of network nodes [11]. The application of cluster intelligence algorithms enables the selection of cluster heads that optimize the energy consumption of the network, thereby extending its operational lifespan.

Thirdly, for heterogeneous networks, there are also many scholars' research on heterogeneous clustering algorithm. Verma Axel and other scholars put forward the ECSSEEC protocol based on enhanced cost and sub-era. In ECSSEEC protocol, the optimal number of clusters is selected by modeling the cost function, and the previously selected cluster heads are rotated again as

normal sensing nodes in the future rounds of the sub-cycle [12]. Das Rahul proposed a large-scale energy-aware trust optimization algorithm for cluster head selection and malicious node detection. The harmonic search genetic algorithm was originally used to select cluster heads according to energy, trust, distance and density. By considering the trust value, this method avoids choosing malicious nodes as cluster heads, and then uses energy-aware trust estimation models within and between clusters to detect malicious nodes, this depends on two modules: direct trust and indirect trust between clusters and within clusters [13]. Pal. Raju proposed a multi-objective binary grey wolf optimizer to find the clustering method in heterogeneous networks, and extended the network life cycle through five objectives: maximizing the overall cluster head energy, minimizing the cluster head compactness, minimizing the number of cluster heads, minimizing the energy consumption from non-cluster heads to clusters, and maximizing the cluster spacing [14]. These scholars have developed heterogeneous wireless sensor networks with different energy nodes. One method of prolonging the network life cycle is to increase the energy available to the cluster head nodes. The comparison between algorithms is shown in Table 1.

Table 1: Comparison of the different types of protocols involved.

Mode	References	Vantage	Drawbacks
Threshold protocol	LEACH.2000[4]	The algorithm is simple, and the cluster head is selected by the threshold.	Cluster heads are selected by threshold, and random selection can lead to irrational combinations of cluster heads.
	CHP-LEACH.2024 [5]		
	MAX LEACH.2023[6]		
Machine learning protocol	LEACH-SA.2023[7]	Through the continuous selection of swarm intelligence, until the reasonable cluster head selection.	Cluster intelligence is used to select the cluster head and the cluster head nodes should be reasonably located. Better reduction of energy consumption.
	Mishra Rashmi.2023[8]		
	PSO-C.2007[9]		
	CGWOA.2024[11]		
Non-uniform protocol	ECSSEEC.2023[12]	The number of nodes within the cluster is not the same, which can avoid the rapid death of the central node.	Clusters with inconsistent number of nodes in the cluster may lead to a large energy consumption gap between clusters.
	Das Rahul.2024[13]		
	Pal. Raju.2024[14]		

The various clustering routing algorithms proposed by the aforementioned scholars have the potential to reduce the energy consumption of wireless sensor networks and to extend their operational lifetime. However, there is a lack of reasonable allocation methods for the election of cluster heads and the selection of path nodes from cluster heads to base stations in the process of algorithm design. In this paper, a chaos mapping Osprey optimization algorithm (CM-OOA) is proposed to reduce network energy consumption, improve clustering efficiency and prolong network life. Firstly, the randomness and ergodicity of chaotic mapping algorithm are used to

search for the global optimal solution. The core of chaotic mapping algorithm is chaotic mapping, which is a discrete nonlinear dynamic system that can produce seemingly random state changes. Chaos mapping algorithm can effectively search in the solution space, so as to find the optimal solution or near optimal solution of the problem. Secondly, by using the Osprey optimization algorithm, the characteristics of local and global optimization can be well balanced. Find out all the optimal solutions or approximate optimal solutions to find the most suitable node as the cluster head, so that each cluster head node has the highest energy, the shortest distance to the base station, the shortest distance from the node to the cluster head and the more balanced distance between cluster heads. Finally, by comparing the distance from the node to the base station with the distance from the cluster head to the base station, and the energy of the cluster head itself, the common node selects the cluster head node and performs the cluster operation. The node to base station Euclidean distance is less than the cluster head node to base station Euclidean distance and will be transmitted directly to the base station. In the inter-cluster routing stage, based on the FA-star heuristic search algorithm, the heuristic function of four factors, namely the distance from the starting node to the forwarding node, the distance from the forwarding node to the base station, the energy of the node and the forwarding times of the node, is optimized. Select the most suitable next-hop routing node from the neighbor nodes composed of all nodes that meet the conditions. For the hot spot phenomenon that may occur in wireless sensor networks, because some nodes directly transmit to the base station, and the inter-cluster forwarding nodes include cluster head nodes and ordinary nodes, the energy consumption is more balanced, which will not cause the nodes to die too quickly, thus prolonging the communication time of the emergency communication network.

2 System model

2.1 Communication network structure model

The topology model of wireless sensor network adopted in this paper is shown in Figure 1. The simulation model assumes that N nodes are randomly distributed in a square area of $M \times M$ and all nodes are wireless sensors of the same type. The network model is shown in Figure 2. In order to accurately calculate the information of the node and ensure that the base station receives and sends data continuously and stably, the node can independently select the appropriate transmission power according to the energy consumption model [15-16]. In order to avoid the influence of bad weather and human factors, network nodes need to meet the following requirements:

- 1) The random dropping area $M \times M$ contains N sensor nodes, and the node positions after dropping are fixed.
- 2) Sensor nodes have unique and different ids.
- 3) The base station has unlimited energy and no signal interference in the area.

- 4) The power sent and received by each sensor node is controllable.
- 5) All sensors have the same properties and their positions remain unchanged relative to the base station.

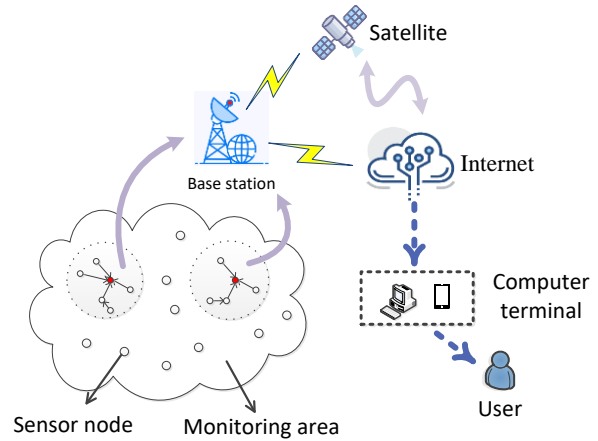


Figure 1: Network topology model.

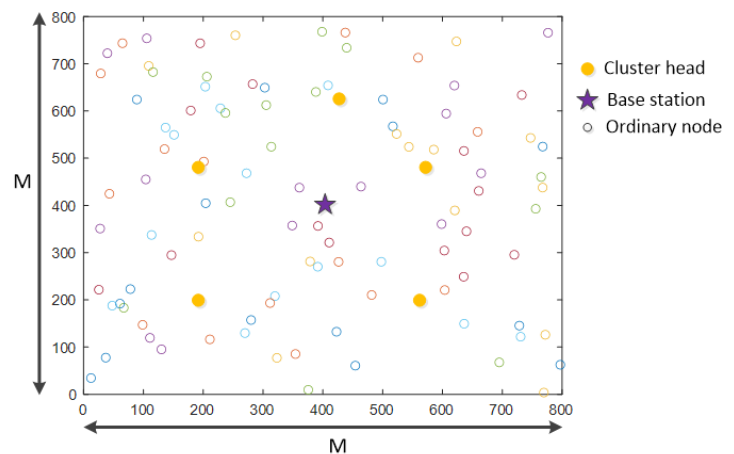


Figure 2: Emergency communication network mode.

