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# Double sink energy hole avoidance strategy for wireless sensor network

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## Abstract

To solve the energy hole problem in wireless sensor networks with double sinks, a double sink energy hole avoidance strategy is proposed. The main idea is that two data sinks are set at fixed positions on both sides of the rectangular network to collect nodes data in the corresponding area of the network. In the network, sensor nodes are organized in non-uniform clusters. Clusters close to sink have a smaller cluster radius, and clusters far from sink have a larger cluster radius. According to the results of threshold training, monitoring area of double sink is dynamically adjusted based on the difference of energy consumption and load of nodes in the double sink monitoring area, so that the energy consumption load of nodes in the double sink monitoring area tends to be the same, so as to avoid the premature occurrence of energy hole phenomenon in the area with large load, leading to network failure. The experimental results demonstrate that the strategy proposed in this paper can efficiently balance the energy dissipation of double sink and prolong the network energy utilization efficiency and network lifetime.

**Keywords:** Energy hole avoidance, Wireless sensor network, Dynamic adjustment strategy, Double sink

## 1 Introduction

In recent years, with the rapid developments of wireless communication and microelectronics technologies, wireless sensor network (WSN) has been widely used in many fields, such as environmental monitoring, wildlife protection, military detection and so on. However, nodes in sensor networks are usually powered by batteries with limited energy. It is difficult for these nodes to replace batteries after deployment; therefore, the serious energy constraints are one obvious issue for wireless sensor networks [1, 2]. In the communication network with multi-hop connections, some nodes not only produce data but also transmit data. As a consequence, the nodes near sink in the network inevitably have a larger data transmission load, which causes the energy exhaustion for these nodes. As a result, an energy hole was formed finally. Because the nodes near the dead node need to carry the communication load of the dead node, which accelerates the decline of these nodes and increase the energy holes, this phenomenon is called 'funnel effect.' After the emergence of energy holes, the data collected by some undead nodes could not be forwarded to sink, which leads to the end of the network life, thus wastes

a large number of energy resources of undead nodes in the network. The simulation results in [3] showed that when there was an energy hole in the network, up to 90% of the remaining energy in the network was wasted when the network life was over. Therefore, avoiding or delaying the formation of energy holes is an effective and reliable way to prolong the lifetime of the whole network. One method of dividing the network into concentric circles and each of these circles owning a layer was proposed in [4], which considered the limitation of energy resources in these networks. A deployment strategy with using the least possible nodes was presented in [5], which prolonged network lifetime by avoiding energy holes and also ensured full sensing and communication coverage. The effective of the proposed method was verified analytically and validated through NS-2-based simulation experiments. A balanced energy consuming and hole alleviating, and energy-aware balanced energy consuming and hole alleviating algorithms were proposed in [6], which adopts data forwarding and routing selection strategy for the entire network, not only to balance the load distribution of entire network, but also to utilize the energy resource efficiently. In [7], dead nodes, packet loss and energy consumption of dead nodes were simulated on network simulator using Double Cost-based Function Routing and the results were compared with Greedy Geographic Routing. In [8], the problem of energy hole creation in depth-based routing techniques and a technique to overcome the deficiencies in existing techniques were devised. Besides addressing the energy hole issue, the proposition of a coverage hole repair technique is also part of this paper. In areas of the dense deployment, sensing ranges of nodes redundantly overlap. An efficient RF energy harvesting scheme using multiple dedicated RF sources to avert energy holes was proposed in [9], and the performance of multi-hop WSN with wireless energy transfer in terms of energy charged, number of energy transmitter's, throughput and outage in the network was verified. Fasee [10] proposes an energy-efficient traffic prioritization for medium access control protocol, which provides sufficient slots with higher bandwidth and guard bands to avoid channels interference causing longer delay. Azam [11] presents a balanced load distribution scheme to avoid energy holes created due to unbalanced energy consumption in UWSNs. Applying the optimal condition, Jia [12] proposes a novel sensor redistribution algorithm to completely eliminate the energy hole problem in mobile sensor network. Sharma [13] proposes a corona model-based approach to enhance network's lifetime by balancing energy depletion rate across network and avoiding energy hole around sink. Sushil [14] proposes a quantum inspired green communication framework for energy balancing in sensor enabled IoT systems. Verma [15] proposes a fuzzy logic-based clustering algorithm for WSN to extend the network lifetime, by utilizing the concept of average energy-based probability and average threshold for appropriate cluster heads selection. Energy-efficient zone-based dual subsink protocol with dual cluster head was presented in [16], which is developed to schedule the data transmission of these relay nodes with mobile sink. In a word, there are two main problems in the existing energy hole avoidance schemes: one is that many schemes are put forward too idealized and difficult to implement, which is easy to cause unnecessary waste of resources; the other is that most of the current schemes only consider the energy problems, and for other aspects, such as network delay, which are still lack of consideration, we should find a balance point to improve the life cycle and reduce the delay as much as possible.

