Research on Cluster Routing Protocol Based on Genetic Algorithm and Astar Algorithm

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In routing protocols for wireless sensor networks, the energy depletion of cluster head nodes and centre nodes is too fast, resulting in a short network life cycle. Aiming at the problem of excessive energy depletion of cluster head nodes and centre nodes in clustering routing protocols for wireless sensor networks, a clustering routing protocol based on genetic algorithm and Astar algorithm (GADM-A) is proposed. Firstly, in the process of selecting cluster head nodes, the optimal cluster head combination is selected by optimising the genetic algorithm and improving the goodness-of-fit function. This is achieved by considering five factors: the energy level of nodes, the number of times a node has become a cluster head, the distance between the cluster heads, the distance between the cluster head and ordinary nodes, and the distance between the cluster head and the base station. Secondly, the Astar algorithm, which is a heuristic function of node energy and transmission distance, is employed to select the optimal path for inter-cluster routing. Finally, the sensor network transmits the information. The GADM-A* algorithm extends the network lifetime by balancing the overall energy consumption of the network. Simulation results show that the proposed protocol has 53% network energy remaining after 1000 rounds of data transmission, which is an average of 34.3% improvement in remaining energy over existing algorithms. The node mortality rate is 12%, which is 45% lower than the average mortality rate of the remaining algorithms.*

Povzetek: Študija predlaga protokol za usmerjanje grozdov v brezžičnih senzorskih omrežjih, ki temelji na genetskem algoritmu in algoritmu Astar (GADM-A). Protokol podaljša življenjsko dobo omrežja in zmanjša porabo energije.*

1 Introduction

A wireless sensor networks are composed of a large number of sensor nodes, the main function is that monitors the information of the target area and transmits the information to the base station [1]. In the context of the Internet of Things (IoT), there are a multitude of potential application scenarios. These include applications in marine, aerospace, military, agricultural, and disaster relief contexts, among others. The low cost and ease of deployment of sensor nodes enables them to cope with a wide range of harsh environments. It can be deployed by drones in areas that are inaccessible or difficult for humans to reach [2-3]. Wireless sensor networks offer convenient data collection and transmission services, yet they also face numerous challenges. For instance, wireless transmission is susceptible to interference, and node resources are constrained [4]. For the security problems in the network, some scholars have used the bio-heuristic algorithm to deal with and solve the security problems of wireless sensors [5]. Due to the limited energy of nodes, the life cycle is short. Therefore, it is a good research direction. Through clustering algorithm, the network life cycle can be extended by optimization [6].

Selecting cluster heads by clustering nodes provides an effective method to prolong the lifetime of wireless sensor networks [7]. The cluster head selection algorithm typically employs three distinct technologies [8]. Many scholars have conducted research on this and achieved many results. The first model is that the traditional routing protocols are used for node selection and network optimization.

Wendi Rabiner Heinzelman first proposed the LEACH protocol, which randomly generates cluster heads with a certain probability p. The data fusion by aggregating nodes reduces energy consumption and prolongs network life cycle, and the cluster head directly transmits data to the base station in a single hop mode [9]. Chafi Safia Amina proposed the W-LEACH protocol by improving and optimizing the leach protocol. This protocol extends the life cycle of wireless sensor networks [10]. Gangal Volkan combined the analytic hierarchy process (AHP) with the LEACH protocol and put forward the LEACH-AHP protocol, which maintains the matrix in nodes, including the potential threshold representing the probability of the node serving as the cluster head [11]. This kind of protocol reduces communication energy consumption by clustering nodes and prolongs network life. The disadvantage of this type of algorithm is that as the computational load increases, the performance is not as expected.

The second type of approach is that intelligent algorithms were introduced into cluster head selection in wireless sensor networks, providing a promising approach [12]. Sajwan Mohit proposed a multi-hop and multi-path routing protocol for underwater wireless sensor networks based on meta-heuristic. GAER-UWSN used the multi-path routing technology of a genetic algorithm to select the best clustering method with the lowest energy consumption [13]. Dinesh K. adopted grey wolf optimization to provide efficient clustering of nodes and adopted improved sea lion optimization to perform efficient routing to solve energy optimization and security problems [14]. A kind of enhanced superior particle swarm optimization algorithm for cluster formation is introduced by K.Solayan, and an energy and life cycle aware routing based on trusted cluster is proposed through this algorithm [15]. Jiang Chang-Jiang proposed an energy-balanced two-layer clustering routing TL-EBC protocol for wireless sensor networks protocol based on the particle swarm optimization algorithm [16]. 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 [17]. Sathyapriya Loganathan scholars proposed PSOE algorithm for cluster head selection by particle swarm optimization algorithm to reduce network transmission energy consumption [18]. These algorithms choose cluster heads more reasonably through intelligent algorithms, this improves the balance of energy consumption in wireless sensor networks. The disadvantage of this type of algorithm is that the computation time is increased.

The third mode is that nonuniform protocols are used to improve algorithm performance. In heterogeneous wireless sensor networks, verma Axel and other scholars put forward the ECSSEEC protocol based on enhanced cost and sub-era [19]. Pal. Raju put forward a multi-objective binary Grey wolf optimizer to find clustering methods in heterogeneous networks, and achieved five goals: maximizing the overall cluster head energy, minimizing the compactness of cluster heads, minimizing the number of cluster heads, minimizing the energy consumption from non-cluster heads to clusters, and maximizing cluster separation [20]. 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, which depends on two modules: direct trust and indirect trust between clusters and within clusters [21]. Chengfa Li suggested to balance the problem of uneven energy consumption in the network by proposing the EEUC protocol of different size clusters [22]. The algorithms in question have demonstrated efficacy in heterogeneous sensor networks. The advantage of this type of algorithm is that the network performance has been effectively improved, but the disadvantage is its weak universality. The comparison between algorithms is shown in Table 1.