There are three main communication modes in the emergency communication network. Firstly, Communication within a cluster. Because information transmission is only between clusters, this method consumes less energy for wireless sensor networks [17]. Secondly, Communication of the same cluster head node. When users are not in the same cluster head node, if communication is needed, the common node will report to the superior cluster head node and communicate with each other through the cluster head node. Thirdly, Communication between different cluster head nodes. When users are neither the same cluster nor the same cluster head node, if communication is needed, ordinary nodes will report to their superior's step by step and contact each other through base stations [18]. In the communication process of wireless sensor network, the third process needs the information transmission of the whole wireless sensor network. User information is transmitted in both directions from ordinary nodes to base stations and then to ordinary nodes, so energy consumption is mainly concentrated in the third mode

[19]. Therefore, this paper mainly studies the energy consumption of the third communication mode.

2.2 Communication energy consumption model

In this paper, the wireless sensor emergency communication network adopts the first-order wireless communication energy consumption model [20], which can be divided into short-distance free space model and long-distance multi-path model according to the transmission distance. The specific formulas are as follows: (1) - (3).

$$E_{Tx}(K, L) = \begin{cases} K * E_{elec} + K * \varepsilon_{fs} * L^2, & L < D_0 \\ K * E_{elec} + K * \varepsilon_{mp} * L^4, & L \geq D_0 \end{cases} \quad (1)$$

$$D_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (2)$$

$$E_{Rx}(K, L) = K * E_{elec} \quad (3)$$

In formulas (1) - (3), E_{Tx} is the energy consumption for sending K bit data; E_{elec} represents the energy consumption associated with the transmission and reception of a single bit of data; ε_{fs} is the loss factor of free space model; ε_{mp} is the energy loss factor of multipath attenuation model; L is the data transmission distance; E_{Rx} is the energy consumption for receiving K bit data.

3 Research on energy consumption of three-layer network

From the network topology diagram, we can see that the data acquisition and transmission stage of wireless sensor networks can be divided into three levels: ordinary node layer, cluster head node layer and base station layer, as shown in the Figure 3.

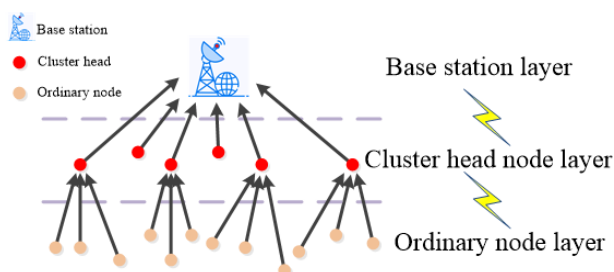


Figure 3: Three-layer network model.

Through the formulas (1) -(3) in the network energy consumption model, the main reasons of energy consumption in the three-layer network can be analyzed respectively. The data transmission of ordinary nodes is the key to energy consumption. When the transmission distance exceeds D_0 , the energy consumption during data transmission will increase sharply, so the appropriate

location of cluster head nodes is very important. Attention should also be paid to the direction of data transmission in the process of ordinary nodes entering the cluster, but the "hot spot effect" around the base station in wireless sensor networks is also the key to extend the network life [21]. Through formula (1), it can be seen that multi-hop transmission is better than single-hop transmission in long-distance transmission. However, in multi-hop transmission, in the process of selecting the next hop node from the cluster head node to the base station, the same next hop node will be selected continuously, resulting in the rapid death of the node. To solve these problems, it contains three main problems:

- 1) Does the cluster head combination affect the network energy consumption?
- 2) How to plan the direction of data transmission to solve the problem of "hotspot effect" where the center node dies quickly?
- 3) Can the multi-hop cluster head node choose the same node as the forwarding node every round?

In the past, many researchers did not comprehensively consider the above problems from the perspective of three-tier network energy consumption model. Some researchers randomly select cluster head combinations, which leads to the irrationality of cluster heads, and then leads to redundant energy consumption. Because the ultimate goal of data is the base station, the data transmission direction can only be close to the base station. However, most researchers do not consider the influence of the clustering operation process of ordinary nodes on the data transmission direction, and all nodes are clustered. This process causes some nodes to transmit data in the opposite direction to the base station, resulting in energy transmitted in the opposite direction. Some researchers also use multi-hop in long-distance transmission, but the forwarding times of the next hop node are not considered, which can not be ignored for the node life.

Aiming at the above three problems, this section will analyze the energy consumption reasons of each layer network from the perspective of three-layer network energy consumption, and put forward a reasonable cluster head selection, data transmission direction planning, and next-hop node selection and processing algorithm in multi-hop mode.

3.1 Reasonable cluster head combination

In the process of selecting cluster head nodes by ordinary nodes, the distances from different cluster head node combinations to nodes are different. Therefore, it has an impact on the overall energy consumption of the network. From the energy transmission formula (1), it can be seen that the distance is directly proportional to the energy consumption. Reasonable cluster head combination can better reduce the energy consumption of sending data due to distance.

In the osprey optimization algorithm (OOA), the optimal position of individual osprey is obtained by updating the position of individual osprey and comparing the fitting

function values of each individual position. However, the osprey optimization algorithm is limited by its slow convergence speed and tendency to converge to the local optimal solution. Aiming at the problems of slow convergence speed and easy to fall into local optimal solution in cluster head combination selection, this algorithm combines population initialization process with K-means++ algorithm and chaotic algorithm to form chaotic osprey optimization algorithm (CM-OOA). The output of chaotic Osprey optimization algorithm is similar to the selection of cluster head combination in wireless sensor networks. As shown in Table 2, there is significant consistency between the characteristics of wireless sensor networks and the principle of chaotic Osprey optimization algorithm.

Table 2: Similarity correspondence table between wireless sensor networks and chaotic mapping osprey optimization algorithm.

WSN	CM-OOA
Sensor node number	Dimension position size
Node group	Individual position of osprey
Cluster head node combination	Optimal individual position of osprey
Combination of all pre-selected cluster head nodes	All positions of osprey population

Good population initialization allows the CM-OOA algorithm to start searching from several different initial starting points, which helps the algorithm to explore multiple regions of the solution space, thus increasing the likelihood of finding a globally optimal solution. If the individuals in the initial population are too concentrated, the algorithm may quickly converge to the local optimal solution and ignore other potentially better solutions. A diverse initial population helps to avoid this. Proper population initialization allows the algorithm to find better solutions at an early stage, thus speeding up the convergence of the whole search process. Therefore, the algorithm in this paper performs the population initialization operation in two ways.

3.1.1 Kmeans++ algorithm for clustering

Initializing the populations is an important step in the CM-OOA algorithm, which uses the Kmeans ++ clustering algorithm for clustering to obtain a more accurate optimal solution. The initial population nodes are selected by the centre position of each cluster group. The calculation of the cluster centre position is based on the application of equations (4) and (5). The effect of the clustering algorithm is shown in Figure 4.

$$X_m = \sum_{i=0}^t X/t \tag{4}$$

$$Y_m = \sum_{i=0}^t Y/t \tag{5}$$

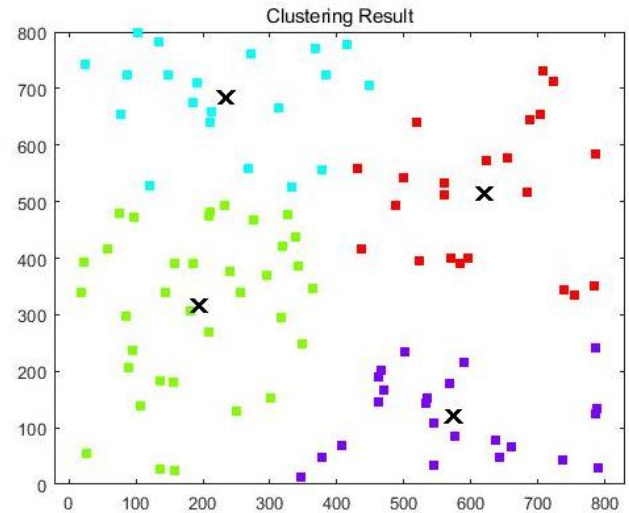


Figure 4: Clustering algorithm effect.

