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Hierarchical clustering routing algorithm based on gray wolf optimization algorithm

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Abstract. In order to further reduce the energy consumption of sensor network nodes and extend the life cycle of sensor networks, a hierarchical clustering routing algorithm (HCGW) based on gray wolf optimization algorithm is proposed. The base station classifies all the nodes according to the distance information, each level adopts a suitable fitness function to determine a plurality of cluster heads according to the gray-wolf optimization algorithm, and the rest nodes form a cluster according to the European distance to select the cluster heads to be joined, Pass data to create a hierarchical multi-hop routing. The simulation results show that the hierarchical clustering routing algorithm can effectively improve the network throughput, save and balance the energy consumption in the network and achieve the purpose of prolonging the network life cycle.

Key words. Wireless sensor networks, Grading, Gray wolf algorithm, Clustering, network throughput.

1. Introduction

The main objective of wireless sensor network (WSN) is to monitor one or several features of the certain region and send these features to the observers. At present, WSN is widely used in many fields, including environmental monitoring, smart city and precision agriculture, etc. The typical WSN consists of a large number of low power consumption and low-cost intelligent sensor nodes and one or several base stations (BS) [1]. The node energy is supplied by the battery with limited energy, the network performance is highly related with the node energy consumption and the battery energy strictly controls the life of WSN. The sensor energy consumption relates to many aspects, where the data transmission the largest energy consumption source. Therefore, the main objective of energy-efficient routing protocol design is to extend the lift cycle of WSN.

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At present, the researchers have proposed different technologies to extend the network life time, where the hierarchy method is effective to solve the energy consumption problem of WSN [2]. In the hierarchy system network structure, the network is divided into different layers and the node executes different tasks. The monitoring area is divided into different clusters by the clustering algorithm; in each cluster, a certain node serves as leading node, called cluster head (CH). Its function is to communicate with the cluster members, collect and aggregate data and send the data to the base station by hierarchical routing and it serves as the communication buffer between the cluster and base station.

The LEACH protocol is the typical clustering protocol and its life cycle increased by more than 15% compared with other planar routing protocols [3]. With further researches on WSN routing protocol, the researchers proposes the Bio-inspired heuristic algorithm to improve the life cycle of WSN, such as ant colony optimization [4], particle swarm optimization [5], artificial bee colony optimization [6] and fuzzy logic [7] etc. The Grey Wolf Optimizer (GWO) is a new Bio-inspired heuristic algorithm proposed by the scholar Mirjalili et al. in 2014 [8]. Such algorithm is derived from simulation of grey wolf colony's predatory behavior and achieves the optimization objectives through the wolf colony tracking, encirclement, chasing and attacking procedures. GWO has the following features, such as simple principle, less parameters to be adjusted, easy to implement and strong global searching ability etc. By comparison, it demonstrates that GWO is superior to PSO, DE and GSA in terms of function solution accuracy and stability [9]. In this paper, the hierarchical clustering routing protocol (HCGW) to extend the network life cycle. In HCGW, the base station is in monitoring area center and considered as the "prey", other nodes are layered based on its distance from the base station, the cluster head is determined in each layer based on the node adaptation function and the data is transmitted to simulate iteration of grey wolf hunting position. The simulation experiment shows that the new algorithm can effectively balance the load, overcome long-distance transmission problem, save energy and extend the network life.

The rest parts of this paper are arranged as below: the second part introduces the mathematical model of grey wolf heuristic algorithm. The third part introduces the proposed new optimization model in details. The fourth part introduces the simulation parameters, performance indexes and simulation results. The fifth part summarizes this paper.

2. GWO

2.1. Original model of GWO

The meta-heuristic algorithm is highly favored by the researchers due to simplicity and flexibility etc. GWO is the most popular meta-heuristic algorithm for theoretical research at present. The main idea of such algorithm is to simulate the social hierarchy and colony hunting behavior of grey wolf family. The grey wolf belongs to Canine family and likes living in groups. Each ethnic group consists of 5-12 grey wolfs on average. The grey wolf family complies with the strict hierarchy system as shown in Fig. 1.