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

Mode	Algorithm	Vantage	Drawbacks
probabiliy protocol	LEACH	The algorithm is simple and selects cluster heads in a random manner.	Random selection of cluster heads results in irrational cluster head selection.
	W-LEACH		
	LEACH-AHP		
group intelligence protocol	TL-EBC	More rational selection of cluster heads with group intelligence.	Cluster intelligence is used to select cluster heads, and the average distribution of clusters causes the centre node to die too quickly.
	CGWOA		
	PSOE		
nonuniform protocol	ECSSEEC	The number of nodes within the cluster is not the same, which can avoid the rapid death of the central node.	Non-uniform clustering may result in too large a gap in the number of nodes between clusters.
	MBGWO		
	LSEAOA		
	EEUC		

The different clustering routing protocols proposed by the above scholars can reduce the energy consumption of the network and extend the network life cycle, but fail to select the cluster head combination and cluster head to base station path transmission nodes reasonably during the protocol design process. In order to solve these problems, this paper proposes a genetic algorithm based clustering routing protocol GADM-A*. The GADM-A* algorithm can well balance local and optimal characteristics. It is crucial to identify the most optimal node as the cluster head among all nodes, ensuring that each cluster head node possesses the highest energy, the shortest distance to the base station, the shortest distance from node to cluster head, and the lowest number of times to become cluster head. In the clustering stage, nodes are clustered according to three criteria: the distance between nodes and base stations, the distance between cluster heads and base stations, and the energy of cluster heads. In the inter-cluster routing stage, the heuristic functions of the distance and energy of forwarding nodes are designed based on the Astar heuristic search algorithm. In order to prevent the hot spot phenomenon of nodes, some of the nodes in the GADM-A* algorithm transmit directly to the base station. The forwarding nodes include cluster head nodes and ordinary nodes, which ensures a more balanced energy loss and prevents the nodes from dying too quickly, thus extending the life cycle of the network.

2 System model

2.1 Network structure model

The wireless sensor network is widely used in the industrial fields Internet of Things to accurately calculate the information of nodes and ensure that the base station receives and sends data continuously and stably [23-24]. Nodes can choose the appropriate transmission power independently according to the energy consumption model to avoid the influence of bad weather and human factors. The network structure model adopted in this paper is shown in Figure 1.

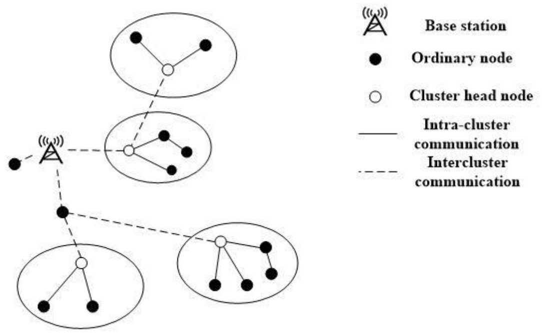

Figure 1: Network structure model.

The network structure needs to meet the following specific requirements:

a) N sensor nodes are in a random dropping area M×M, and the node positions after dropping are fixed.

b) Sensor nodes have unique and different ID.

c) The base station has unlimited energy and no signal interference in the area.

d) The power sent and received by each sensor node is controllable.

e) All sensors have the same properties and their positions remain unchanged relative to the base station.

2.2 Energy consumption model

This paper employs the first-order wireless communication energy consumption model, which is dependent on the signal transmission distance. This distance can be categorized into two distinct models: the short-distance free space model and the long-distance multi path model[25]. The first-order wireless communication energy consumption model is shown in formulae (1) ~ (3).

$$E_{Tx}(k,L) = \begin{cases} kE_{elec} + k\varepsilon_{fs}L^2, L < L_0 \\ kE_{elec} + k\varepsilon_{mp}L^4, L \geq L_0 \end{cases} \quad (1)$$

$$L_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (2)$$

$$E_{Rx}(k,L) = kE_{elec} \quad (3)$$

In formulae (1) ~ (3), the E_{TX} is the energy consumption for sending k bit data. The E_{elec} is the energy consumption for sending and receiving 1 bit data. The ε_{fs} is the loss factor of the free space model. The ε_{mp} is the energy loss factor of the multi path attenuation model [26]. L is the data transmission distance and E_{RX} is the energy consumption for receiving k bit data.

3 Materials and methods

In the GADM-A* algorithm, the optimal individual is obtained through the continuous iterative updating of the population, whereby the fitness function values of each round of the population are compared [27-28]. This algorithm is very similar to the clustering algorithm, and the wireless sensor network and GADM-A* algorithm have similar correspondence, as shown in Table 2.

Table 2: Similar correspondence between wireless sensor networks and GADM-A*.

WSN	GADM-A*
Sensor node number	genetic sequence
Node group	Individual chromosome sequence
Cluster head node combination	Individuals with the optimal fitness function
Combination of all pre-selected cluster head nodes	population

The detailed process of the algorithm is given below:

Step 1. Population initialization

$P(t) = \{P_1(t), P_2(t), ..., P_n(t)\}$ represents a population that has been iterated for t times and contains n individuals. Each individual Pi(t) can be expressed as a set of chromosomes, in which each gene represents a node Nk. Population individuals $P_i(t) = \{N_1(t), N_2(t), ..., N_k(t)\}$.

Step 2. Fitness function

$F=\text{fitness}(P_i(t))$ is the fitness value of each individual $P_i(t)$ at time t, which is used to evaluate individual problem-solving ability.

Step 3. Selection operation

S(P(t)) means selecting individuals from the current population P(t) to form a new population. The selection process is usually based on the principle of "survival of the fittest", and the fitness value S_i and genes $\{CH_{22}(t), CH_{23}(t) ...\}$ of individuals with the highest fitness are preserved.