3.1.2 Chaos mapping optimization

Initializing the population by Logistic chaotic mapping can enhance the global search ability and help CM-OOA algorithm jump out of the local optimal solution [22]. The randomness and unpredictability of Logistic chaotic mapping can prevent the algorithm from converging to the local optimal solution prematurely. Logistic chaotic mapping can adapt to different search spaces and optimization problems, and has good universality. Therefore, Logistic chaotic mapping can be easily combined with Osprey optimization algorithm to form CM-OOA algorithm, so as to make better use of their respective advantages to deal with the problem. Logistic chaotic mapping formula is as follows:

$$P_{i+1} = \alpha * P_i * (1 - P_i) \tag{6}$$

In the formula, α is the control parameter, and the value is taken in (0,4]. P_i is the transformation of the coordinates of the initial population into polar angles as an initial value.

The detailed process of CM-OOA algorithm:

Step 1. Population initialization.

The virtual initialization of the Osprey cluster is achieved by means of the circular symmetric chaotic mapping algorithm and the K means++ clustering algorithm.

Step 2. Initialization of osprey population based on location mapping algorithm.

The virtual position of the initialized osprey population is obtained, and the real node number in the wireless sensor network is mapped by the Euclidean distance d from the node to the virtual position and the energy e of the node itself. The osprey population is initialized to $P(t) = \{Pt_1, Pt_2, Pt_3, \dots\}$, and the individual Pt_i position of osprey is $Pt_i = \{X_{i1}, X_{i2}, X_{i3}, \dots\}$.

Step 3. Calculate the fitness function.

F_i =fitness ($P_{i(t)}$) is the fitness value of individual $P_{i(t)}$ of osprey at time t , which is used to evaluate the strength of solving energy consumption problems at the position of osprey.

Step 4. Osprey individuals look for schools of fish.

Through the comparison of fitness values, the individual positions of osprey whose fitness values are smaller than their own are combined as fish schools, $Fish = \{P_{k(t)} | k \in \{1, 2, \dots, N\} \wedge F_k < F_i\} \cup \{P_{best}\}$.

Step 5. Individual fishing of osprey.

In Step 3, the osprey individual P looks for his own Fish school. If the Fish school fish is empty, it is considered that the osprey individual X has successfully caught the target fish and directly goes to Step 5 for the osprey individual to eat fish. Otherwise, the osprey individual P randomly selects a target Fish in the fish school fish for fishing operation. Because the node coordinates are two-dimensional, the coordinates X and Y are calculated separately for fishing operation. The formula of specific fishing process is as follows:

$$P_{t,jx}^{Fish} = P_{t,jx} + R_{t,j} * (P_{Fishx} - I_{t,j} * P_{t,jx}) \quad (7)$$

$$P_{t,jy}^{Fish} = P_{t,jy} + R_{t,j} * (P_{Fishy} - I_{t,j} * P_{t,jy}) \quad (8)$$

In formulas (7) - (8), $R_{t,j}$ is a number randomly generated between $[0,1]$; $I_{t,j}$ is randomly selected between 1 and 2; $P_{t,jx}$ is the X coordinate position of osprey individual P in the J -th dimension of the T -th round; P_{Fishx} is the x coordinate position of the target fish x of the osprey individual p ; $P_{t,jy}$ is the Y coordinate position of osprey individual P in the J -th dimension of the T -th round; P_{Fishy} is the y coordinate position of the target fish y of the osprey individual p .

Step 6. Osprey individuals eat fish.

In Step 4, the position of individual P of osprey changes. First, the process Step 2 Location Mapping maps the position of the individual osprey to the network node number [23]. Secondly, the fitness value before and after the change of osprey individual is judged to judge whether the osprey individual catches the target fish. Finally, if the fitness value is greater than that before the change, the osprey individual P fails to catch the target fish successfully, and the process is directly carried out in Step 6. Otherwise, the osprey individual P successfully catches the target fish and eats the fish. Because the node coordinates are two-dimensional, the coordinates x and y are calculated separately for fish eating operation. The specific formula for eating fish is as follows:

$$P_{t,jx}^{Fish} = P_{t,jx} + (lb_t + R_{t,j} * (ub_t - lb_t))/t \quad (9)$$

$$P_{t,jy}^{Fish} = P_{t,jy} + (lb_t + R_{t,j} * (ub_t - lb_t))/t \quad (10)$$

In formulas (9) - (10), $R_{t,j}$ is a number randomly generated between $[0,1]$; ub_t is the upper boundary of the dimension coordinate; lb_t is the lower boundary of the dimension coordinate; $P_{t,jx}$ is the X coordinate position of osprey individual P in the J -th dimension of the T -th round; $P_{t,jy}$ is the Y coordinate position of osprey individual P in the J -th dimension of the T -th round; T is the number of rounds of population iteration.

Step 7. New osprey population position.

$P(t+1) = \{\dots\}$ indicates a new generation of osprey population generated by individual osprey searching for fish, individual osprey catching target fish and individual osprey eating fish [24].

Step 8. Algorithm termination condition.

The algorithm repeats the operations from Step 3 to Step 7 until the maximum number of iterations is reached.

Step 9. Algorithm output.

The optimal individual fitness value and osprey position are obtained, that is, the optimal cluster head combination.

Step 10. Ordinary nodes into the cluster operation.

By calculating the fitness function of clustering and comparing and selecting, ordinary nodes select the optimal clustering node for clustering operation.

Step 11. Data transfer operation.

The initial node selects the jump node through heuristic search FA-star algorithm for data transmission.

Firstly, CM-OOA algorithm iteratively updates the individual position of the osprey population, compares the individual position fitness values and selects the smallest individual fitness value, that is, the optimal individual position of the osprey. Secondly, ordinary nodes enter the cluster by calculating the fitness value of the cluster head. Finally, the improved FA-star algorithm is used for inter-cluster routing transmission. The detailed flow of CM-OOA algorithm is shown in Figure 5.

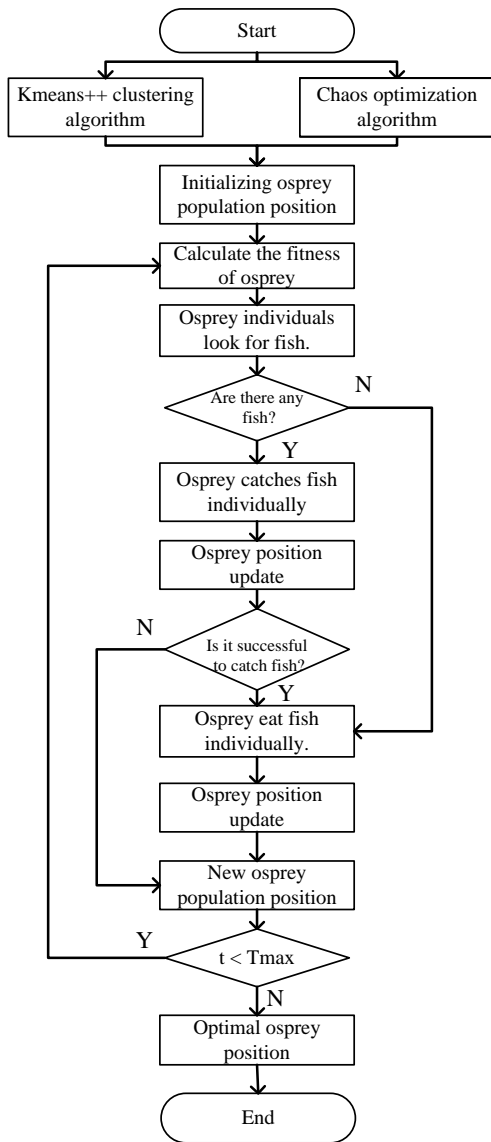


Figure 5: Flow chart of selecting cluster head by CM-OOA algorithm.

