

## *Retraction*

# **Retracted: A Dynamic Hierarchical Clustering Data Gathering Algorithm Based on Multiple Criteria Decision Making for 3D Underwater Sensor Networks**

### **Complexity**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] X. Song, W. Sun, and Q. Zhang, "A Dynamic Hierarchical Clustering Data Gathering Algorithm Based on Multiple Criteria Decision Making for 3D Underwater Sensor Networks," *Complexity*, vol. 2020, Article ID 8835103, 14 pages, 2020.

## Research Article

# A Dynamic Hierarchical Clustering Data Gathering Algorithm Based on Multiple Criteria Decision Making for 3D Underwater Sensor Networks

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Data gathering is the basis of monitoring applications in an underwater sensor network, and excellent network coverage and data transmission reliability are the guarantees for the quality of monitoring tasks. However, the energy consumption of the nodes is too fast due to the heavy load of the cluster heads closer to the sink when data is transmitted between cluster heads (CHs) and the sink by multihop, which leads to an energy hole problem in an underwater sensor network of clustering technology. Aiming to address this problem, we propose a dynamic hierarchical clustering data gathering algorithm based on multiple criteria decision making (DHCDGA) in a 3D underwater sensor network. Firstly, the entire monitoring network is divided into many layers. For selecting a cluster head in each layer, multiple criteria decision making of an intuitionistic fuzzy Analytic Hierarchy Process (AHP) and hierarchical fuzzy integration is adopted. Furthermore, a sorting algorithm is used to form a clustering topology algorithm to solve the problem that there is the only node in one cluster. Then, an energy-balanced routing algorithm between clusters is proposed according to the residual energy of the node, the depth, and the number of neighbor nodes. Finally, the simulation results show that DHCDGA can not only effectively balance the energy consumption of the network and prolong the network lifetime but also improve network coverage and data gathering reliability.

## 1. Introduction

With the development of science and technology, the ocean, which covers 70% of the earth's surface area, plays an important role in the development of smart city [1, 2]. With the rise of the marine economy, countries all over the world pay more and more attention to the rights and interests of the ocean, and humans urgently need new technologies to observe and develop the ocean [3]. Underwater sensor networks are one of the hot ocean observation technologies that have emerged in the recent years [4, 5]. Underwater sensor networks have broad applications in many military and civilian fields, for example, for ocean exploration and development [6], for disaster warning and forecast [7], for environmental monitoring [8], and submarine detection [9]. Therefore, the

underwater sensor network has attracted widespread attention from domestic and foreign researchers.

Compared with traditional sensor networks [10], the main feature of underwater sensor networks is the use of underwater acoustic communication [11]. The absorption rate of radio signals in the water is very high, the signal propagation distance is limited, and the distance of underwater radio communication is generally not more than 100 meters. Therefore, it is not suitable for the needs of long-distance communication in underwater sensor networks [12]. Besides, the optical signal cannot be transmitted over long distances in seawater, its medium has a high absorption rate, and it is easily blocked, refracted, and reflected by various creatures and obstacles in the sea [13]. Therefore, underwater sensor networks use acoustic communication [14, 15]. The underwater acoustic channel has the

remarkable characteristics of high delay, high bit error rate, and low communication bandwidth [16, 17]. This makes the traditional sensor network communication protocol not directly applicable in underwater, which brings challenges to the protocol design of the underwater sensor network. In summary, the environment of underwater acoustic communication is harsh and the data transmission rate is very low. Therefore, it is of great significance to study the data gathering of underwater sensor networks.

There has been a lot of research studies on the data gathering strategy of underwater sensor networks. DBR [18] was a flat data gathering algorithm that provided a solution for the networking of underwater sensor networks in the early years. However, flat data gathering algorithms are often used in smaller networks. If the network scale is large, nodes close to the sink will undertake too much data forwarding and consume a lot of energy. This causes the nodes near the sink to die prematurely and form an energy hole. The death of these nodes will cause the rapid death of the surrounding nodes. Therefore, delaying the appearance of energy holes helps to prolong the network lifetime. Compared with the flat data gathering algorithm, the clustering data gathering algorithm can balance the energy load of the network. Hence, to adapt to a large-scale network environment, the use of clustering data gathering algorithms can alleviate the appearance of energy holes and effectively prolong the network lifetime.