Step 4. Full crossover operation

$C(p_i(t), p_j(t))$ means that individual $p_i(t)$ and individual $p_j(t)$ are crossed to generate new individuals. Individual p_i (t) = $\{CH_1$ (t), CH_{12} (t), ..., CH_k (t)$\}$ and individual p_j (t) = $\{CH_{11}$ (t), CH_2 (t), ..., CH_k (t)$\}$ adopt the intersection mode as a multi-point discontinuous intersection. The $p_i(t)$ and $p_j(t)$ individuals exchange gene fragments that are not included in each other by one-by-one comparison. After cross transformation, we have individuals P_I (t) = $\{CH_{11}$ (t), CH_2 (t), ..., CH_K (t)$\}$ and individuals $P_J(t)$ = $\{CH_1$ (t), CH_{12} (t), ..., CH_K (t)$\}$.

Step 5. Double mutation operation

$M(p_i(t))$ means that individual $p_i(t)$ is mutated to introduce new genetic information. Individual $P_i(t)$ randomly changes individual genes with a certain probability in the process of free mutation to increase the diversity of the population. Free mutation operation is a random change of individual genes, with individual p_i (t) = $\{CH_{13}$ (t), CH_{24} (t), ..., CH_k (t)$\}$. Evolutionary mutation operation is to preserve the excellent genes in the genes of the excellent individuals in the previous population, and the mutation is in the excellent direction, with individuals pi (t) = $\{CH_{22}$ (t), CH_{23} (t), ..., CH_k (t)$\}$.

Step 6. New generation population

P(t+1) = {...} represents a new generation of population generated by selection, crossover and mutation operations.

Step 7. Terminal condition

The algorithm repeats the operations from step 2 to step 6 until the maximum number of iterations is reached.

Step 8. The GADM-A* algorithm output

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

Step 9. Cluster entry operation

By calculating and comparing the fitness function, ordinary nodes select the nodes that enter and leave the cluster for clustering operation.

Step 10. Data transmission operation

The initial node selects the jump node through the heuristic search Astar algorithm for data transmission.

The GADM-A* algorithm has the global search ability of a genetic optimization algorithm and the ability to deal with complex problems [29]. The GADM-A* algorithm employs an iterative process of population update, fitness value comparison, and selection of the optimal individual, defined as the individual with the smallest fitness value. Secondly, ordinary nodes enter the cluster by calculating the fitness value of the cluster head. Finally, the inter-cluster routing transmission is carried out by Astar algorithm. The detailed flow of the GADM-A* algorithm is shown in Figure 2.

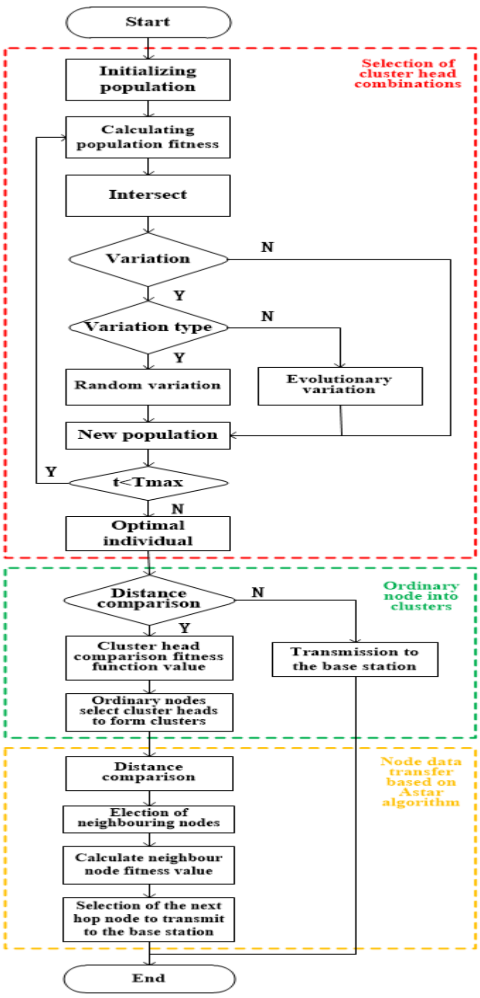

Figure 2: GADM-A* algorithm flow chart.

4 Algorithm implementation

4.1 Optimal cluster head size

Node energy consumption is an important criterion for evaluating network quality, and the number of cluster heads plays a vital role in the whole network [30]. In GADM-A* algorithm, the network energy consumption is divided into ordinary nodes transmitting cluster head E_1, ordinary nodes directly transmitting base station E_2, cluster head nodes receiving intro-cluster node data E_3, cluster head nodes fusing data E_4 and cluster head nodes sending data to the base station E_5. The nodes deployed in the a×a model are evenly distributed, (N-n) nodes are evenly distributed in CK circular clusters, and n nodes are directly transmitted to the base station, so the energy consumption for one round of network transmission, is given as formula (4):

$$E_{ALL} = \mathrm{CK} * (E_1 + E_3 + E_4 + E_5) + E_2 \quad (4)$$

The energy consumption of common nodes in each cluster is given as formula (5):

$$E_1 = \left(k * E_{elec} + k * \varepsilon_{fs} * d_{cntoCH}^2\right) * ((N-n)/CK - 1) \quad (5)$$

Ordinary nodes directly transmit the energy consumption of base stations, which is given as formula (6) :

$$E_2 = \left(k * E_{elec} + k * \varepsilon_{fs} * d_{cntoCH}^2\right) * n \quad (6)$$

The cluster head node receives the energy consumption of nodes in the cluster, which is given as formula (7):

$$E_3 = k * E_{elec}((N-n)/CK - 1) \quad (7)$$

The cluster head node fuses the energy consumption of nodes in the cluster, which is given as formula (8)

$$E_4 = k * E_{DA}((N-n)/CK) \quad (8)$$

Energy consumption transmitted from cluster head node to base station is given as formula (9):

$$E_5 = k * E_{elec} + k * \varepsilon_{fs} * d_{CHtoBS}^2 \quad (9)$$

In formula (9), d_{CHtoBS} is the distance from the cluster head node to the base station.