3.2 Planning of data transmission direction

In wireless sensor networks, all nodes are clustered, so when the nodes are close to the base station, they will still be clustered. As shown in Figure 6, it causes the problem that the node data is transmitted outward first and then inward. From the energy consumption model, it can be calculated that the energy consumption of all nodes in data clustering is E_2 , while the energy consumption of nodes in direct transmission is E_1 . From formulas (11) - (12), it can be concluded that the direct transmission mode of some nodes has low energy consumption.

$$E_1 = K * E_{elec} + K * \epsilon_{fs} * L_1^2 \tag{11}$$

$$E_2 = 2 * K * E_{elec} + K * \epsilon_{fs} * (L_2^2 + L_3^2) \tag{12}$$

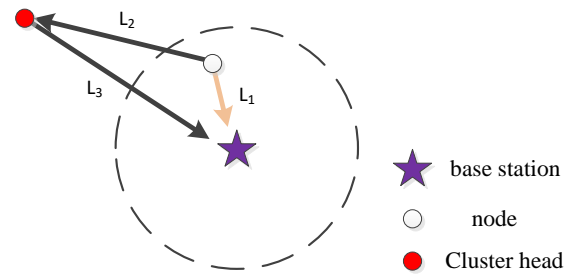


Figure 6: Data flow direction comparison chart.

In order to solve the problem of data transmission direction, the algorithm is based on the mathematical midline theorem. As shown in Figure 7, when the common node is located in the midline of the link from the cluster head node to the base station, the distances from the common node to the cluster head and the base station are equal [25]. Therefore, when $d_3 > d_1$, the common node will perform the cluster head selection operation. CM-OOA algorithm reduces energy consumption by preventing nodes from transmitting far away from the base station. As shown in Figure 8, the cluster head node CH_2 will be selected first when the distance d_3 from the common node to the base station is greater than the distance d_2 from the cluster head node CH_2 to the base station. Although it can be seen from the figure that the distance d_4 from the common node to the cluster head node CH_1 is smaller than the distance d_5 from the cluster head node CH_2 , the cluster head node $\{CH_2, \dots\}$ of the common node will be pre-selected with less energy. If the pre-selected cluster head set is empty, data is directly transmitted to the base station.

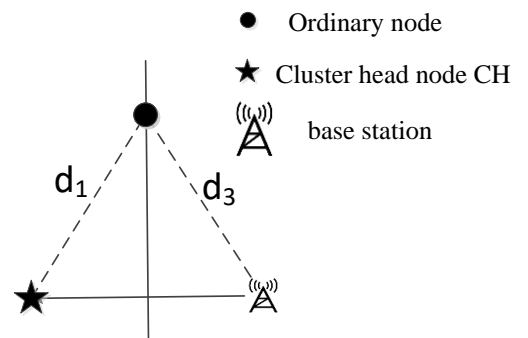


Figure 7: Median line

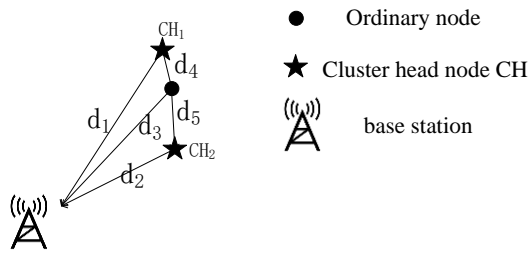


Figure 8: Cluster head selection model of common nodes.

3.3 Best next hop node

According to the energy consumption model, transmission energy consumption is directly proportional to the square of distance, and data transmission is the main energy consumption of wireless sensor networks. According to the geometric cosine theorem and the first-order radio network energy model [26]. Therefore, the algorithm in this paper adopts multi-hop mode for data transmission.

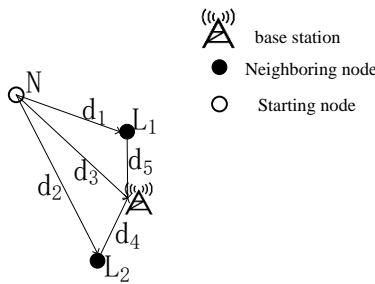


Figure 9: Neighbor node selection model.

In the process of multi-hop data transmission, FA-star algorithm and heuristic search are used to select the transmission path. The destination base station is reached by finding the minimum cost of the path [27]. In this algorithm, the neighbor nodes are selected in the same way as the cluster heads in the clustering algorithm. The Euclidean distance d_1 from the start node N to the neighboring node is less than the Euclidean distance d_3 from the start node to the base station, so the neighboring node chooses L_1 . As shown in Figure 9, the starting node n of the neighboring node $\{L_1, \dots\}$ directly transmits if the neighboring node is empty.

4 Design of CM-OOA algorithm

In this paper, the energy consumption of three-layer network is analyzed in detail, and the clustering algorithm of CM-OOA network is proposed by combining the chaotic Osprey optimization cluster head combination selection algorithm with the data transmission direction and the best next hop strategy. The algorithm is divided into cluster head selection stage, cluster establishment stage and data transmission stage. The algorithm flow chart is shown in the Figure 10.

4.1 Cluster head selection

In the process of cluster head combination selection, firstly, the number of cluster head nodes in the network is calculated and the CM-OOA algorithm population is initialized. The virtual nodes are output by CM-OOA algorithm, and the virtual nodes are mapped to the real network to output the real and reasonable cluster head combination.

4.1.1 Size of optimal number of cluster heads

The energy consumption of nodes is an important factor affecting the communication time of emergency communication network, and the number of cluster heads plays a vital role in the whole network [28-29]. The main consumption of emergency communication is divided into ordinary nodes transmitting cluster head E_{pt} , ordinary nodes directly transmitting base station E_{cp} , cluster head nodes receiving intra-cluster node data E_{cn} , cluster head nodes fusing data E_r , and cluster head nodes sending data to base station E_{cj} . The nodes deployed in the $a \times a$ model are evenly distributed, and $(N-n)$ nodes are evenly distributed in KN circular clusters, and n nodes are directly transmitted to the base station, so the energy consumption for one round of network transmission is:

$$E_{ALL} = KN * (E_{pt} + E_{cn} + E_r + E_{cj}) + E_{cp} \quad (13)$$

The energy consumption of common nodes in each cluster is:

$$E_{pt} = (k * E_{elec} + k * \epsilon_{fs} * d_{cntoCH}^2) * \left(\frac{N-n}{KN} - 1\right) \quad (14)$$

The energy consumption of ordinary nodes directly transmitting base stations is:

$$E_{cp} = (k * E_{elec} + k * \epsilon_{fs} * d_{cntoCH}^2) * n \quad (15)$$

The cluster head node receives the energy consumption of nodes in the cluster as follows:

$$E_{cn} = k * E_{elec} * \left(\frac{N-n}{KN} - 1\right) \quad (16)$$

The energy consumption of nodes in cluster head node fusion cluster is:

$$E_r = k * E_{DA} * \left(\frac{N-n}{KN}\right) \quad (17)$$

The energy consumption transmitted from the cluster head node to the base station is:

$$E_{cj} = k * E_{elec} + k * \epsilon_{fs} * d_{CHtoBS}^2 \quad (18)$$

In the formula, d_{CHtoBS} is the distance from the cluster head node to the base station.