At present, clustering data gathering algorithms are mainly focused on traditional ground wireless sensor networks. Its network topology is a two-dimensional flat network. These algorithms cannot be directly applied to the environment of a 3D underwater sensor network. Regarding the clustering data gathering algorithm of the 3D underwater sensor network, some theoretical research studies have been studied by many researchers. However, most of the algorithms are based on the clustering data gathering algorithm of the two-dimensional ground sensor network. These two-dimensional clustering algorithms have been transplanted into the three-dimensional underwater sensor network environment. They do not consider the mobility of nodes and unknown location information so that they cannot solve the problem of clustering data gathering in underwater sensor networks. The main deficiencies are as follows:

- (1) Little consideration is given to the impact of node mobility on the network. The clustering data gathering algorithms of two-dimensional sensor networks mostly use flat static sensor networks as the research premise, ignoring the impact of node movement on the network topology.
- (2) A two-dimensional sensor network can use GPS to determine the distance between nodes, but GPS cannot be used to locate an underwater sensor network. There is a large error in the way of wireless measurement distance, and underwater measurement distance has become another hot issue.
- (3) At present, most clustering data gathering of underwater sensor networks use energy as a measure to select cluster heads or design clustering algorithms

based on underwater characteristics. They rarely consider coverage and data transmission reliability. Hence, this is difficult to ensure network coverage and data collection reliability, which is a fatal defect for monitoring applications in underwater sensor networks. Accordingly, some scholars have begun to study cluster algorithms for sensor network coverage preservation and data gathering reliability. The data gathering algorithm with coverage preservation and reliability can reduce the rate of the decline of network coverage, at the same time, and the reliability of data gathering is guaranteed. Current research focuses on data gathering algorithm with the coverage preservation and data gathering reliability in traditional wireless sensor networks [19]. Little work on the clustering data gathering algorithm is suitable for coverage preservation and data gathering reliability in underwater sensor networks.

In this paper, we propose a dynamic hierarchical clustering data gathering algorithm based on multiple criteria decision making in 3D underwater sensor network. Aiming at these problems, the contributions of this paper are as follows:

The entire monitoring network is divided into layers. In each layer, multiple criteria decision making of an intuitionistic fuzzy AHP and hierarchical fuzzy integration is adopted in the phase of selecting a cluster head.

A sorting algorithm is used to form a clustering topology algorithm to solve the problem that there is only one node in one cluster.

According to the residual energy of the node, the depth, and the number of neighbor nodes, an energy-balanced routing algorithm is proposed between cluster heads.

In the simulation, DHCDGA is compared with leach-coverage-U and NULCPR, in terms of network lifetime and other five performances. The simulation results show that DHCDGA can not only effectively balance the energy consumption of the network and prolong the network lifetime but also improve network coverage and data gathering reliability.

The remainder of this paper is organized as follows. The related work of the field is introduced in Section 2. After introducing the network model and energy consumption model, in Section 3, a detailed description of the proposed clustering data gathering algorithm is presented in Section 4. In Section 5, we analyze the DHCDGA theoretically. Section 6 presents and analyzes six performance metrics of the DHCDGA in comparison with two other data gathering algorithms, and we conclude the paper in Section 7.

## 2. Related Work

By now, some work has been finished on improving energy efficiency or coverage preservation or data gathering reliability for 2D wireless sensor networks. However, there are

only a few clustering algorithms improving the above-mentioned three factors in a joint way for 3D underwater wireless sensor networks. Some clustering algorithms have been introduced in Section 1. In this section, we only briefly review some other typical clustering algorithms and considering coverage preservation and data gathering reliability.

Leach-coverage-U [20] was modified from the LEACH and the virtual grid routing protocols. The CPCHSA algorithm was added based on LEACH to achieve the best sensing coverage. Different nodes were assigned different probabilities of being a cluster head to maximize the network sensing coverage. However, Leach-coverage-U does not focus on data gathering reliability in underwater sensor networks. NULCPR [21] was a distributed unequal cluster size and hierarchical coverage-preserving routing algorithm. Spatially, the network was gradually built up from the sink node to the outside. Logically, a downward tree structure with the sink node as the root was constructed. The farther the node was from the Sink, the lower the level in this tree structure. Each layer ran the NCPR algorithm independently to complete the cluster head election, and each layer of the cluster head established a connection link with the upper node to ensure network connectivity. At the same time, the communication radius of nodes in each layer gradually increased as the number of network layers increased. In this way, the communication radius of the node was smaller and the cluster density was larger in the area close to Sink, and the communication radius was larger and the cluster density was smaller in the area far away from Sink. Hence, the energy consumption was balanced and the network lifetime is prolonged. However, NULCPR only considers energy efficiency and coverage preservation and ignores the reliability of data gathering.