Distance from common node to cluster head node in each cluster is given formula (10):

$$d_{cntoCH} = \sqrt{\rho * \iint (x^2 + y^2)\, dx\, dy} = a^2/\sqrt{2\pi * CK} \quad (10)$$

Considering the above-mentioned formula (4)-(10), and calculating the CK value when E_{ALL} is minimized by deriving the overall energy consumption of the network in one round, the optimal number of cluster heads CK is got by formula(11) given as follows:

$$\mathrm{CK} = \sqrt{(N * \varepsilon_{fs} * a^2)/(2\pi * (\varepsilon_{fs} * d_{CHtoBS}^2 - E_{elec}))} \quad (11)$$

4.2 Initial stock selection

Good population initialization allows the GADM-A* 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 a locally optimal solution while ignoring other potentially better solutions. A diverse initial population helps to avoid this. Proper initialization of the population allows the algorithm to find better solutions at an early stage, thus speeding up the convergence of the whole search process. Therefore, initializing the population is an important step in the GADM-A* algorithm, which uses the Kmeans clustering algorithm for clustering in order to have a more accurate optimal solution for this algorithm. The initial population nodes are selected by the centre position of each clustered group. The calculation of cluster centre positions is based on the application of formula (12) and (13).

$$\boldsymbol{X_m} = \sum_{i=0}^{t} \boldsymbol{X}/\boldsymbol{t} \quad (12)$$

$$\boldsymbol{Y_m} = \sum_{i=0}^{t} \boldsymbol{Y}/\boldsymbol{t} \quad (13)$$

4.3 Design fitness function

In order to optimize the selection of cluster heads and improve the network's lifespan, once the optimal number of cluster heads has been determined, the fitness function is set according to the state of nodes and the position of the 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 [32]. The fitness function of this algorithm is designed from the following five aspects: the energy of nodes, the number of times nodes become cluster heads, the distance between cluster heads, the distance between cluster heads and each node, and the distance between cluster heads and base stations.

The energy level of the node itself: it is the reciprocal of the remaining energy of the current node. The cluster head node is the key condition to support the network operation[33]. When the energy of the node is high, the reciprocal is smaller, and the node can forward data better under the same conditions. It should be selected as the cluster head, as formula (14) given:

$$f_1 = 1/E_N \tag{14}$$

The number of times a node becomes a cluster head: Nodes serving as cluster heads for many times will lead to rapid energy consumption and death of nodes, and reduce the network life cycle [34]. To prevent a node from frequently becoming a cluster head excessively, the number of times a node becomes a cluster head can be represented by G. Furthermore, the probability of being selected as a cluster head should be increased if the number of times a node becomes a cluster head is low, as indicated by formula (15) :

$$f_2 = G_N \tag{15}$$

Distance level between cluster heads: it is the reciprocal of the sum of distances between cluster head nodes. A cluster head's position determines the data transmission distance of nodes entering the cluster. Cluster heads should be evenly dispersed to reach the distance of all nodes, as given in formula (16) :

$$f_3 = 1/\sum dis(CH_i, CH_j) \tag{16}$$

Distance between cluster head and each node: the sum of the distances from cluster head node to all nodes are calculated. Energy consumption in the network cycle is mainly determined by node transmission. The sum of the positions of all nodes in the cluster should be smallest to minimize the energy consumption of data transmission, as given by formula (17):

$$f_4 = \sum dis(N_j, CH_i) \tag{17}$$

Distance from cluster head to the base station: the sum of distances from all cluster head nodes to the base station BS is calculated. The transmission of the cluster head node is the energy consumption of the second part of the network cycle, and the distance from the cluster head node to the base station determines the energy consumption of the cluster head node [35]. 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, as given in formula (18) :

$$f_5 = \sum dis(CH_i, BS) \tag{18}$$

Based on five factors: node energy, the number of cluster heads, the distance between cluster heads, the distance between cluster heads and nodes, and the distance between cluster heads and base stations, the fitness function is designed by weight control, which is given as formula (19).

$$fitness = \alpha_1 f_1 + \alpha_2 f_2 + \alpha_3 f_3 + \alpha_4 f_4 + \alpha_5 f_5 \tag{19}$$

In formula (19), $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ and α_5 are weight factors and satisfy $\sum \alpha_i = 1$.

4.4 Weight value of fitness function

The fitness function needs to determine the weight of each sub-function. In previous clustering algorithms, the weights are typically selected based on experience and then adjusted through different environments [36]. In this algorithm, the weights of sub-functions are determined by the Analytic Hierarchy Process (AHP), which can determine the weights of sub-functions more scientifically, thus improving the accuracy of fitness function values. The analytic hierarchy process is as follows:

Step1. Constructing judgment matrix

In GADM-A* algorithm, five sub-functions are respectively denoted as A_1, A_2, A_3, A_4 and A_5. A_1 represents the energy level of nodes, A_2 represents the frequency of cluster heads, A_3 represents the sum of distances between cluster heads, A_4 represents the sum of distances between cluster heads and each node, and A_5 represents the sum of distances between cluster heads and base stations [37]. Then, all the sub-functions are compared in pairs to determine their relative importance. A judgment matrix is constructed as shown in Table 3.

Table 3: Judgment matrix table.

	A_1	A_2	A_3	A_4	A_5
A_1	1	3	3	1/2	2
A_2	1/3	1	1/3	1/2	1/2
A_3	1/3	3	1	2	1/2
A_4	2	2	1/2	1	1/2
A_5	1/2	2	2	2	1

Step2. The characteristic root λ_{max} with the largest absolute value of the matrix and the characteristic vector corresponding to λ_{max} are calculated.