The distance from the common node to the cluster head node in each cluster is:

$$d_{cntoCH} = \sqrt{\rho * \iint (x^2 + y^2) dx dy} = \frac{a^2}{\sqrt{2\pi * KN}} \quad (19)$$

Sorting out the above equations (13) - (19), calculating the value of KN when E_{ALL} is minimized by deriving

the overall energy consumption of the network in one round, and obtaining the optimal number of cluster heads KN as follows:

$$KN = \sqrt{\frac{N * \epsilon_{fs} * a^2}{2\pi * (\epsilon_{fs} * d_{CHtoBS}^2 - E_{elec})}} \tag{20}$$

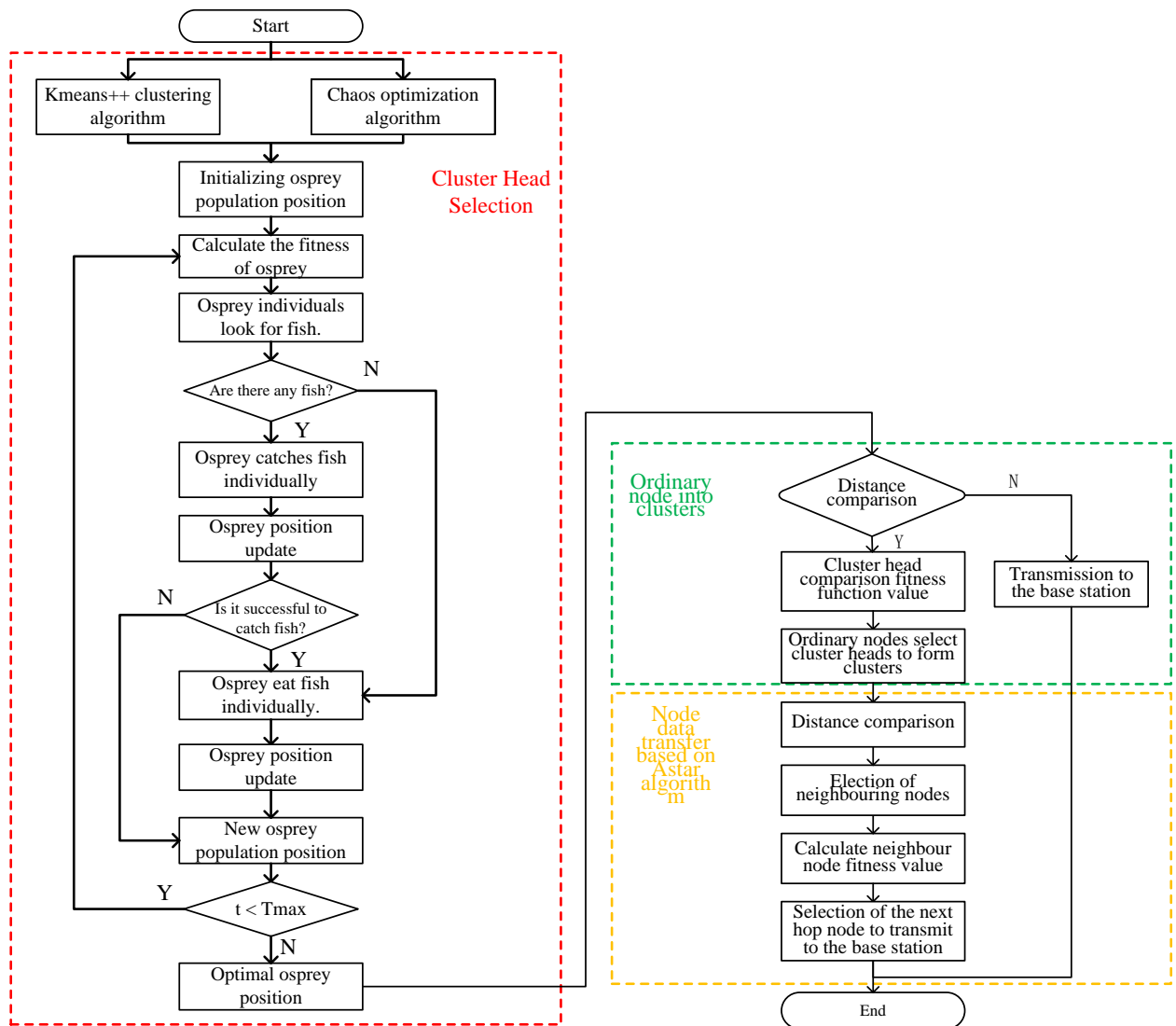


Figure 10: Flow chart of CM-OOA algorithm.

4.1.2 Population initialisation

In order to avoid the problems of slow convergence speed and easy to fall into local optimal solution of Osprey optimization algorithm, this algorithm maps the initial population by chaos. The detailed flow of the chaotic mapping algorithm is shown in Algorithm 1.

Algorithm 1: Pseudo-code of circular symmetric chaotic mapping algorithm.

Algorithm 1: Initialization of osprey population by chaotic mapping algorithm

Begin:

Calculate the polar angle from the node to the base station

Obtaining the polar angle and converting the polar angle into the initial value of the mapping.

Using Logistic mapping, Equation (9)-(10) introduces chaotic characteristics.

The chaotic characteristics are inversely transformed to obtain a new polar angle.

Obtain a new polar angle and calculate the virtual coordinates in the mapped rectangular coordinate system.

End

4.1.3 Location mapping

The coordinates of nodes in wireless sensor networks are all random, but the coordinate positions change randomly after CM-OOA algorithm. After the coordinate of CM-OOA algorithm is transformed separately from the X axis and the Y axis, there may be no real node at this coordinate [30]. Therefore, CM-OOA algorithm designs a position mapping function through the Euclidean distance to the virtual position and the energy of the real node, and maps the coordinates at the virtual position to the nodes in the actual coordinate space through the position. The location mapping formula is as follows:

$$F = \theta_1 * d + \theta_2 * E \tag{21}$$

In the formula, d is the Euclidean distance from the virtual position to the node; E is the energy of the node; θ_1 and θ_2 are weight factors and satisfy $\theta_1 + \theta_2 = 1$.

The detailed flow of the location mapping algorithm is shown in Algorithm 2.

Algorithm 2: Pseudo-code of position mapping algorithm.

Algorithm 2: The virtual position is projected to the real node through the mapping function.

Begin:

Calculating Euclidean distance d from all nodes to virtual position coordinates

Obtain the energy e of all nodes themselves.

Calculate the position mapping function by formula (4)-(5)

By comparing the function values, the node numbers of virtual coordinates projected into the real network are selected.

End

4.1.4 Design CM-OOA algorithm adaptation function

In order to optimize the selection of cluster heads and improve the life cycle of the network, after determining the optimal number of cluster heads, the fitness function is set according to the state of nodes and the position of pre-selected cluster heads [31]. The cluster head node is responsible for the data forwarding of ordinary nodes. Therefore, the selection of cluster head should have the characteristics of high energy, reasonable location and less times of becoming a cluster head. The fitness function of CM-OOA algorithm is designed from the following six aspects: the energy of nodes, the distance between cluster heads, the distance between cluster heads and each node, the distance from cluster heads to base stations, the variance of the distance from cluster heads to base stations, and the variance of the distance from cluster heads to cluster heads.