All those researchers above mentioned have positive effect to investigate the energy hole in wireless sensor network. They adopt different data transmission strategies, sensor node deployment strategies [17], non-uniform clustering [18] and appropriate routing protocols [19] are used to delay or avoid the occurrence of energy hole as much as possible. However, most of these strategies are to balance the energy consumption load of nodes in the single sink monitoring area as much as possible in the single sink network environment, so as to avoid energy hole. In the multi-sink environment with larger network scale, how to make the nodes in different sink monitoring areas have balanced energy consumption, so as to avoid the energy hole phenomenon, which has become an urgent problem to be solved. With the purpose of avoiding the energy hole problem in large-scale sensor networks, an energy hole avoidance strategy based on double sink nodes is proposed in this paper.

Compared with the existing energy hole avoidance strategy, the main contributions of this paper can be summarized as follows.

- 1 To solve the energy hole problem in wireless sensor networks with double sinks, a double sink energy hole avoidance (DS-EHA) strategy is proposed.
- 2 Double sink divides the network into two areas for monitoring. According to the load difference between the nodes in the double sink monitoring area, this method dynamically adjusts the area of the double sink monitoring area and solves the energy hole problem in the double sink network by the way of double sink cooperative work.
- 3 A novel end adjustment threshold training mechanism is proposed, which makes the adjustment of double sink monitoring area more efficient and reasonable.

The organization of this paper is as follows. Section 1 introduces the research background and development status of the subject. Section 2 illustrates the wireless sensor network system model and problem descriptions. The DS-EHA design scheme in detail is presented in Sect. 3, including the cluster routing strategy, the dynamic adjustment strategy of double sink monitoring area and the selection of target threshold. Then, network environment parameter selections for the proposed algorithm and simulation comparison are shown in Sect. 4. Section 5 concludes this paper.

## 2 System model and problem description

### 2.1 System model

#### 2.1.1 Network deployment model

Assuming that there are  $N$  sensor nodes in total, each node has the same initial energy and is randomly distributed in a two-dimensional rectangular region. Each node is pre-assigned with a unique identifier ID in the whole network, and they can obtain the distance from the signal source according to the strength of the received signal. The two sink nodes are arranged symmetrically on both sides of the rectangular network, and their transmitting power can be adjusted and can communicate with each other.

Energy consumption model.

The same energy model in the literature [20] is adopted in this paper:

- 1 The energy required by the sensor to transmit a  $k$ -bit data packet to the node at distance  $d$  is

$$E_{Ti}(k, d) = \begin{cases} kE_{elec} + k\partial_{fs}d^2kE_{elec} + k\partial_{fs}d^2, & d < d_0 \\ kE_{elec} + k\partial_{mp}d^4 & d \geq d_0 \end{cases} \quad (1)$$

- 2 The energy required to receive a  $k$ -bit packet is

$$E_{Ri}(k) = kE_{elec} \quad (2)$$

where  $d_0 = \sqrt{\partial_{fs}/\partial_{mp}}$ ,  $d_0$  is the threshold, when the distance between sending node and receiving node is less than  $d_0$ . The energy dissipation of the data transmitted by the sender is proportional to the square of the distance. Otherwise, it is proportional to the fourth power of distance.  $E_{elec}$  represents the energy consumption per bit of data sent or received,  $\partial_{fs}d^2$  and  $\partial_{mp}d^4$  are the energy consumption of transmitting data amplifier per bit.

## 2.2 Problem description

Each node has a different communication range, for example, node  $i$  has a communication range of  $R_i$ . Therefore, if a node is not in the communication range of another node, it cannot communicate directly, and the forwarding of the relay node is required. By the idea of wheel, before the start of each round to calculate the best position of the base station and the base station in the epicycle position is unchanged, the cycle is represented by  $T$ . The base station shall be within the permitted area.

In this paper, the graph is used to represent the wireless sensor network.  $E$  represents the communication link in the network. If there is a link between node  $i$  and node  $j$ , the edge  $(i, j) \in E$ . Because some nodes close to the base station consume energy too fast, they are the bottleneck of the entire network. If there is only one sink at rest in the network, it will be difficult to avoid forming "energy volution" near the sink. In addition, obtaining a good energy balance often leads to a large network delay, so it is necessary to design a routing algorithm to make a balance between energy optimization and delay reduction.