Through the above matrix calculation, the characteristic root with the largest absolute value is λ_{max}, and its corresponding feature vector is $(a, b, c, d, e)^T$.

Step3. The feature vector is processed to make the sum of the elements of the processed feature vector equal to 1. The calculation process is shown in formulas (20) ~ (24).

$$a/(a+b+c+d+e) = \alpha_1 \tag{20}$$

$$b/(a+b+c+d+e) = \alpha_2 \tag{21}$$

$$c/(a+b+c+d+e) = \alpha_3 \tag{22}$$

$$d/(a+b+c+d+e) = \alpha_4 \tag{23}$$

$$e/(a+b+c+d+e) = \alpha_5 \tag{24}$$

The weights processed by AHP are α_1,α_2,α_3,$\alpha_4$and α_5, and satisfy the following requirements $\sum \alpha_i = 1$.

The improved fitness function enables the calculation of the functions of all individuals, with the gene sequence of the best individual being selected. Flow chart of the algorithm Function 1 is shown in the Table 4.

Table 4: Improved cluster head node selection.

Function 1: Select cluster heads according to the improved fitness function.
Begin:
Initializing network nodes and initializing the number of network populations.
Calculate the fitness value of population individuals, and keep the individual gene and fitness value with the minimum fitness value.
While t<tmax do.
The whole population crosses $C(p_i(t), p_j(t))$.
Individual variation $M(p_i(t))$ of all populations.
Update population.
Calculate the fitness value of the new population.
Update Individual gene with minimum fitness value and fitness value.
t = t + 1.
return Individual gene with minimum fitness value.
End

4.5 Ordinary node into clusters

The purpose of common nodes into clusters is that the energy consumption for direct data transmission are reduced. And it is clear from the energy model that the consumption is mainly due to distance. Therefore, the GADM-A* algorithm reduces the energy consumption by preventing the nodes from occurring transmission away from the base station. The mathematical median line theorem is as shown in Figure 3.

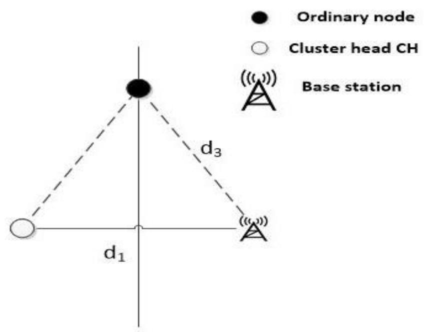

Figure 3: Median line.

When the ordinary node is located on the median line of the link from the cluster head node to the base station, the distance from the ordinary node to the cluster head and base station is the same. Therefore, when $d_3>d_1/2$ ordinary nodes will perform cluster head selection operation through algorithm Function 2.

The clustering ordinary nodes can reduce the energy consumption of direct data transmission. From the energy consumption model, it can be observed that the energy consumption is mainly affected by the distance factor [38]. Therefore, this algorithm reduces energy consumption by preventing nodes from transmitting far away from the base station. As shown in Figure 4, 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 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 $\{CH_2\ldots\}$ of the common node will be pre-selected with less energy. If the pre-selected cluster head set is empty, the node data is directly sent to the base station.

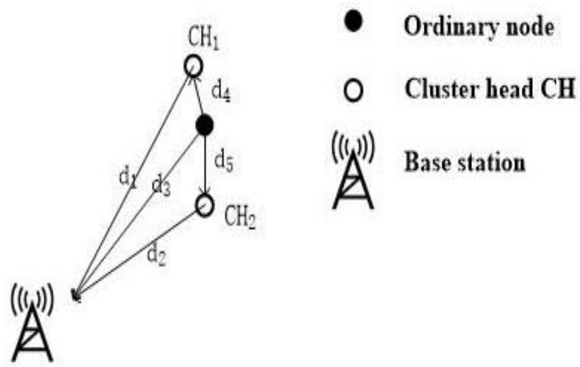

Figure 4: Cluster head selection model of common nodes.

Through the fitness function value of cluster head nodes, the pre-selected cluster head with the minimum value is compared, i.e., the cluster head node of ordinary nodes[39]. The fitness function of this algorithm is shown in formula (25) given.

$$\mathrm{F} = \beta_1 \mathrm{E} + \beta_2 \mathrm{dis}(\mathrm{N}, \mathrm{CH}) \quad (25)$$

In formula (25), dis(N,CH) indicates the distance from the common node to the pre-selected cluster head node, and E represents the energy of the pre-selected cluster head node in the current round. β_1 and β_2 are weight influencing factors and satisfy $\beta_1 + \beta_2 = 1$. The weights are calculated by AHP as $\beta_1 = 0.6$ and $\beta_2 = 0.4$.

According to the improved fitness function, the algorithm Function 2 flow is shown in Table 5.

Table 5: Ordinary node clustering.

Function 2: According to the improved fitness function, ordinary nodes select appropriate cluster heads for clustering operation.
Begin: Obtaining the cluster head node set in algorithm Function 1. 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. Calculate the fitness value of the pre-selected cluster head. Ordinary nodes select the cluster head node and perform cluster entry operation. End.

4.6 Node data transfer based on Astar algorithm

Data transmission is the main energy consumption in wireless sensor networks and cannot be avoided altogether. Therefore, the energy consumption can only be as minimal as possible. From the trilateral relationship of obtuse triangle, it is known that the square of the longest side is greater than the sum of the squares of the other two sides. Therefore the proposed algorithm uses multiple hops for data transmission.

In the course of routing, the Astar algorithm and heuristic search are used to select transmission paths and reach the destination base station by finding the minimum cost [40]. The selection of neighbor nodes in this algorithm is the same as pre-selecting cluster heads in the clustering algorithm. Figure 5 shows the neighboring nodes {L_1 ...} of the starting node n. If the neighbor node is empty, the base station is directly transmitted.