The energy level of the node itself: the reciprocal of the remaining energy of the current node. The cluster head node is the key condition to support the network operation [32]. If the energy of the node is higher, the

reciprocal is smaller, and the node can forward data better under the same conditions, it should be selected as the cluster head.

$$F_1 = 1/E_i \tag{22}$$

The level of Euclidean distance between cluster heads: the reciprocal of the sum of distances between cluster head nodes. The location of the cluster head determines the distance of data transmission by the nodes entering the cluster. Cluster heads should be evenly dispersed to reach the distance of all nodes.

$$F_2 = 1/\sum dis(CH_i, CH_j) \tag{23}$$

Euclidean distance between cluster heads and nodes: the sum of the distances from cluster head node to all nodes. Energy consumption in network cycle mainly comes from node transmission. The sum of the positions of all nodes in the cluster is the smallest, so as to minimize the energy consumption of data transmission.

$$F_3 = \sum dis(N_j, CH_i) \tag{24}$$

Euclidean distance from the cluster head to the base station: the sum of distances from all cluster head nodes to base station BS. The transmission of cluster head node is the energy consumption of the second part of the network cycle, and the distance from cluster head node to base station determines the energy consumption of cluster head node [33]. Therefore, the sum of the distances from the cluster head node to the base station is the smallest, and the information can be transmitted to the base station with the least energy consumption.

$$F_4 = \sum dis(CH_i, BS) \tag{25}$$

The variance of the Euclidean distance from the cluster head to the base station: variance of distance from all cluster heads to base station. Because there is more than one cluster head node, and only the sum of the distances from the cluster head to the base station is kept to the minimum, there may be a very long distance between a node and the base station. Therefore, by adding the variance of the distance from the cluster head to the base station to control the distance between the cluster head and the base station, all the distances from the cluster head to the base station can be better kept to be the minimum.

$$F_5 = Var(\sum dis(CH_i, BS)) \tag{26}$$

The variance of the cluster head to cluster head Euclidean distance: variance of cluster head to cluster head distance [34]. There is more than one cluster head node, so it is necessary to prevent the distance between them from appearing some deviations that are very close and some are very far away. Therefore, by adding the variance of the distance from cluster head to cluster head to control the gap between cluster heads, the distribution of all cluster heads can be better maintained and more reasonable.

$$F_6 = Var(\sum dis(CH_i, CH_j)) \tag{27}$$

Based on the energy of nodes, the distance between

cluster heads, the distance from cluster heads to nodes, the distance from cluster heads to base stations, the variance of the distance from cluster heads to base stations and the variance of the distance from cluster heads to cluster heads, the fitness function is designed by weight control:

$$Fitness = \alpha_1 * F_1 + \alpha_2 * F_2 + \alpha_3 * F_3 + \alpha_4 * F_4 + \alpha_5 * F_5 + \alpha_6 * F_6 \tag{28}$$

In the formul hierarchical analysis method to calculate the weightsa, $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ and α_5 are weight factors and satisfy $\sum \alpha_i = 1$.

According to the improved fitness function, the fitness functions of all osprey individuals are calculated, and the optimal position of osprey individuals is selected. The algorithm flow is shown in Algorithm 3.

Algorithm 3: Pseudo-code of cluster head node selection algorithm.

Algorithm 3: Select the cluster head according to the improved fitness function.

Begin:

Initializing a network node to obtain the initialized osprey population position.

Calculate the fitness value of the osprey individual, and keep the individual position and fitness value with the minimum fitness value.

While $t < t_{max}$ do

By comparing the fitness values of osprey population, the individual fish school of osprey is generated.

All osprey individuals began to fish.

Position mapping of osprey individuals after fishing

Update osprey position

if Fitness value of osprey position before fishing > Fitness value of osprey position after fishing

After successful fishing, osprey individuals began to eat fish.

Position mapping of osprey individuals after eating fish

end

Update The location of the new osprey population

Update Individual osprey with minimum fitness value and fitness value

$t = t + 1$

Return The position and fitness value of osprey with minimum fitness value

End

4.2 Cluster establish stage

In the stage of cluster establishment, in order to prevent reverse data transmission, the ordinary nodes of the base station first judge whether to enter the cluster or not. Some nodes directly transmit data to the base station to reduce the influence of "hot spot effect" in the network. By comparing the fitness values of cluster head nodes, the appropriate cluster head nodes are selected. The clustering algorithm is shown in Algorithm 4.

Through the fitness function value of cluster head nodes, the preselected cluster head with the minimum value is compared. That is, the cluster head node of ordinary nodes. The fitness function of this algorithm is as follows:

$$F = \beta_1 * E + \beta_2 * dis(N, CH) \tag{29}$$

In the formula, dis (N, CH) denotes the Euclidean distance from the common node to the head node of the pre-selected cluster, and E represents the energy of the pre-selected cluster head node in the current round. $\beta_1=0.4$ and $\beta_2=0.6$ are weight factors and satisfy $\beta_1+\beta_2=1$.

Algorithm 4: Ordinary node cluster.

Algorithm 4: Network node cluster establishment.

Begin:

Obtaining cluster head node set from algorithm 3.

If Ordinary nodes satisfy the selection of cluster head nodes.

If Meet the conditions of pre-selecting cluster heads for ordinary nodes.

The cluster head is put into the reselected cluster head set.

Else.

Ordinary nodes are put into the set of direct transmission base stations.

End.

Else

Nodes directly transmit data to the base station without joining the cluster.

End

Calculate the fitness value of the pre-selected cluster head.

Ordinary nodes select the cluster head node and perform cluster entry operation.

End.

4.3 Node data transfer based on FA-star algorithm

The network data transmission process in this paper adopts multi-hop mode. The heuristic function of Astar

algorithm is optimized by the energy of nodes and the forwarding times of nodes, which avoids the problem of selecting nodes with the same next hop continuously. Select the most suitable data transmission path. The clustering algorithm is shown in Algorithm 5.

Through the heuristic function of neighbor nodes, the neighbor nodes with the minimum value are compared. That is, the next hop node of the starting node. The heuristic function of FA-star algorithm is as follows:

$$F = \gamma_1 * E + \gamma_2 * dis(N, L) + \gamma_3 * dis(L, BS) + \gamma_4 * G \tag{30}$$

In the formula, E represents the energy of neighboring nodes, G represents the forwarding times of neighboring nodes, dis(N,L) represents the distance from the starting node to neighboring nodes, and dis(L,BS) represents the distance from neighboring nodes to the base station. γ_1 , γ_2 , γ_3 and γ_4 are the weight influencing factors and satisfy $\gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 = 1$.

Algorithm 5: Network data transmission

Begin:

The cluster head node set and the direct transmission set in the acquisition algorithm 3 are merged into the initial node set.

while Starting node \neq base station.

If Meet the condition of neighbor nodes

Ordinary nodes are put into the set of neighboring nodes.

End.

If Neighbor node set is empty.

The originating node sends data directly to the base station.

Else.

Calculate the heuristic function comparison function value of neighboring nodes, select the next hop node and transmit data.

End.

End.

End.