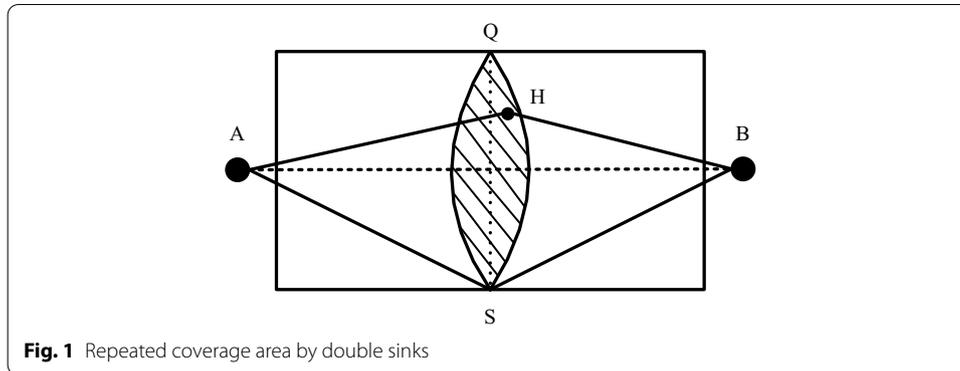
## 3 DS-EHA scheme design

For large-scale wireless sensor networks, this paper adopts the double sink network structure. For the following two reasons, firstly, the communication ability of sensor nodes is limited, in addition, the communication range of sink nodes responsible for data receiving and processing is also difficult to cover the whole network.

Definition 1. As shown in Fig. 1, A and B are sink-1 and sink-2, AS and BS are the perceptual diameter of sink-1 and sink-2, respectively. H is a node in the region, SQ is the perception dividing line, and the shadow area is in the monitoring area of sink-1 and sink-2 at the same time. Shadow area is called the repetitive coverage area of the network.

### 3.1 Cluster routing strategy

In order to balance the energy consumption of each cluster in the network, the nodes in DS-EHA are organized in a non-uniform way. The clusters close to sink have smaller



cluster radius, while those far from sink have larger cluster radius. As shown in Fig. 1, node H is in the repeated coverage area of the network. According to the signal strength of the received broadcast message, node H calculates the distance  $\overrightarrow{AS}$  and  $\overrightarrow{BS}$  from sink-1 and sink-2, respectively. Then, node H calculates the distance  $d_h$  between the node and the perceived boundary according to formula (3).

$$d_h = \frac{\overrightarrow{AS}^2 - \overrightarrow{BS}^2 + \overrightarrow{AH}^2 - \overrightarrow{BH}^2}{2\overrightarrow{AB}} \quad (3)$$

where  $\overrightarrow{AH}$  and  $\overrightarrow{BH}$  are the distance from node H to sink-1 and sink-2, respectively, and  $\overrightarrow{AB}$  is the horizontal distance between sink-1 and sink-2, as shown in Fig. 1. If  $d_h \geq 0$  is greater than or equal to 0, node H is at the right of the perceived boundary. If  $d_h < 0$ , node H is at the left of the perceived boundary, node H is clustered in the sink-1 monitoring region, and the data is transmitted to the sink-1 direction. When nodes are clustered, they transmit data to sink in a multi-hop mode. The cluster-head node with the largest residual energy and closer to the sink is selected as the next-hop data forwarding node in its neighbor cluster heads.

### 3.2 Dynamic adjustment strategy of double sink monitoring region

Assume that the monitoring area of sink-1 and sink-2 is equal at the beginning of the network. The randomness of node distribution in the network makes it difficult for the number of nodes in the sink-1 and sink-2 monitoring area and the load of nodes in the routing process to be the same. If the load difference between nodes in the sink-1 and sink-2 monitoring area is large at the beginning, the load difference between nodes in different sink monitoring areas will be larger and larger as time goes on, and the nodes in the area with higher load will die earlier, thus resulting in the phenomenon of energy evolution. In order to balance the load of nodes in the network and avoid the occurrence of energy evolution, the DS-EHA algorithm proposed by us is oriented by the load difference between double sink nodes and dynamically adjusts the area of double sink monitoring area.

#### 3.2.1 Adjust the design of discriminant function

The energy consumption rate of the nodes in the sink-1 and sink-2 monitoring area can well reflect the load difference of the nodes in the sink-1 and sink-2 monitoring area.

The higher the energy consumption rate of the node, the greater the load of the node in the region. After each round of data collection, the difference value of energy consumption rate of nodes in the sink-1 and sink-2 monitoring area was used as the adjustment discrimination function value of the current round of the network in DS-EHA algorithm. If the energy consumption rate of nodes in the sink-1 monitoring area is higher than sink-2, the area of sink-1 monitoring area will be reduced. The reduced data in the sink-1 monitoring area were transmitted to the sink-2 monitoring area. Conversely, if the energy consumption rate of nodes in the sink-1 monitoring area is smaller than sink-2, the area of the sink-1 monitoring area will be increased.