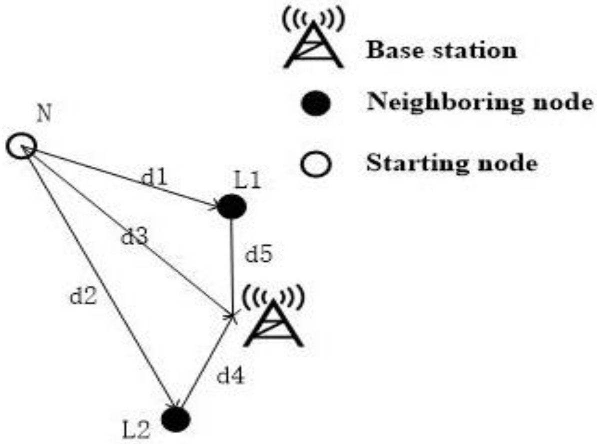

Figure 5: Neighbor node selection model.

The heuristic function of neighbour nodes enables the comparison of the neighbour nodes with the minimum value, namely the next hop node of the starting node [41]. The heuristic function is shown in formula (26).

$$\mathrm{F} = \gamma_1 E + \gamma_2 dis(N, L) + \gamma_3 dis(L, BS) \quad (26)$$

In formula (26), E represents the energy of neighboring nodes, $\mathrm{dis}(N, L)$ represents the distance from the starting node to neighboring nodes. And the $\mathrm{dis}(L, BS)$ represents the distance from neighboring nodes to the base station. γ_1, γ_2 and γ_3 are weight influencing factors and satisfy $\gamma_1 + \gamma_2 + \gamma_3 = 1$. The weights of this algorithm are calculated by AHP as $\gamma_1 = 0.55$, $\gamma_2 = 0.3$ and $\gamma_3 = 0.15$.

Based on the improved heuristic function, the flow of the Astar algorithm Function 3 is shown in Table 6.

Table 6: Inter-cluster routing transmission.

Function 3: Routing transmission between clusters according to the improved heuristic function.
Begin: The cluster head node set and the direct transmission set in the acquisition algorithm 1 are merged into the initial node set. while Starting node ≠ 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 directly transmits the base station,break.

Else.

Calculate the heuristic function of neighbor nodes, select the next hop node and transmit data.

End.

End.

End.

5 Experimental and data analysis

5.1 Experimental parameter setting

In order to test the simulation effect of the GADM-A* algorithm in prolonging the network life cycle, the algorithm is compared and analyzed on the MATLAB R2023b platform [42-43]. The experiments demonstrated the superiority of the GADM-A* algorithm in terms of energy consumption, number of dead nodes and number of surviving nodes of the network system, when compared to the LEACH protocol with threshold random selection of cluster heads, EEUC protocol with non-uniform clustering and PL-EBC protocol based on Particle Swarm Optimization Algorithm, CGWOA protocol based on Grey Wolf Optimization Algorithm and PSOE protocol. From the first-order wireless communication energy consumption model (1) ~ (3), L_0 = 87 can be calculated. Assuming that the experimental area is uniformly divided into 100 blocks and each node is located at the center of each cell block, the 100 nodes are randomly distributed within the 800 m × 800 m experimental simulation area. The experimental simulation area of 800 m × 800 m can be used for the communication between the two modes. The experimental area can better contain the free space and multi-path fading communication mode. The base station is located in the center of the area. The optimum number of cluster heads can be obtained by formula (11), k = 0.04 * n. The specific parameters are shown in Table 7.

Table 7: Experimental parameter table.

parameter	numerical value
Number of network nodes (units)	100
Network area size/m^2	800×800
Energy loss coefficient of free space model$(p_j/bit\ /m)$	10
Energy loss coefficient of multi-path attenuation model$(p_j/bit\ /m^2)$	0.0013
Node initial energy E_0/J	3
Population iteration times	30
Network operation times	1000

The simulation system is designed as shown in Figure 6.

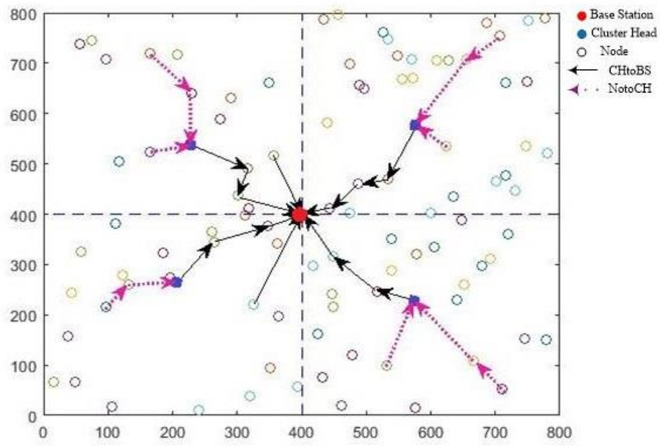

Figure 6: System simulation results.

5.2 Analysis of system energy change

The residual energy of wireless sensor network system reflects the length of the network life cycle and indicates that the more the residual energy, the longer the network life cycle [44]. The network energy of the six algorithms changes as a whole, as shown in Figure 7:

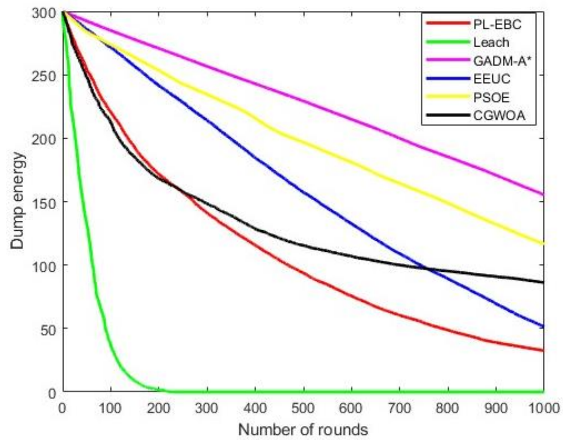

Figure 7: System residual energy change.