5 Experimental simulation analysis

5.1 Experimental parameters

In order to examine the simulation effectiveness of CM-OOA algorithm in extending the network life cycle, the algorithms are compared and analyzed on MATLAB R2023b platform. The advantages of the basic algorithm LEACH algorithm and the latest cluster classification algorithms PSO-C algorithm, CGWOA algorithm and the CM-OOA algorithm in this paper are verified in terms of

energy consumption of the network system, the number of dead nodes and the number of surviving nodes. The energy consumption of data fusion process is neglected, because the communication mode is two-way, and only one communication direction is calculated for the convenience of calculating energy consumption. Because of the close distance between users and nodes, the energy consumption is negligible [35]. An 800m \times 800m experimental simulation area is drawn and 100 X-axis coordinates and 100 Y-axis coordinates are randomly generated to combine into 100 nodes, and the base station is located in the center of the area. From formula (20), the optimal number of cluster heads is $KN = 0.04 * n$. The specific parameters are shown in Table 3.

Table 3: Experimental parameter table.

Parameter	Numerical value
Number of network nodes	100
Network area size	800m \times 800m
Base station coordinate position	(100,100)
Energy loss coefficient of free space model	10 P _i /bit/m ²
Energy loss coefficient of multipath attenuation model	0.0013 P _i /bit/m ²
Node initial energy	4 J
Number of networks running rounds	1000 rounds

5.2 Analysis of energy change of emergency communication system

The residual energy of wireless sensor network system reflects the life cycle of emergency communication network [36-37]. The more residual energy, the longer the communication time of emergency communication network. The network energy of the four algorithms changes as a whole, as shown in Figure 11.

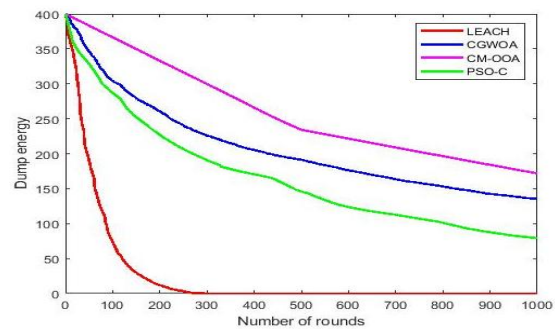


Figure 11: Changes of residual energy in emergency communication network.

Of the 1000 rounds of energy consumption, the LEACH algorithm consumed all of its energy in the 250th round, the PSO-C algorithm had 23% of its energy remaining after the 1000th round, the CGWOA algorithm had 35% of its energy remaining after the 1000th round, the CM-OOA algorithm still had 43% of its energy in the 1000th round, and it consumed it slower than the other algorithms from the 0th to 1000th rounds. It can be seen that, compared with other algorithms, the CM-OOA algorithm selects the optimal cluster head through the chaotic mapping osprey optimisation algorithm, taking node energy and node transmission distance as the main factors, and the variance of the distance from the cluster head to the base station and the variance of the distances between the cluster heads as the auxiliary factors, and performs the cluster selection based on the information, and performs the cluster selection based on the distance of the information transmission and the node energy in the clustering stage, instead of using a single inter-cluster distance as weights, instead of using node energy and number of node forwards, distance from start node to neighbouring nodes and distance from neighbouring nodes to base station. The FA-star algorithm with heuristic function can better reduce the energy consumption and extend the life cycle of emergency communication network.

5.3 Analysis of the number of dead nodes in the network

The number of dead nodes in wireless sensor networks reflects the overall stability of the network. The more dead nodes, the greater the impact on the overall emergency communication network, the smaller the coverage area and the faster the death rate [38]. The number of dead nodes of the four algorithms changes, as shown in Figure 12:

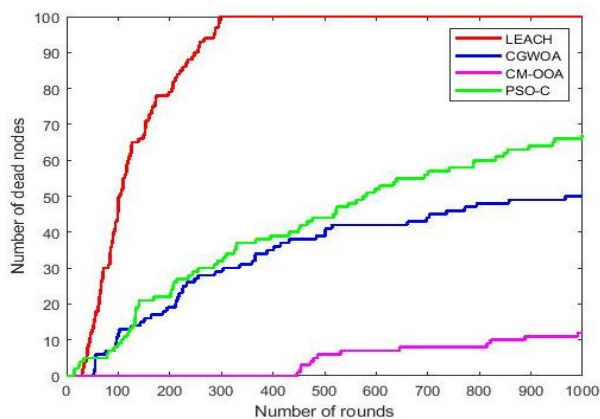


Figure 12: Changes in the number of dead nodes in communication networks.

In Figure 12, the various algorithms start to show dead nodes after 30 rounds, the LEACH algorithm clearly shows dead nodes after about 35 rounds, and almost all nodes die after 300 rounds, while the PSO-C algorithm's rate of dead nodes grows faster.

Although CGWOA algorithm appears dead nodes later than PSO-C algorithm, the localised death rate is faster, which should not be ignored. In contrast, the CGWOA algorithm has better overall changes than the PSO-C and LEACH algorithms, and grows much slower than the CM-OOA algorithm. The CM-OOA algorithm's dead nodes grow relatively slowly, with only 13% of dead nodes after 1,000 rounds. The CM-OOA algorithm balances the network's overall energy consumption, spreads out the energy loss to all the nodes, and prevents the nodes from localised death and extends the duration of emergency communication.

5.4 Analysis of changes in the number of surviving nodes in the network

When emergency communication wireless sensor network nodes are used in dangerous processes such as emergency rescue and disaster relief survey, they will not be replaced frequently, and at the same time, they are limited by the energy of nodes [39]. Therefore, for the same environment, the more nodes survive, the fewer dead nodes, and the longer the communication time. The number of surviving nodes of the four algorithms varies from 0 to 1000 rounds, as shown in Figure 13:

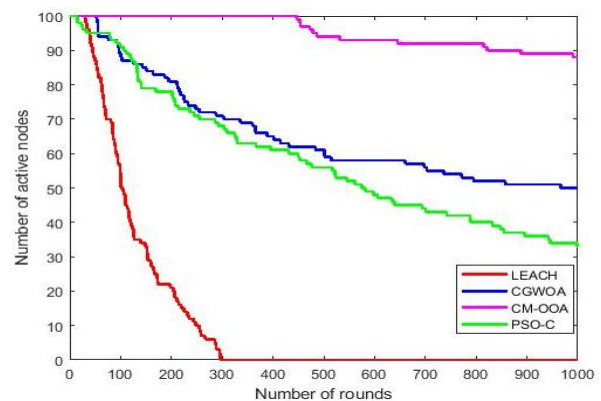


Figure 13: Changes in the number of surviving nodes in communication networks.

After 1,000 rounds of energy consumption in the emergency communication network, it can be seen from Figure 13 that the nodes of the LEACH algorithm are almost all dead after 300 rounds, and the nodes of the PSO-C algorithm have 33% active nodes remaining after 1,000 rounds [40]. The CGWOA algorithm, after experiencing a slow decline, slowly tends to be stable after 550 rounds, until only 50% active nodes remain after 1,000 rounds. After 1000 rounds, the CM-OOA algorithm still has 8% nodes, which improves the time of information communication, good stability, suitable for information data collection in special environments, and gives full play to the optimisation ability of the CM-OOA algorithm. The improvement of fitting function further optimises the accuracy and efficiency of cluster head election. FA-star algorithm reduces the energy consumption of cluster heads in inter-cluster route construction, avoids the premature death of cluster heads, and gives full play to the sensor's ability to transmit information in the whole network.

5.5 Comparative analysis of node data transmission delay

Another key criterion is the network transmission delay. This is highly dependent on the distance between nodes in the transmission path. In the same experimental setting, this paper compares the network delay by the average transmission distance of the network of nodes. The average transmission distance of four algorithms from 0 to 1000 rounds of data transmission is shown in Figure 14.