The current network rotation is represented by  $m$ ,  $h$  is the region where the node belongs to,  $h \in (1, 2)$ ,  $Judge(x)$  is the adjustment discrimination function of the network,  $Judge(m)$  is the value of the adjustment discrimination function of the current wheel, and  $Judge(T)$  is the end adjustment threshold.  $\varphi_m^h$  represents the energy consumption rate of the nodes in the sink monitoring area in each round,  $E_{inti-m}^h$  represents the residual energy of the nodes in the sink monitoring area at the beginning of each round,  $E_{rem-m}^h$  represents the residual energy of the nodes after each round, and then, the energy consumption rates of the nodes in sink1 and sink2 monitoring area are respectively:

$$\varphi_m^h = \frac{E_{inti-m}^h - E_{rem-m}^h}{E_{inti-m}^h} \tag{4}$$

According to formula (4), the adjustment discrimination function of the network is:

$$Judge(m) = \left| \varphi_m^1 - \varphi_m^2 \right| \tag{5}$$

### 3.2.2 Implementation of dynamic adjustment strategy

Through the dynamic adjustment of the sink-1 and sink-2 perception radius, the area of the sink-1 and sink-2 monitoring area was adjusted. AS can be seen from Fig. 1, when the sink-1 and sink-2 sensing radii changed, the change value of the repeated region in the monitoring area was  $\Delta S$ , and the step size adjustment factor was  $\lambda$ . The length of the rectangular region in this paper was  $W$ , the width was  $Z$ , and the total area was  $S_{wz}$ .  $\vec{AS}'$  and  $\vec{BS}'$  were sink-1 and sink-2, respectively. After adjusting the area of the monitoring area, then

$$S_{wz} = \lambda \Delta S \tag{6}$$

$$\Delta S = \frac{Z}{2} \left| \sqrt{4\vec{AS}^2 - Z^2} - \sqrt{4\vec{BS}^2 - Z^2} \right| \tag{7}$$

$$\vec{AB} = \sqrt{\vec{AS}'^2 - \left(\frac{Z}{2}\right)^2} - \sqrt{\vec{BS}'^2 - \left(\frac{Z}{2}\right)^2} \tag{8}$$

According to formulas (6), (7) and (8), the sink-1 and sink-2 sensing radii can be obtained after adjusting the area of the monitoring area. If  $\varphi_m^1 - \varphi_m^2 \geq 0$ , the monitoring area of sink-1 should be reduced, then

$$\vec{AS}' = \left( \vec{AS}^2 - \frac{W}{\lambda} \sqrt{4\vec{AS}^2 - Z^2} + \left( \frac{W}{\lambda} \right)^2 \right)^{\frac{1}{2}} \tag{9}$$

If  $\varphi_m^1 - \varphi_m^2 < 0$ , the monitoring area of sink-1 should be increased, then

$$\vec{AS}' = \left( \vec{AS}^2 + \frac{W}{\lambda} \sqrt{4\vec{AS}^2 - Z^2} + \left( \frac{W}{\lambda} \right)^2 \right)^{\frac{1}{2}} \tag{10}$$

The perceived radius of the corresponding sink-2 detection region is:

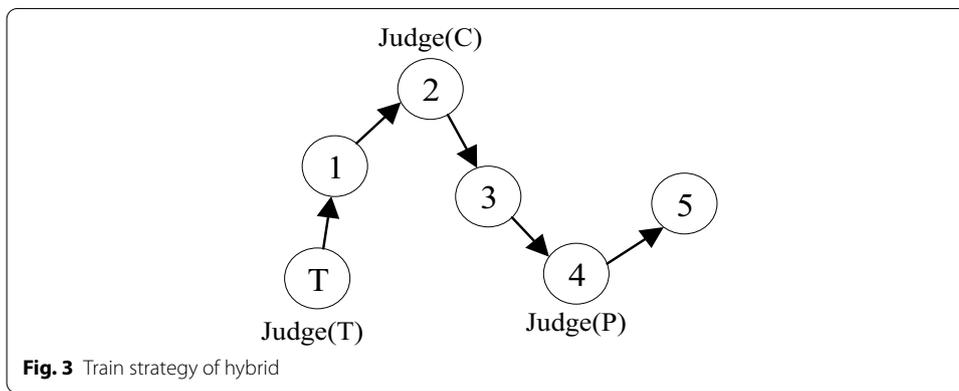
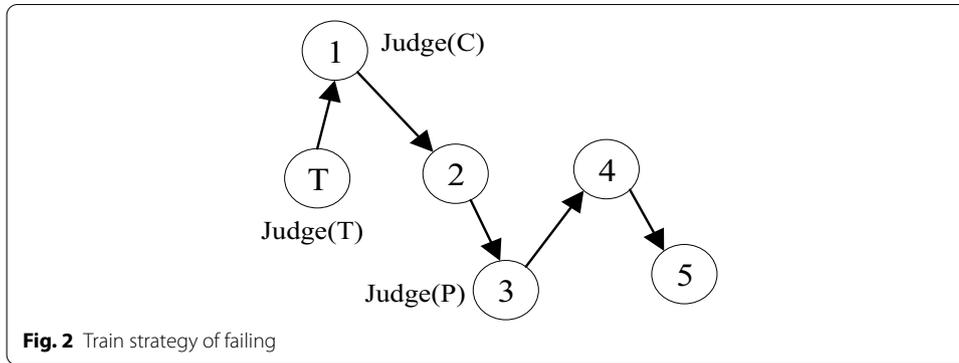
$$\vec{BS}' = \left( \vec{AB}^2 - 2\vec{AB} \sqrt{\vec{AS}'^2 - \left( \frac{Z}{2} \right)^2} + \vec{AS}'^2 \right)^{\frac{1}{2}} \tag{11}$$