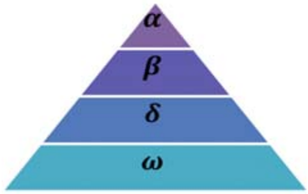

Fig. 1. Grey wolf colony hierarchy chart

In the grey wolf family, its social position can be divided into 4 layers from top to bottom, respectively including wolf α, wolf β, wolf δ and wolf ω. The wolf α is the leader wolf, responsible for determining the time, place and strategy of sleeping and hunting; the second layer is wolf β and wolf β is the subordinate wolf, mainly responsible for assisting the leader wolf to manage the wolf colony and taking the place of wolf α when wolf α is missed; the third layer is wolf δ which is directed by wolf α and wolf β, but wolf δ can direct wolf ω in the bottom layer. The wolf ω is mainly responsible for balancing the internal relationship.

The group hunting is an important part of grey wolf's social activities. Muro et al. introduce the main hunting procedures in the literature [10] as below:

(1) Track, chase and get close to the prey;

(2) Chase, encircle and harass the prey until the prey stops moving;

(3) Attack the prey.

Fig. 2 describes the hunting behavior of grey wolf in details.

Fig. 2. Grey wolf hunting behavior: (A) chase, get close to and track the prey; (B-D) Chase, encircle and harass; (E) stop moving and attack

2.2. Mathematical model and algorithm

(1) Social hierarchy modeling

To construct the mathematical model for the grey wolf's social hierarchy, the solution with optimal adaptation is named as wolf α. Therefore, the second and third optimal solution is respectively named as wolf β and wolf δ. The alternative solution is considered as wolf ω. In GWO, the searching (optimization) is directed by wolf α, wolf β and wolf δ followed by wolf ω.

(2) Hunting model

1) Prey encirclement

To simulate the grey wolf's encirclement behavior by the mathematical model, the Formula 1 and 2 is introduced.

$$\vec{D}=\left|\vec{C}.\vec{X}_p(t)-\vec{X}(t)\right| . \tag{1}$$

$$\vec{X}(t+1)=\vec{X_p}(t)-\vec{A}.\vec{D} . \tag{2}$$

Where, t represents the current iteration, the vector $\vec{A}$ and $\vec{C}$ is coefficient vector, the vector $\vec{X_p}$ is the prey's position vector and vector $\vec{X}$ is the grey wolf's position vector.

The formula of vector $\vec{A}$ and $\vec{C}$ is shown as below:

$$\vec{A}=2\vec{a}.\vec{r_1}-\vec{a} . \tag{3}$$

$$\vec{C}=2.\vec{r_2} . \tag{4}$$

In the iteration process, the vector $\vec{a}$ is linearly reduced to 0 from 2; $\vec{r_1}$ and $\vec{r_2}$ is the random vector in [0, 1].

2) Hunting and attack

GWO hunting is led by α; β and δ occasionally participates hunting. To mathematically simulate the grey wolf's hunting behavior, it is supposed that α (the optimal candidate solution) and β and δ have better understanding of the prey's potential position. Therefore, the first three optimal solutions obtained till now are maintained and other search agents (including ω) are required to update its position based on the position of the optimal search agent.

$$\vec{D_\alpha}=\left|\vec{C_1}.\vec{X_\alpha}-\vec{X}\right| . \tag{5}$$

$$\vec{D_\delta}=\left|\vec{C_3}.\vec{X_\delta}-\vec{X}\right| . \tag{6}$$

$$\vec{D_\delta}=\left|\vec{C_3}.\vec{X_\delta}-\vec{X}\right| . \tag{7}$$

$$\vec{X_1}=\vec{X_\alpha}-\vec{A_1}.\left(\vec{D_\alpha}\right) . \tag{8}$$

$$\vec{X_2}=\vec{X_\beta}-\vec{A_2}.\left(\vec{D_\beta}\right) . \tag{9}$$

$$\overrightarrow{X_3}=\overrightarrow{X_\delta}-\overrightarrow{A_3}.\left(\overrightarrow{D_\delta}\right). \tag{10}$$

$$\overrightarrow{X}(t+1)=\frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3}. \tag{11}$$

The Formula (8) to (10) respectively defines the step length and direction of wolf β towards α and β and δ. The Formula 11 represents the current position of α. The specific procedures are shown in Fig. 3.