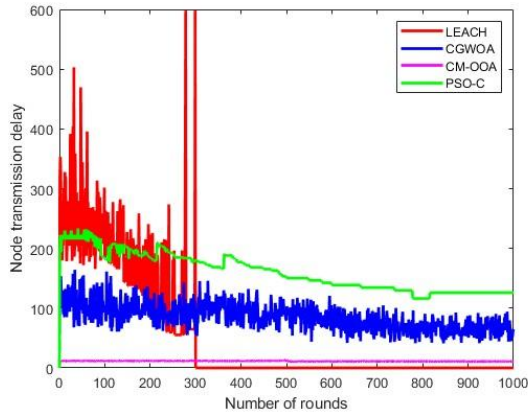


Figure 14: The average variation in node transmission distance per round.

Figure 14 shows that the average transmission distance of Leach protocol is greater than the other protocols. In contrast, the CM-OOA algorithm has the lowest transmission distance profile and the average transmission distance is lower than the other protocols. The comparison of the average transmission distance in every 100 rounds is presented in Figure 15.

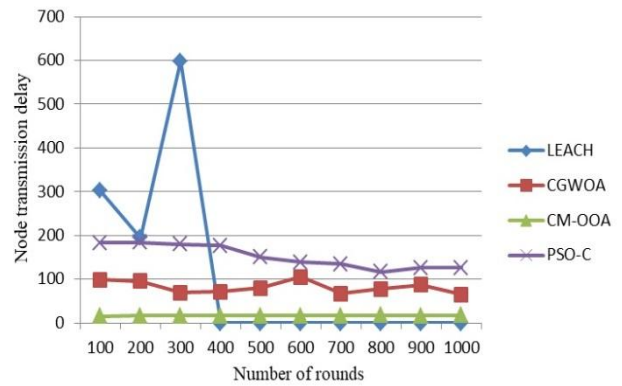


Figure 15: A comparison of the average transmission distance of nodes is presented.

A comparison of the average transmission distance for each 100-round interval in Figure 15 reveals that the average transmission distance of the CM-OOA algorithm is 80% less than that of the CGWOA protocol. Furthermore, the average transmission distance of the CGWOA protocol is 90% less in the initial stages and 30% less in the subsequent stages than that of the PSO-C protocol. The transmission distance of the LEACH protocol is zero due to the death of all nodes after 400 rounds.

5.6 Comparison of results of surviving nodes in areas of different sizes

Equation (2) with the data from the experimental environment allows the calculation of the thresholds for the two types of communication, and the number of surviving nodes after 0, 500 and 1000 rounds of data

Table 4: Comparison of the number of surviving nodes in different rounds.

Area size	round	LEACH	CGWOA	CM-OOA	PSO-C
1000*1000	0r	100	100	100	100
	500r	0	45	83	30
	1000r	0	35	61	17
800*800	0r	100	100	100	100
	500r	0	60	93	55
	1000r	0	50	88	32
600*600	0r	100	100	100	100
	500r	28	76	97	81
	1000r	0	63	90	61

transmission is comparatively analyzed for three different geographical regions: a 1000*1000 area (characterised by a high percentage of multi-path fading communication methodology), an 800*800 area (where the percentage of both communication methodologies is approximately equal) and a 600*600 area (where the percentage of free space communication methodology is high). The results are presented in tabular form in Table 4.

As illustrated in Table 4, the expansion of the working area of the wireless sensor network is associated with a reduction in the network's overall life cycle. The primary

cause of this phenomenon is the rise in the average number of hops traversed by data packets on their transmission path, coupled with the expansion of the distance between nodes within a cluster. This results in an exponential growth in the energy expenditure associated with data transmission.

The number of nodes directly reflects the life cycle of the network. In larger area networks, cluster heads further away from the base station die quickly. When there are 100 nodes in a 600*600 area, the CM-OOA algorithm has 90 surviving nodes after 1000 rounds of data

transmission, which is a 27% improvement in the number of surviving nodes compared to the CGWOA algorithm and a 29% improvement in the number of surviving nodes compared to the PSO-C algorithm. When the number of nodes in 800*800 area is 100, after 500 rounds of data transmission, the number of surviving nodes of LEACH algorithm, CGWOA algorithm, CM-OOA algorithm and PSO-C algorithm decreases by 28%, 16%, 4% and 26% respectively compared to that of 600*600 area, and the number of surviving nodes of CM-OOA and CGWOA algorithms are relatively stable. However, in the 1000*1000 region, the CM-OOA algorithm only reduces the number of surviving nodes by 39% after 1000 rounds of data transmission. In addition, the CM-OOA algorithm has 61 surviving nodes after 1000 rounds of data transmission in the 1000*1000 range, which is a 26% increase in the number of surviving nodes compared to the CGWOA algorithm. In the CM-OOA algorithm, the central selection of cluster head nodes and the use of multi-hop transmission further prolong the network life cycle. Therefore, the CM-OOA algorithm has the longest network life cycle, which proves that the scalability and stability of the CM-OOA algorithm is much better than the other four algorithms.

6 Conclusion

In this manuscript, an optimization algorithm based on chaotic mapping osprey optimization is proposed to prolong the duration of emergency communication by reducing energy consumption. The fitness function is improved by node energy, the distance between cluster heads, the distance from cluster heads to nodes, the distance from cluster heads to base stations, the variance of the distance from cluster heads to base stations and the variance of the distance between cluster heads. CM-OOA algorithm updates the position of the best individual based on fitness value, giving full play to the advantages of global search and convergence, and balancing the network energy consumption in each cluster. In the inter-cluster routing communication stage, FA-star algorithm based on heuristic function is used to reduce the energy consumption of cluster head nodes.

The location of cluster head node in this algorithm is more reasonable and the energy consumption of data path transmission is lower. Compared with LEACH, PSO-C and CGWOA. Through the comparative analysis of the results, the energy consumption of the whole network is reduced. The number of surviving nodes in the network is the largest, which effectively improves the life cycle of the emergency communication network.

7 Discussion

In this study, the energy consumption of wireless sensor networks is deeply discussed through the three-layer network model, and an energy-efficient clustering algorithm based on Osprey optimization and heuristic path is proposed. The osprey optimization algorithm can improve the energy of nodes, the distance between cluster heads, the distance from cluster heads to nodes,

the distance to clusters, the frequency of base station heads and cluster heads, etc. CM-OOA algorithm is used to update the population and select the best individual based on the fitness value, which has the advantage of global search convergence and balance the consumption of network energy in each cluster. In the inter-cluster routing stage of communication, the heuristic function based on Astar algorithm is used to reduce the consumption of energy cluster head nodes and alleviate the hot spot effect. The analysis results show that the algorithm reduces the node mortality and the maximum number of surviving nodes in the whole energy consumption network, which effectively improves a part of the life cycle network.

In this manuscript, the CM-OOA algorithm only considers the energy consumption of emergency communication and does not consider network security. In the next step, we will continue to optimize the algorithm and optimize the security of this algorithm as much as possible. Prevent malicious attacks on nodes, which can cause energy consumption and data theft of nodes, so that network information security is guaranteed to a certain extent. The algorithm is combined with the practical situation and applied in the real emergency communication network.

Availability of data and materials

This paper proposes an emergency communication algorithm for wireless sensor networks based on chaos mapping and osprey optimization. The specific information of the paper can be exchanged with the author.

Conflict of interest

The authors confirm that the content of this article has no conflict of interest.

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