The LEACH protocol consumes all the energy in round 189, the PL-EBC protocol has 16% energy remaining in round 1000. And the EEUC protocol has 23% energy remaining in round 1000, the CGWOA and PSOE protocols respectively have 30% and 40% energy remaining in round 1000. The GADM-A* algorithm still has 50% energy in round 1000 and consumes energy slower than the other algorithms from round 0 to round 1000. Compared to the other algorithms, the GADM-A* algorithm selects the optimal cluster head by improving the genetic algorithm with node energy and node transmission distance as the main factors. The number of times a node becomes a cluster head and the distance between the cluster heads as the secondary factors, and the cluster selection in the clustering phase is based on the transmission distance and the node energy and not weighted by a single distance between clusters. And the Astar algorithm is used to select the optimal cluster head based on the node energy and design heuristic function for path planning.

5.3 Analysis of the change in the number of dead nodes

The number of dead nodes in wireless sensor networks reflects the overall stability. The more dead the nodes, the greater the impact on the whole network and the faster the death rate [45]. The number of dead nodes of the six algorithms changes, as shown in Figure 8:

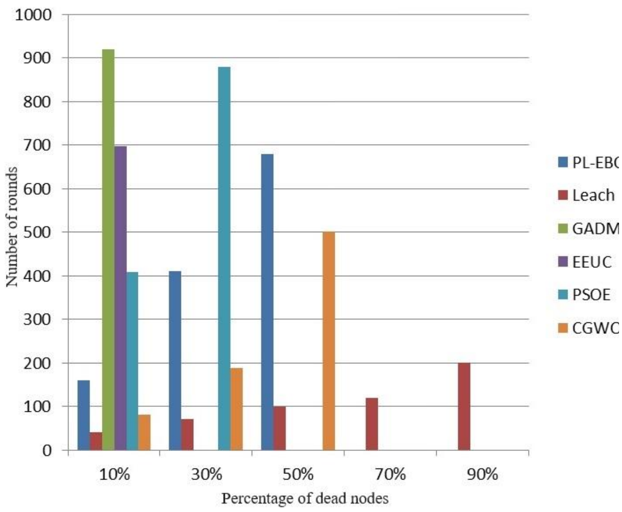

Figure 8: Changes in the number of dead nodes.

The number of rounds of data transfer for all the algorithms with the same number of dead nodes can be clearly seen from Fig. (8). When the dead nodes reach 10% of the total nodes, Leach algorithm goes through only 30 rounds, CGWOA algorithm goes through 84 rounds to reach, PL-EBC algorithm reaches 10% through 176 rounds of dead nodes, whereas the GADM-A* algorithm, the EEUC algorithm and the PSOE algorithm go through 400 rounds before they reach 10% node death. Although neither the EEUC algorithm nor this paper's algorithm reaches 30% node death after 1000 rounds, the EEUC algorithm locally dies faster. The PSOE algorithm reaches 30% node death after 890 rounds. The LEACH algorithm has faster node death than CGWOA, PSOE, EEUC and PL-EBC algorithms. In contrast, it can be seen that GADM-A* algorithm has relatively stable nodes, with only 13% of nodes dead after 1000 rounds. In a word, the GADM-A* algorithm balances the overall energy consumption of the network, spreads the energy loss to all the nodes, avoids localized deaths , prolonging the network life cycle.

5.4 Analysis of the change in the number of surviving nodes

Wireless sensor network nodes are frequently employed in dangerous processes, such as military operations, emergency rescue and disaster relief surveys, and are not typically replaced frequently. However, these are limited by the energy of nodes. Therefore, for the same environment, the more the nodes survive, the fewer the dead nodes, and hence more data are collected. The number of surviving nodes of the six algorithms varies from 0 to 1000 rounds, as shown in Figure 9.

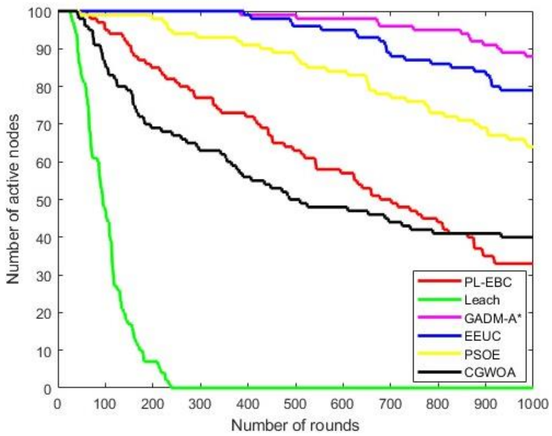

Figure 9: Changes in the number of surviving nodes.

Almost all LEACH nodes died after 240 rounds, nodes of PE-EBC and CGWOA protocols died after 100 and 98 rounds respectively. EEUC protocol died faster than GADM-A* algorithm, PSOE protocol starts to have dead nodes after 200 rounds and has a faster rate than EEUC protocol. The GADM-A* algorithm still has 88% nodes survive after 1000 rounds, which improves the data transmission time. The GADM-A* algorithm is stable and suitable for data collection in special environments, has good optimization capabilities. The improvement of fitting function further optimizes the accuracy and efficiency of cluster head election. Astar algorithm reduces the energy consumption of cluster heads in inter-cluster route construction and avoids the premature death of cluster head nodes, which has the ability to collect and transmit information throughout the network.

5.5 Comparative analysis of node data transmission delay

Another crucial criterion is network transmission delay. This is largely determined by the distance between nodes in the transmission path. In the same experimental setting, this paper compares the network delay by the average distance transmitted by the node network. The mean transmission distance of the six algorithms varies from 0 to 1000 rounds, as illustrated in Figure 10.