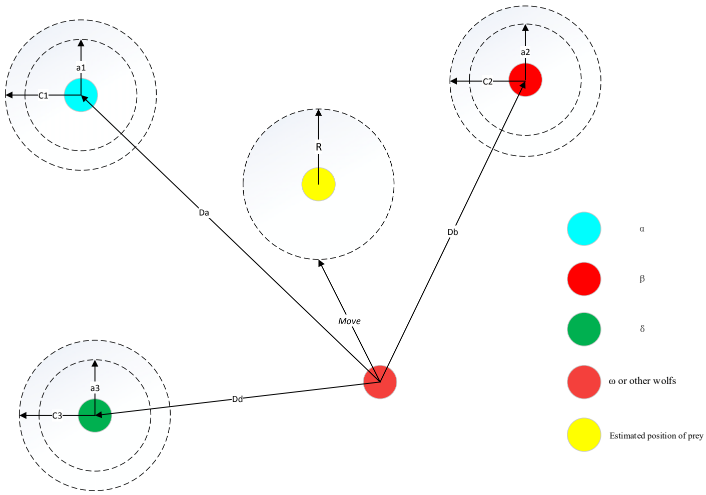

Fig. 3. Schematic diagram of GWO

The algorithm steps of GWO are described below:

1: Initialize the random wolf colony within upper and lower limit of wolf variables;

2: Calculate the adaptation value of each wolf;

3: Select the first three wolfs with optimal adaptation, respectively called as α, β, δ;

4: Use the Formula (5) to (10) to update other wolf (ω);

5: Update the parameters, a, A, C;

6: If the condition is not satisfied, go to step 2;

7: Output the position of α.

In this paper, the sensor node represents for the wolf colony and the base station (BS) represents for the prey.

3. GWO-based hierarchical clustering optimization algorithm

HCGW adopts the round robin similar with LEACH and each round includes the following steps: ① simulate GWO to divide the network into several layers based on the relationship between signal reception and transmission and distance. Each node determines which layer it belongs to based on its position and distance from base station. ② The number of cluster head in each layer shall be determined by the base station based on adaptation function. The adaptation function includes the residual energy and relative centrality of node its distance from the based station. ③ After the cluster head is determined, all member nodes select the nearest cluster head to form the cluster. ④ The node in cluster communicates with the cluster head in single hop and GWO communication route is established between cluster heads to avoid long-distance transmission. ⑤ The cluster head is reselected based on residual energy and round-robin time of cluster head to establish the new route and maintain the route.

3.1. Network model [11]

HCGW makes the following assumptions for network model: ① the base station is in monitoring area center, can continuously supply the energy and has the corresponding calculation ability; ② the sensor node is randomly distributed in monitoring area, powered by the battery with limited energy and can perceive its residual energy; ③ once the node is deployed, its position will not be changed and the node can know its distance from other nodes by RSSI; ④ the node can adjust the transmitting power based on the network requirements.

3.2. Energy model [12]

WSN is the random channel and conforms to the free space model and multi-path attenuation model. The energy consumed by the basic layer node in the process of transmitting k bit data is shown as below:

$$E_{Tx}(k,d) = E_{elec}(k) + E_{mp}(k,d) = \begin{cases} kE_{elec} + k\varepsilon_{fs}d^2 & d \le d_0 \\ kE_{elec} + k\varepsilon_{mp}d^4 & d \ge d_0 \end{cases} \tag{12}$$

Where, E_{elec} is the total energy consumed in the process of completing one-time reception and transmission, ε_{fs} and ε_{mp} depends on the parameters of transmission circuit and receiving circuit, d is the distance between the transmission node and receiving node; the formula of d_0 is shown as below:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}\,. \tag{13}$$

d_0 is the distance threshold and boundary value of communication distance of the free space model and multi-path attenuation model.

3.3. Network layering

As shown in Fig. 4, supposed that the network can be divided into L layers, based on the energy model formula (12), the node whose distance from the base station is less than d_0 is divided as the first layer and marked as α layer. The residual nodes are successively marked as β layer and δ layer etc. Supposed that d is the distance of node from base station, d max represents for the longest distance of node from the base station in the network.

$$d_{\max}= MAX\left(d\left(SN_i, BS\right)\right) . \tag{14}$$

$$L = \left[2 \times \frac{d_{\max}}{d_0}\right] . \tag{15}$$

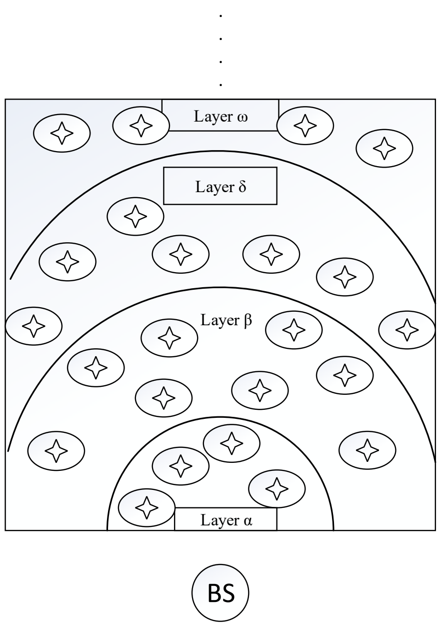

Fig. 4. Schematic diagram of network layering

Then the node SN_i is in layer l:

$$l = \left[2 \times \frac{d_i}{d_0}\right] . \tag{16}$$

By layering, the communication distance can be less than or equal to d_0 when the cluster head transmits the data by layers and the energy consumption caused by long-distance transmission can be reduced.