CBEER [22] was an event-driven energy-efficient routing approach called clustering-based energy-efficient routing. In CBEER, a BS was responsible to run the routing scheme to optimize the cluster head (CH) selection for cluster creation. By cluster head selection, dynamic clusters were established. In this way, finding the shortest routing paths and consuming energy uniformly became possible in the entire network. Otherwise, a novel evolutionary algorithm based clustering was used to realize the reduction of energy consumption. For avoiding energy consumption of the same CHs, the CHs included in the current routing path were deleted from the other paths in the routing table. However, CBEER does not focus on coverage preservation and data gathering reliability. HENPC [23] was an energy-efficient clustering algorithm for magnetic induction-based underwater wireless sensor networks. The clustering protocol included two main parts. First, the jellyfish breathing algorithm was constructed based on the node contribution density to optimize the cluster size. Second, a node adjustment was built based on the Voronoi diagram to obtain an appropriate number of selected CHs. However, HENPC only focuses on energy efficiency, and it is not suitable for network scenarios with the request of high network coverage and data gathering reliability.

SMO [24] was a clustering approach based on spider monkey optimization. It resolved the node mobility caused

by the water current. Due to the node mobility, it led to transmission errors, link loss, collisions, and congestion, if not well handled. SMO was fit for heterogeneous underwater wireless sensor networks. There were three different roles in the network. They were cluster heads, local leaders, and global leaders. They worked together to provide energy-efficient data gathering. However, CBEER does not focus on coverage preservation and data gathering reliability. QERP [25] was a Quality-of-Service (QoS) aware evolutionary routing protocol for underwater wireless sensor networks. It addressed the challenge caused by reliable data delivery. For example, impairments of the acoustic transmission were caused by excessive noise, extremely long propagation delays, high bit error rate, low bandwidth capacity, multipath effects, and interference. QERP could improve the packet delivery ratio and reduce average end-to-end delay and overall network energy consumption. However, QERP is not suitable for network scenarios with the request for high network coverage. CUWSN [26] was an energy-efficient routing protocol selection for a cluster-based underwater wireless sensor network. In CUWSN, the multihops communication technique was adopted to reduce network energy. For further reducing energy consumption, CUWSN selected the cluster coordinator node and cluster head. The proposed CUWSN reduced power consumption by selecting the cluster coordinator node and cluster head to get a maximum lifetime of the network. However, CUWSN only considers energy efficiency, and it is not suitable for network scenarios with the request of high network coverage and data gathering reliability.

In [27], a fuzzy- and PSO-based clustering scheme using energy and distance parameters was proposed. The nodes were clustered by fuzzy clustering algorithms based on the geographical locations and the probability of belongingness of the sensor nodes. An improved PSO was used to select a cluster head. The process of cluster head selection considered multifactors to minimize energy consumption. However, the clustering scheme does not consider other factors, such as network coverage ratio and reliability of data gathering. MLCEE [28] was a multilayer cluster-based energy-efficient protocol for UWSNs. The goal of MLCEE mainly addressed the issue of a hotspot, high error rate, and high consumption of energy. In MLCEE, the entire network region was firstly divided into different layers from the surface to bottom and in every layer. Then, the second stage was the clustering of the nodes at the same layers. Finally, the cluster head selected the next-hop among the CHs based on the greater fitness value, small Hop-id, and small layer number. Although MLCEE has improved energy efficiency and data gathering reliability, it does not consider network coverage. FCMMFO [29] was a hybrid clustering method based on fuzzy c means and the moth-flame optimization method to improve the performance of the network. FCMMFO adopted FCM to divide the network. Theoretically, the optimal number of clusters could be determined by the elbow method. By MFO, the optimal locations of the cluster heads could be obtained. However, the clustering factor does not consider other factors, such as network coverage ratio and reliability of data gathering in an underwater sensor network.