Figure 10 illustrates that the average transmission distance of the Leach protocol is greater than that of the other protocols. This is because, after 230 rounds, all the nodes are dead, resulting in a transmission distance of 0. In contrast, the transmission distance curve of the GADM-A* algorithm is at the lowest level, with an average transmission distance that is lower than the other protocols.

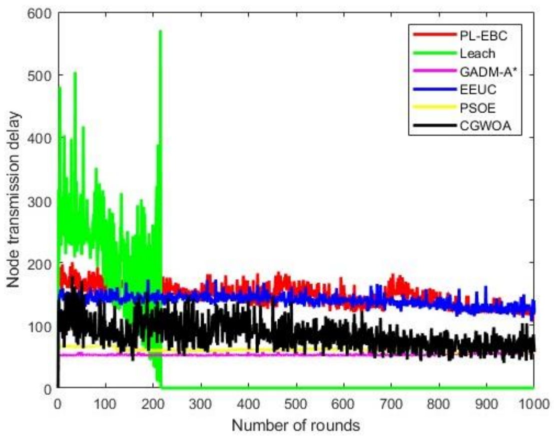

Figure 10: The average variation in node transmission distance per round.

The comparison of the average transmission distance in every 1000 rounds is presented in Figure 11.

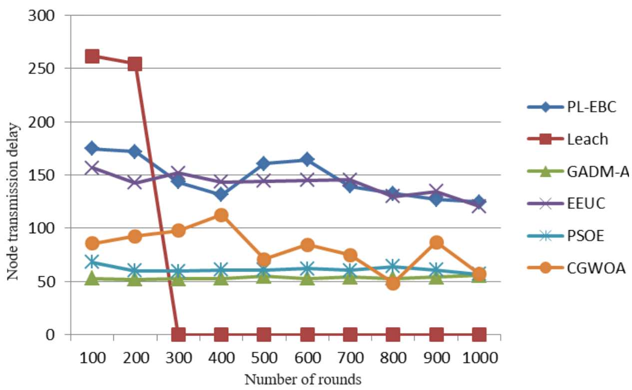

Figure 11: A comparison of the average transmission distance of nodes is presented.

A comparison of the average transmission distance for each 100-round interval in Figure 11 reveals that the average transmission distance of the GADM-A* algorithm is 16% less than that of the PSOE protocol. Furthermore, the average transmission distance of the PSOE protocol is 58% less than that of the EEUC and PL-EBC protocols.

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

This paper compares the number of surviving nodes after 0, 500 and 1000 rounds of data transmission in three different areas: a 1000*1000 area (high percentage of multi-path fading communication method), an 800*800 area (roughly the same percentage of both methods) and a 600*600 area (high percentage of free space communication method). The results are presented in Table 8.

Table 8: Comparison of the number of surviving nodes in different rounds.

		PL-EBC	Leach	GADM-A*	EEUC	PSOE	CGWOA
1000*1000	0	100	100	100	100	100	100
	500	27	0	94	12	79	49
	1000	10	0	73	4	34	37
800*800	0	100	100	100	100	100	100
	500	60	0	97	94	83	46
	1000	33	0	88	78	64	40
600*600	0	100	100	100	100	100	100
	500	90	16	98	96	97	71
	1000	82	0	94	93	86	59

From Table 8, it can be seen that as the working area of the wireless sensor network increases in size, the overall network life cycle decreases. The main reason for this is the increase in the average number of hops on the transmission path as well as the distance between the nodes in the cluster, which leads to an exponential increase in the amount of energy consumed for data transmission.

In a network with a large area, the cluster heads that are far away from the base station die quickly. With 100 nodes in a 600*600 area, the GADM-A* algorithm has 94 surviving nodes remaining after 1000 rounds, which improves the number of surviving nodes by 37% compared to the CGWOA algorithm and 8% compared to the PSOE algorithm. When the number of nodes in the 800*800 area is 100, the number of surviving nodes after 500 rounds of data transmission respectively decreases by 33%, 100%, 1%, 2%, 14%, and 35% compared to the 600*600 area. The GADM-A* algorithm and the EEUC algorithm are relatively stable. However, the number of surviving nodes of GADM-A* algorithm after 1000 rounds of data transmission in 1000*1000 region is reduced by only 22%. In addition, the GADM-A* algorithm has 73 surviving nodes after 1000 rounds of data transmission in the 1000*1000 area, which increase 49% in the number of surviving nodes compared to CGWOA algorithm. For the GADM-A* algorithm, centre-of-mass selection of cluster head nodes and multi-hop transmission are used to further extend the network life cycle. Therefore, the network life cycle of GADM-A* algorithm is the longest, which proves that the scalability and stability of GADM-A* algorithm is much better than the other 5 algorithms.

6 Discussion

In this paper, a cluster routing algorithm based on Genetic Algorithm and through minimum cost Astar path is proposed. The fitness function is improved by energy of nodes, distance between cluster heads, distance from cluster head to node, distance from cluster head to base station and frequency of cluster head. The GADM-A* algorithm is used to update the population and select the best individual based on the fitness value, which has the advantage of global search and convergence and balances the network energy consumption of each cluster. In the communication phase of inter-cluster routing, Astar algorithm based on heuristic function is used to reduce the energy consumption of cluster head nodes. The analysis of the results shows that the algorithm has a reduced node mortality rate, reduced energy consumption of the entire network, and the maximum number of surviving nodes in the network, which effectively improves the life cycle of the network.

7 Conclusion

In future research, the optimize will be continued by certain methods to make the protocol consume less energy and reduce the running time of the protocol. The algorithm will be integrated with the IoT model under agriculture to collect and transmit data in agriculture. It will be more reasonable and convenient to deal with the problem of data in large agricultural fields and more reasonable to grow agriculture.

Availability of data and materials

This paper proposes a clustering routing algorithm based on genetic algorithm and minimum through cost Astar path, which improves the efficiency through fitness function. 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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