3.4. Cluster head selection method based on adaptation principles

After the sensor network is layered, in each layer, the node adaptation is calculated based on the adaptation function and adaptation rules and one or several nodes with higher adaptation are selected as the cluster head of this layer.

(1) Residual energy of node

The residual energy of node E_{RE} represents for the maximum node energy left after several times of round robin of network.

$$E_{RE}= E_{init} - E_r \,. \tag{17}$$

Where, E_{init} represents the initial energy and E_r represents the node energy consumption after several times of round robin.

(2) Node density

The node density refers to the number of nodes in unit area and is represented by neighboring node number of SN_i in d_0 communication range. The larger the node density, the more the neighboring node of such node, the smaller the energy consumption in data exchange with surrounding nodes. The node density is represented byP_{SN_i}:

$$P_{SN_i}=\frac{N}{\pi \cdot d_0^2} \,. \tag{18}$$

N represents the number of nodes in d_0 communication range.

(3) Node centrality C_i

The node centrality C_i represents the closeness degree of node SN_i with its neighboring node. The smaller theC_i, the closer to the neighboring node, the lesser the energy required for communication.

$$C_i=\sqrt{\left(x_i - \frac{1}{n}\sum_j^n x_j\right)^2 + \left(y_i - \frac{1}{n}\sum_j^n y_j\right)^2} \,. \tag{19}$$

Where, x_i represents horizontal coordinate of node SN_i and represents vertical coordinate of node SN_i.

(4) Adaptation function

The cluster head is selected based on the adaptation function: in GWO, the adaptation function is very important in prey searching mechanism. The function input is node features, including the residual energy of node (E_{RE}), node density and node centrality; the output is the adaptation value whether the node can become the cluster head.

$$f\left(CH_i\right) = q_1 \left|\frac{P_{SN_i}}{C_i}\right| + q_2 \sum E_{RE} \,. \tag{20}$$

Where, is the random number in [0, 1]. The adaptation threshold value is set. The node with adaptation value greater than such threshold value will be selected as the cluster head.

(5) Adaptation rules

HCGW adopts the comprehensively evaluated self-adaption standards. The node with many residual energy, larger node density and higher centrality will have high priority. HCGW includes 27 (3*3*3=27) adaptation standards as shown in Table 1.

Table 1. Adaptation rules

Adaptation rules	Residual energy	Node density	Centrality	Adaptation
1	Small	Low	Low	Very low
2	Small	Low	Medium	Very low
3	Small	Low	High	Very low
4	Small	Medium	Low	Very low
5	Small	Medium	Medium	Very low
6	Small	Medium	High	Very low
7	Small	High	Low	Very low
8	Small	High	Medium	Very low
9	Small	High	High	Very low
10	Medium	Low	Low	Slightly low
11	Medium	Low	Medium	Slightly low
12	Medium	Low	High	Medium
13	Medium	Medium	Low	Slightly low
14	Medium	Medium	Medium	Medium
15	Medium	Medium	High	Slight high
16	Medium	High	Low	Slightly low
17	Medium	High	Medium	Medium
18	Medium	High	High	Slight high
19	Large	Low	Low	Slightly low
20	Large	Low	Medium	Medium
21	Large	Low	High	Slight high
22	Large	Medium	Low	Medium
23	Large	Medium	Medium	Slight high
24	Large	Medium	High	High
25	Large	High	Low	Medium
26	Large	High	Medium	High
27	Large	High	High	Very high

3.5. Formation of cluster

After the cluster head node is determined, the *Invite-Msg* should be sent, including the identification code and position of cluster head as shown in Fig. 5 and then waiting for cluster member to participate in the cluster.

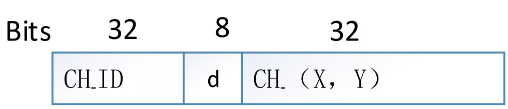

Fig. 5. *Invite-Msg* message

After the *Invite-Msg* is received, the member node calculates the approximate distance to each cluster head and participates in the cluster head with minimum distance to form the cluster structure.