### 3.3 Selection of target threshold

When the adjustment discriminant function  $Judge(m)$  is greater than or equal to the end adjustment threshold  $Judge(T)$ , continuing to dynamically adjust the area of the sink-1 and sink-2 monitoring area until  $Judge(m) < Judge(T)$ , ending the adjustment of the area of the sink-1 and sink-2 monitoring area, that is, the area of the sink-1 and sink-2 monitoring area remains unchanged. It can be seen that the end of the adjustment threshold  $Judge(T)$  size directly affects the adjustment of the sink-1 and sink-2 monitoring area. If the end adjustment threshold is set too small, the network may be in an adjustment state all the time. If the setting of the end adjustment threshold is too large, it may cause the network to stop the adjustment, and the load of nodes in the sink-1 and sink-2 monitoring area is still significantly different. Both are detrimental to extending network life. In order to make the adjustment of double sink monitoring area more efficient, a reasonable end adjustment threshold is needed. DS-EHA constructs threshold training trees according to the value of each adjustment discriminant function in the network and obtains the current optimal end adjustment threshold through the threshold training tree.

In the process of ending threshold training strategy, assuming that  $Judge(C)$  and  $Judge(P)$  represent training thresholds and optimal training values, respectively, the end of the adjusting threshold  $Judge(T)$  initial value is a negative integer, if the discriminant function value  $Judge(m)$  of the current wheel of the network is greater than the end adjustment threshold  $Judge(T)$ , began to adjust the area of the double sink monitoring area, and construct a threshold training tree at the same time, start training the new  $Judge(T)$ , on the contrary, the area of the double sink monitoring area with  $Judge(T)$ 's value remains the same.

The process of constructing threshold training tree is as follows: firstly, the  $Judge(T)$  of the end adjustment threshold is taken as the root node, and the value of the discriminant function of each round is taken as the leaf node. The number in the leaf node represents the current number of rounds. The arrow pointing up indicates that the value of the discriminant function of the current round is larger than that of the previous round. The arrow pointing down indicates that the discriminant function value of the current round



is smaller than that of the previous round. As shown in Fig. 2, in the end of threshold training process, if the value of each leaf node shows a downward trend (e.g., ① → ②) before obtaining the optimal training value Judge(P) for this training, then this kind of training method is called the downward trend training method. On the contrary, as shown in Fig. 3, if there is an upward and downward trend (① → ② → ③) at the same time before the optimal training value is obtained, this kind of training method is called the mixed trend training method.

### 3.3.1 Downtrend training method

As shown in Fig. 2, because of  $Judge(1) > Judge(T)$ , it is necessary to construct threshold training tree to find a new end adjustment threshold.  $Judge(2) < Judge(1)$ , which indicates that the load of nodes in sink-1 and sink-2 monitoring area tends to be balanced by dynamically adjusting the monitoring area of sink-1 and sink-2. At this time, we need to continue to adjust the monitoring area of sink-1 and sink-2 through the dynamic adjustment strategy of double sink monitoring area. Until sink-1 and sink-2 are obtained, the optimal area of monitoring area is obtained. The value of leaf nodes ① and ② shows a downward trend, indicating that the load of nodes in the network is tending to be balanced. When the first reverse trend point (leaf node ④) appears in the downward trend, the threshold training is completed. The values of the adjustment discriminant function corresponding to leaf node ① and leaf node ③ are the training threshold and the optimal training value of the threshold training, respectively.

$$\text{Judge}(C) = \text{Judge}(1) \ \& \ \text{Judge}(P) = \text{Judge}(3) \quad (12)$$

The cumulative mean value of all the leaf nodes between the training threshold  $\text{Judge}(C)$  and the optimal training value  $\text{Judge}(P)$  is taken as the new end adjustment threshold of network, as shown in Fig. 2. The new end adjustment threshold of network is:

$$\text{Judge}(T) = \frac{\sum_{m=1}^3 \text{Judge}(m)}{3} \quad (13)$$

$\text{Judge}(T) \rightarrow \textcircled{1} \rightarrow \textcircled{2} \rightarrow \textcircled{3} \rightarrow \textcircled{4}$  is called a complete downward trend training.