### 3. System Model

In this section, we will introduce three models used in our clustering data gathering algorithm. They are the network model, the energy consumption model, and the node motion model.

**3.1. Network Model.** This paper assumes that there are the following properties in the underwater sensor network:

- (1) Sensor nodes are randomly deployed to form a three-dimensional underwater network, and the communication link between the nodes is reliable and two-way symmetrical.
- (2) There is a sink on the water. Its computing power and energy are not limited, and it can carry out wireless transmission.
- (3) The node moves within a certain range under the influence of water flow. We assume that the maximum offset distance is  $r$ .
- (4) Nodes can obtain their depth value, and each node is equipped with low-cost depth-sensing hardware.
- (5) The distance between nodes can be calculated according to the signal transmission strength.
- (6) DHCDGA is a periodic data gathering service. The nodes periodically gather data from sensors to sink in the underwater sensor network.

**3.2. Energy Consumption Model.** The algorithm in this paper adopts the same energy consumption model for underwater acoustic communication as in [30]. For underwater sensor nodes, the energy consumption of sending a message is about ten times that of receiving a message and idle listening. Therefore, the energy consumption of sending messages accounts for a large proportion of the total energy consumption, and reducing the energy consumption of sending messages means that the total energy consumption of the entire network can be reduced. The algorithm in this paper uses the energy consumption generated by sending the message as the main parameter to measure the total energy consumption of the entire network. Assume that  $P_o$  is the minimum power required by the node to receive messages normally; if the power attenuation function for the broadcasting distance  $x$  is  $A(x)$ , the transmission power should at least reach  $P_o A(x)$  to ensure that the node can receive the message. Assuming that the sending delay of a node sending  $l$  bit data is  $T_p$ , the energy consumed by sending  $l$  bit data  $E_{tx}(l, x)$  is

$$E_{tx}(l, x) = T_p P_o A(x), \quad (1)$$

in which  $A(x)$  is a function variable related to the underwater acoustic propagation model and the transmission frequency, which can be expressed as

$$A(x) = x^k a^k, \quad (2)$$

in which  $k$  is the related parameter of the underwater acoustic propagation model. When  $k$  is 1, it is a cylindrical

propagation model, and when  $k$  is 2, it is a spherical propagation model. Usually,  $k$  is 1.5 to represent the actual underwater acoustic propagation model.  $a$  is related to frequency  $f$  and can be obtained from the energy absorption coefficient  $\partial(f)$ .

$$a = 10^{\partial(f)/10}, \quad (3)$$

in which the energy absorption coefficient is

$$\partial(f) = 0.11 \frac{f^2}{1 + f^2} + 44 \frac{f^2}{4100 + f^2} + 2.75 \times 10^{-4} f^2 + 0.03. \quad (4)$$

**3.3. Node Motion Model.** To be able to simulate the motion state of the node in the water more accurately, the following conditions need to be considered when establishing the node motion model. Since the node is fixed at the bottom of the water, the depth of the node can be changed by adjusting the length of the anchor chain. The nodes in this state are affected by the water flow and the traction of the anchor chain and move within a certain range [31]. Figure 1 shows the node force in the underwater environment.

As shown in Figure 1, the force analysis of the node shows that the node is subjected to the lateral impact force  $F$ , buoyancy  $f$  of the water flow, and the tensile force  $T$  of the anchor chain to the node (ignoring the gravity of the node). These three forces constitute a set of balance forces. We set that the maximum angle between the anchor chain and the vertical direction is  $\alpha$ ,  $\tan \alpha = F/f$ . It is worth noting that we do not research on fluid mechanics. For simplification, the maximum offset distance of node movement is given in Section 6. Nodes perform random waypoint movement within this offset distance [32].

## 4. DHCDGA

Firstly, after the network is initialized, it will be layered according to the initial information. DHCDGA is implemented in each layer. The time unit of DHCDGA is round. Each round is divided into a cluster topology establishment phase and a data transmission phase. In the cluster establishment phase, multiple criteria decision making of an intuitionistic fuzzy AHP and hierarchical fuzzy integration is adopted to select cluster head so that cluster topology of unequal size is established. Namely, the cluster farther from the sink on the water surface has a larger cluster size, and the cluster closer to the sink has a smaller cluster size. In the data transmission phase, according to the remaining energy of the node, the depth, and the number of neighbor nodes, an energy-balanced routing transmission between cluster heads is proposed. The schedule architecture of DHCDGA is shown in Figure 2.