3.6. Route setup and maintenance

In the data transmission phase, all nodes transmit the data to cluster head, the cluster head conducts the data preprocessing by compression and optimization etc. and then transmits the data to the cluster head node in the upper layer with higher priority based on layer priority, successively transmits the data until the cluster head in the first layer $CH1n$ transmits the data to BS. At this time, the multi-hop routing similar to grey wolf hierarchy system is established.

When the residual node energy of one cluster head in one layer is less than half of average energy E_{ave}, the cluster head should be reselected and the new cluster structure should be constructed. In the same time, the route should be established between upper and lower layers. After a long time T, the route of the whole network will be updated. Compared with the global cluster head selection mechanism of LEACH protocol, the local cluster head selection mechanism proposed by HCGW can greatly save the calculation cost and broadcasting costs and achieve local optimum.

4. Simulation results and analysis

To evaluate the HCGW algorithm performance, the simulation experiment is conducted by using Matlab and the comparison is made with LEACH algorithm. Table 2 lists the simulation parameter settings. The following performance indexes should be considered in evaluation:

(1) Number of survived network node and network life cycle over time;
(2) Residual node energy in each round;
(3) Number of data package received by BS.

4.1. Adaptation function model

The adaptation function simulation results for HCGW algorithm is shown in Fig. 6. As shown in Fig. 6, when the residual energy is small, the node adaptation is very low however the node centrality and node density change. When the residual node energy reaches at a certain amount, the node adaptation will increase with increasing of centrality and node density. This shows that the residual node energy it the most important factor to determine the node adaptation and the centrality and node density also have impacts on adaptation.

Table 2. Simulation parameter setting

Parameter	Parameter value	Unit
Region size	40000	m2
Number of nodes	200	
BS coordinate	(100,100)	m
Initial energy	0.5	J
Message length	4000	Bytes
E_{elec}	50	nJ/bit
ε_{fs}	10	pJ/(bitm^2)
ε_{mp}	0.0013	pJ/(bitm^4)
α (super)	1	
β (advanced)	2	
Data length	100	Bytes
Adaptation function probability P_1	0.7	
Adaptation function probability P_2	0.3	
Parameter	Parameter value	Unit
Region size	40000	m2
Number of nodes	200	
BS coordinate	(100,100)	m
Initial energy	0.5	J
Message length	4000	Bytes
E_{elec}	50	nJ/bit
ε_{fs}	10	pJ/(bitm^2)
ε_{mp}	0.0013	pJ/(bitm^4)
α (super)	1	
β (advanced)	2	
Data length	100	Bytes
Adaptation function probability P_1	0.7	
Adaptation function probability P_2	0.3	

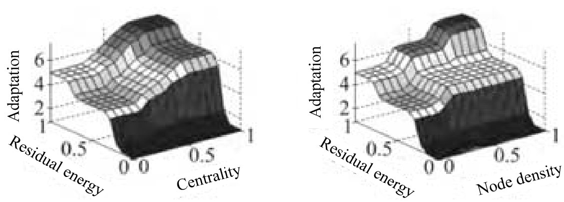

Fig. 6. HCGW adaptation model simulation result

4.2. Survival number of life cycle of network node

The network life cycle is the total activation time of WSN, which is determined by the network initialization time and node death time.

1) First Node Died (FND): it means the time from WSN initialization to the death of first node. The longer the time, the mode stable the network.

2) Half Node Died (HND): it means the death time of half nodes of WSN. Such time interval represents the network energy consumption.

3) Last Node Died (LND): it means the survival time before all network nodes die, which represents the network life cycle.

Table 3 lists round number of FND, HND and LND and average network energy consumption per round for HCGW and LEACH algorithms. The larger the quantity of FND, the better the optimization completed. Fig. 7 shows the comparison of number of survived nodes and network life cycle.

Table 3. Comparison of HCGW and LEACH network life cycle data

	Round number of FND	Round number of HND	Round number of Last Node Died
LEACH	80	300	610
HCGW	258	500	1020

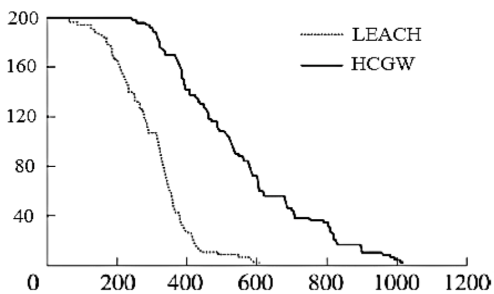

Fig. 7. Comparison of HCGW and LEACH node survival number

According to Table 3 and Fig. 7, it can be seen that the FND time is 80 rounds for LEACH and 258 rounds for HCGW and the time of HCGW is about two times later than that of LEACH. The LND time is 610 rounds for LEACH and 1020 rounds for HCGW. HCGW conducts the network layering; in each layer, the different number of cluster heads is selected. If the layer close to base station has many cluster heads, it can sufficiently reduce the transmission tasks for such cluster head and thus extend the network life cycle.