### 3.3.2 Mixed trend training method

As shown in Fig. 3, before obtaining the optimal training value for this training, there are both upward trend ( $\textcircled{1} \rightarrow \textcircled{2}$ ) and downward trend ( $\textcircled{2} \rightarrow \textcircled{3} \rightarrow \textcircled{4}$ ) leaf nodes. The value of leaf node  $\textcircled{2}$  is larger than that of leaf node  $\textcircled{1}$ . The area of sink-1 and sink-2 monitoring area needs to be adjusted to reduce the load difference between two sink nodes. Assuming that the value of leaf node 3 is smaller than that of leaf node 2 by adjusting, and the value of leaf node shows a downward trend, the first inverse trend leaf node (leaf node $\textcircled{5}$ ) is found by referring to the downward trend training method, and training threshold of the mixed trend training and optimal training value are obtained.

$$\text{Judge}(C) = \text{Judge}(2) \ \& \ \text{Judge}(P) = \text{Judge}(4) \quad (14)$$

Then, the new end adjustment threshold in the network is:

$$\text{Judge}(T) = \frac{\sum_{m=2}^4 \text{Judge}(m)}{3} \quad (15)$$

$\text{Judge}(T) \rightarrow \textcircled{1} \rightarrow \textcircled{2} \rightarrow \textcircled{3} \rightarrow \textcircled{4}$  is called a complete downward trend training.

After threshold training, sink-1 and sink-2 search the table  $NT(m)$  to find and follow the perception radius of sink-1 and sink-2 in the wheels corresponding to the optimal training value  $\text{Judge}(P)$ . As shown in Fig. 2, sink-1 and sink-2 start from the fifth round and follow the perception radius of sink-1 and sink-2 in the third round. In Fig. 3, sink-1 and sink-2 begin with the sixth round and follow the perceptual radius of sink-1 and sink-2 in the fourth round. Until the discriminant function value  $\text{Judge}(m) > \text{Judge}(T)$  of the first  $m$  round, the threshold training tree is reconstructed with the value of  $\text{Judge}(T)$  as the root node, and a new round of threshold training is started.

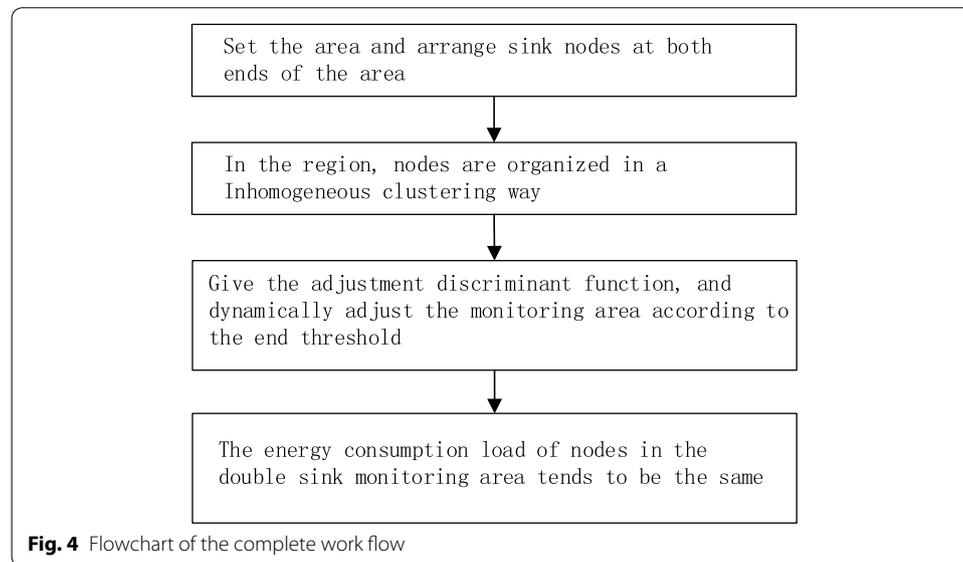
## 4 Simulation experiment and analysis

### 4.1 Environment setting and parameter selection

In order to verify the effectiveness of the DS-EHA algorithm proposed in this paper, the EEUC (energy-efficient uneven clustering), DSR (dynamic source routing) and DS-EHA algorithms are simulated by MATLAB simulation software under the same conditions, and several performance indicators of the algorithms are compared and analyzed. In the experiment, each algorithm is equipped with two sinks. The data of sensor nodes are

**Table 1 Simulation experiment parameters table**

Parameter names	The parameter value	Parameters to describe
Rectangular area	1000 m × 300 m	Length × width
$m$	500	Number of nodes
$E_{\text{init}}$	1 J	Node initial energy
$E_{\text{elec}}$	60 nJ/bit	Radiofrequency energy consumption coefficient
$\partial_{\text{fs}}$	12 pJ/bit/m <sup>2</sup>	Energy consumption coefficient of power amplification
$\partial_{\text{mp}}$	0.0012 pJ/bit/m <sup>4</sup>	Energy consumption coefficient of power amplification
Sink-1	Coordinates (0, 150)	Sink-1 position
Sink-2	Coordinates (1000, 150)	Sink-2 position
$k$	1000 bit	Packet size