**4.1. Cluster Selection.** In this subsection, the cluster head nodes in the network are selected. Multiple criteria decision making of an intuitionistic fuzzy AHP and hierarchical fuzzy integration is adopted to select the cluster head. To achieve energy efficiency while taking into account service quality requirements, the main criteria for cluster head selection are

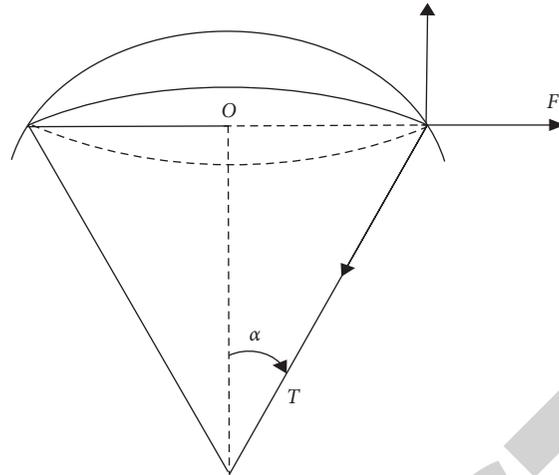


FIGURE 1: Node force.

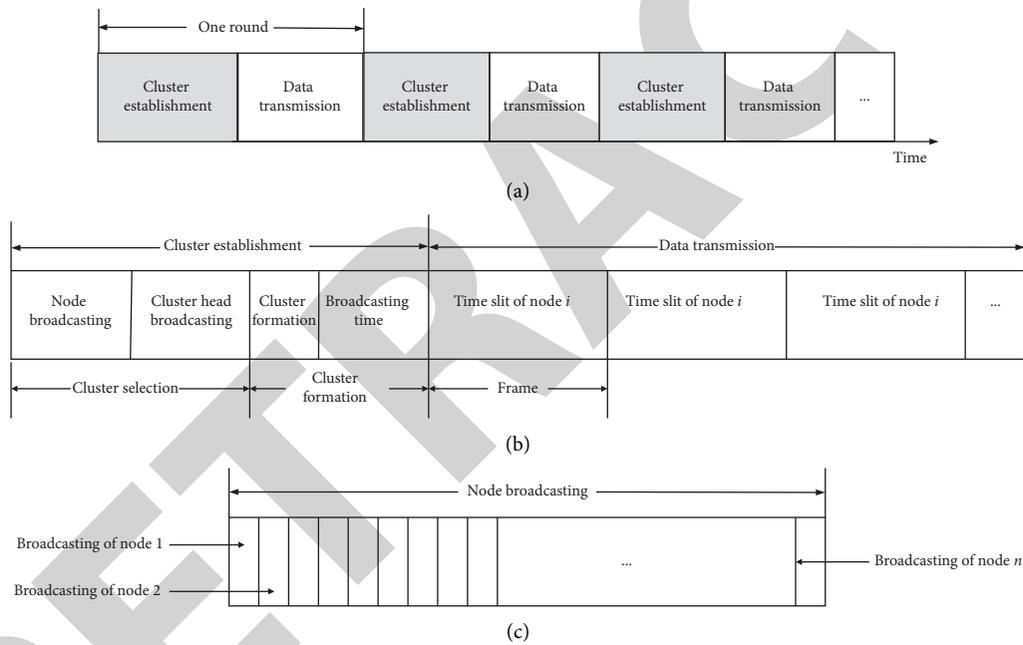


FIGURE 2: Schedule architecture of DHCDGA.

defined as energy status, service quality status, and node location status. Furthermore, each main criterion has two subcriteria. They are residual energy, message cost, coverage factor, link reliability, number of neighbor nodes, and depth factor. According to multiple factors affecting the selection of cluster heads, we have established a comprehensive evaluation hierarchical structure showed in Figure 3. It is mainly for a comprehensive evaluation of various indicators selected by cluster heads.