4.3. Network energy consumption

Fig. 8 and Fig. 9 are the comparison charts of residual energy and residual energy deviation for HCGW and LEACH. HCGW comprehensively considers many factors, such as residual energy and node density etc. Its cluster head is selected in more reasonable way and the multi-hop routing is selected to reasonably optimize the data transmission path and reduce the data transmission energy consumption. The residual node energy deviation reflects energy balance effects and the small deviation shows the more balanced energy consumption.

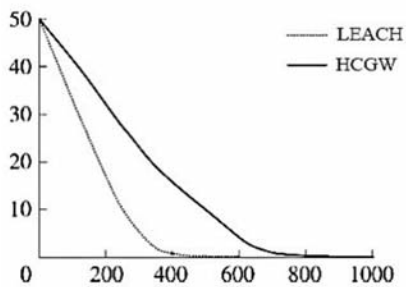

Fig. 8. Network energy consumption comparison

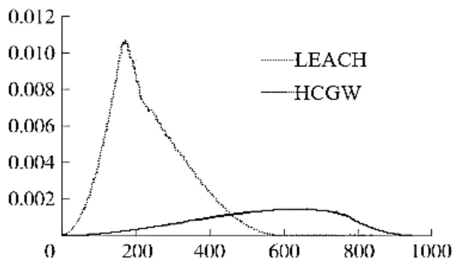

Fig. 9. Residual energy deviation of node

According to Fig. 8 and Fig. 9, it can be seen that the network energy consumption of HCGW is obviously lower than that of LEACH and its network load balance effects are superior to that of LEACH.

4.4. Network throughput

The network throughput is used to measure the network capacity of WSN [13]. It is determined by the total number of bit received by the receiver in unit time. The network throughput of WSN is determined by the number of data package transmitted to base station in unit time. Its formula is as below:

$$T(\text{Throughput}) = \frac{\text{Number of data package * Length of data package * 8}}{\text{Network running time}}. \quad (21)$$

According to Fig. 10, it can be known that in the whole life cycle, LEACH protocol transmits 15600 data packages and HCGW protocol transmits 34000 data packages, exceeding 118% of that of LEACH protocol. By comparison, it can be known that HCGW protocol has higher data transmission capability, better network performance and higher utilization rate.

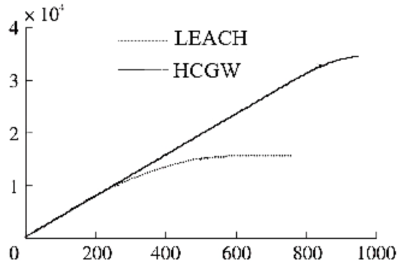

Fig. 10. Number of data package received by the base station

In LEACH protocol, the node must directly communicate with the cluster head, but the base station is far away from the sensor node, which increases the energy consumption in communication process and thus influences the network life cycle. Furthermore, in LEACH protocol, the communication between cluster head and base station is conducted always in single hop, which causes large energy waste. By comparative analysis, the HCGW improved based on GWO can effectively overcome restrictions and defects of LEACH protocol and achieve global optimization of sensor network life and stability.

5. Conclusion and prospect

For the reasonable aspects of LEACH protocol in cluster head selection and data transmission process, the GWO-based WSN hierarchical clustering routing algorithm is proposed in this paper. By taking overall consideration of residual node energy, node density and node centrality, the adaptation function is proposed to determine the cluster head, which is the core and main innovation point in this paper. In addition, the local cluster head updating system reduces the overall network energy consumption. According to the grey wolf hierarchy system, the multi-hop routing is designed for layer-by-layer data transmission to reduce the energy consumption in long-distance data transmission and further extend the network life cycle. By simulation comparison, the performance of HCGW algorithm is greatly improved than that of LEACH protocol. The subsequent work is to further optimize the multi-hop routing time delay of super-large scale network and make further researches by using other intelligent optimization algorithms.

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