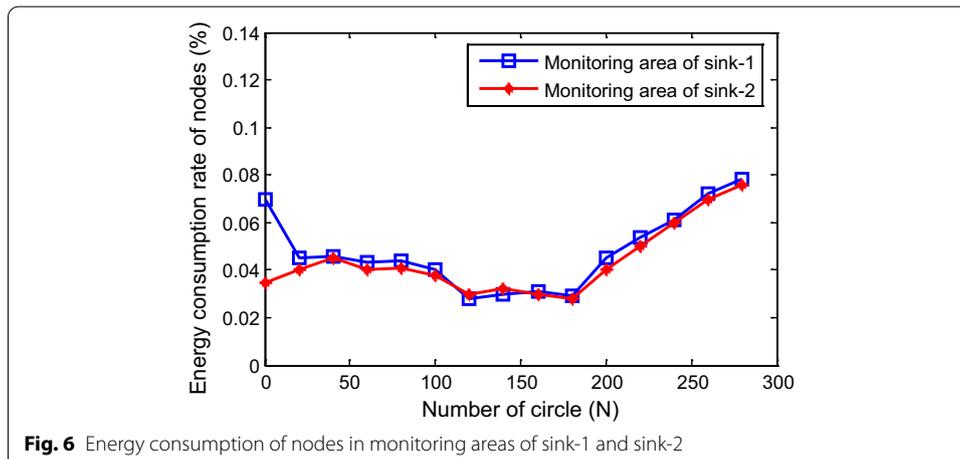
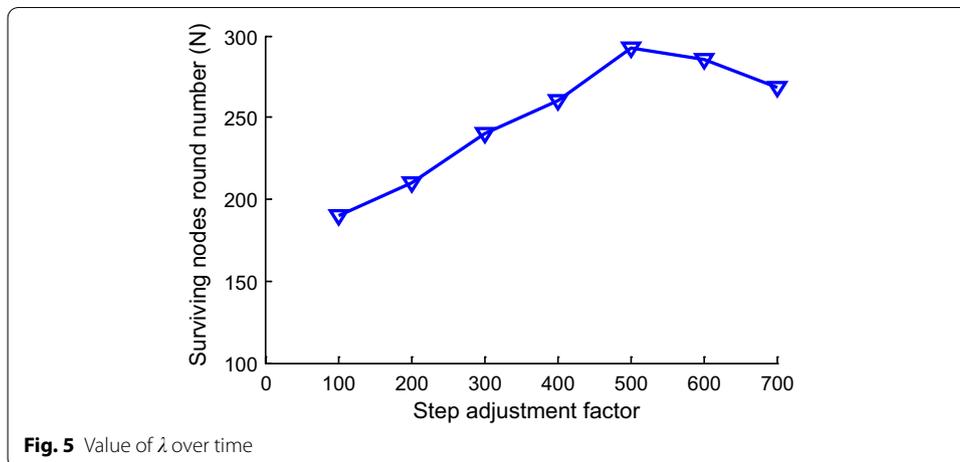


not fused, and only the energy consumed by the sensor nodes to receive and send data is counted. The simulation environment parameters are shown in Table 1, and the general flowchart of the whole working process is shown in Fig. 4.

The value of step adjustment factor  $\lambda$  directly affects the load of nodes in the network and the performance of threshold training strategy. The smaller the value of  $\lambda$ , the larger the adjustment range of network, the larger the value of  $\lambda$ , the smaller the adjustment range of network. If the area adjustment range of the double sink monitoring area is too large, the load of the nodes between the two sinks will fluctuate greatly, and it is difficult for the node load to reach equilibrium. If the adjustment range is too small, the load of double sink nodes will take a long time to reach equilibrium. As shown in Fig. 5, when  $\lambda = 500$ , the number of surviving rounds of nodes reaches the maximum, and the network has the longest lifetime. The simulation experiments in this paper all take  $\lambda = 500$ .

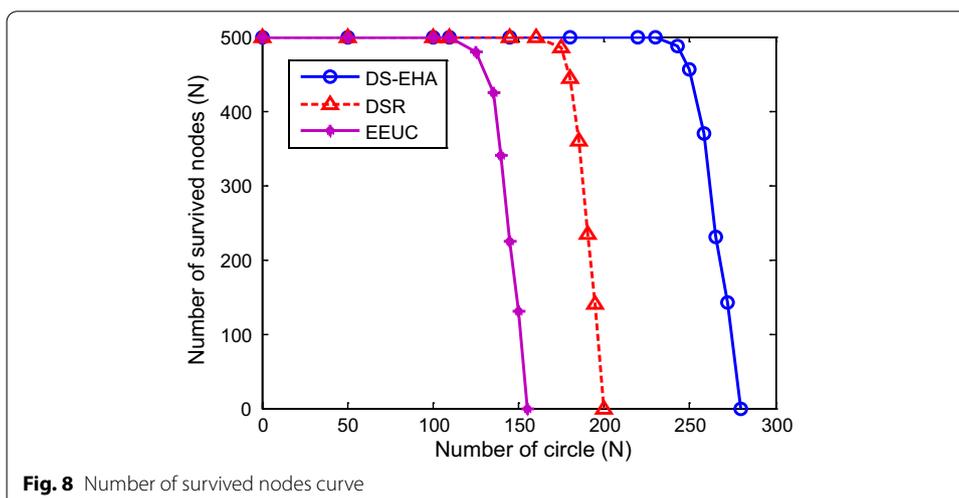
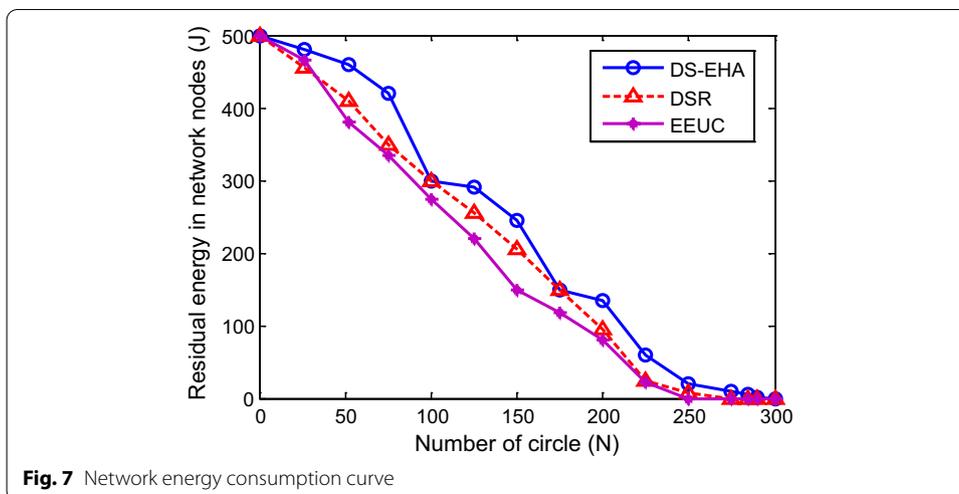
#### 4.2 Simulation experiment analysis

The change curve of the energy consumption rate of the nodes in the sink-1 and sink-2 monitoring area with the number of adjustment rounds is shown in Fig. 6. At



the beginning, the load difference between the two sink nodes is large. At the beginning of a new round of data collection, the new sensing radius is used to broadcast messages to realize the adjustment of double sink monitoring area, so that the load between the two sink nodes tends to be balanced.

In order to verify the superiority of the proposed algorithm in this paper, on the DS-EHA algorithm proposed in this paper with algorithm based on the conventional algorithm of DSR, EEUC algorithm for energy consumption test experiments, specific test results are shown in Figs. 7 and 8, with the increase in the whole network adjustment round number, DS-EHA algorithm nodes remaining energy is always higher than the other two algorithms, DS-EHA algorithm by dynamically adjusting the area of the double sink monitoring area, effective balance the load between the double sink node, prolong the network lifetime. As shown in Fig. 8, in the default simulation environment, the network life of DS-EHA is 28% higher than that of DSR algorithm and 36% higher than that of EEUC algorithm.



### 4.3 Results and discussion

Compared with the simulation results of existing EEUC and DSR energy hole avoidance strategies, the proposed algorithm in this paper has two advantages. Firstly, two areas for monitoring in the network are divided by double sink, and DEAS dynamically adjusts the area of double sink monitoring area according to the load difference between nodes in double sink monitoring area. Hence, the problem of energy hole in double sink network is solved effectively by the way of double sink cooperative work. Secondly, a new training mechanism of end adjustment threshold is proposed, which makes the adjustment of double sink monitoring area more efficient and reasonable.

### 5 Conclusion

In order to solve the problem of uneven load of nodes in the sink monitoring area under the double sink structure, the strategy of dynamically adjusting the area of the double sink monitoring area is adopted in this paper. The problem of energy hole in the network

is effectively avoided, and the load of nodes in the network is more balanced through the way of double sink cooperative work. And the algorithm proposed in this paper has better performance in energy efficiency and network life through the comparative simulation analysis.

#### Abbreviations

DS-EHA: Double sink energy hole avoidance; WSN: Wireless sensor network; EEUC: Energy-efficient uneven clustering; DSR: Dynamic source routing.

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#### Authors' contributions

CSX and HQZ are the main writer of this paper. They completed method and writing of the whole paper. ZY provided some important suggestions for the cluster routing strategy and experimental methods. LX provided some important suggestions for dynamic adjustment strategy of double sink monitoring area. All authors read and approved the final manuscript.

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#### Availability of data and materials

Not applicable.

#### Competing interests

The authors declare that the work described was original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part.

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