4.1.1. *Comprehensive Attribute Evaluation Value of the Cluster Head (h).* In the initialization phase, each node broadcasts an initialization message *INITIAL\_UN\_MES* to the network, which includes the node's ID, remaining energy, communication radius, and the distance between layers. The

node can locate the depth in the water to determine the level of the node. Nodes can estimate the distance between nodes based on the strength of their received signals. After the initialization phase is completed, each node can calculate the maximum and minimum residual energy of neighboring nodes, the number of neighboring nodes, and other information according to the neighbor node table. In this way, each node can obtain the evaluation value of each attribute in the comprehensive evaluation hierarchy of the cluster head.

(1) *Residual Energy.* In a clustered topology network, there is a huge difference in energy consumption between cluster heads and member nodes because the cluster head is responsible for receiving data from member node, fusing data, and relaying data to other cluster heads. In the underwater sensor network, the power supply cannot be replaced due to

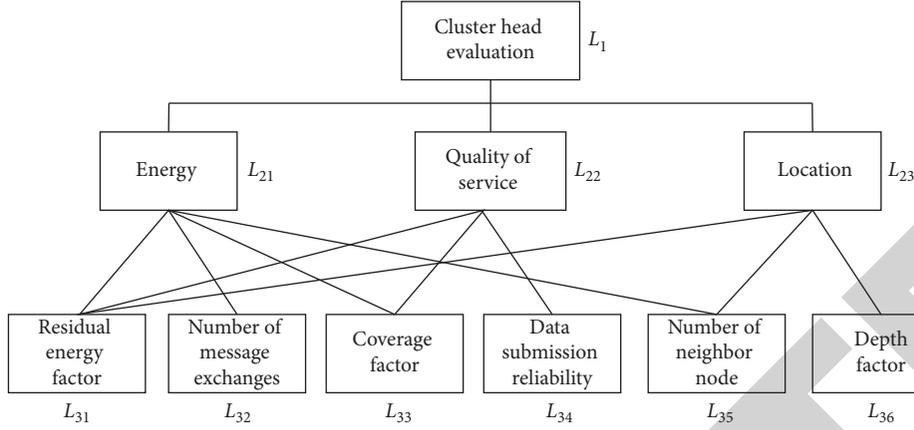


FIGURE 3: Comprehensive evaluation hierarchical structure of the cluster head.

environmental restrictions. Hence, energy is the most important and scarce resource. The evaluation value of residual energy is defined as follows:

$$E_i = \frac{E_r - E_{\min}}{E_{\max} - E_{\min}}, \quad (5)$$

in which  $E_r$  is the residual energy of node  $i$ .  $E_{\max}$  and  $E_{\min}$  are the maximum and minimum residual energy in the neighbor nodes of node  $i$ , respectively. The higher the value of  $E_i$  is, the more the residual energy is and the smaller the energy limit of the node is.

(2) *Number of Message Exchanges*. The number of message exchanges is mainly reflected in the total number of messages sent and received by nodes from the beginning of the network initialization stage to the establishment of the cluster topology. Since both sending and receiving messages consume the energy of the node, the number of exchanges of messages directly affects the energy consumption of the node. The evaluation value of the number of message exchanges is defined as follows:

$$M_i = \frac{M_T - M_C}{M_T}, \quad (6)$$

in which  $M_T$  is the total number of messages received and sent by all its neighbor nodes and  $M_C$  is the total number of messages received and sent by node  $i$ . The smaller the  $M_C$  value is, the higher the message cost  $M_i$  is.

(3) *Coverage Factor*. Coverage preservation is one of the most basic issues to ensure the Quality-of-Service (QoS). Selecting a node with better coverage as the cluster head can effectively prolong the functional time and make the residual energy of the node more. In a three-dimensional underwater sensor network, the coverage factor is the main factor to judge the QoS of a node. Its evaluation value is defined as follows [18]:

$$r(i) = \frac{\text{volume}\left(\left(\bigcup_{j \in N(i)} a_j\right) \cap (a_i)\right)}{\text{volume}(a_i)}, \quad (7)$$

in which  $a_i$  represents the perception area of node  $i$ .  $a_j$  represents the perception area of node  $j$ . Node  $j$  is the

neighbor node of node  $i$ .  $r(i)$  is the ratio of the volume intersection of the perception area of node  $i$  and its neighbor nodes to the perception area of node  $i$ . The larger the value of  $r(i)$  is, the larger the volume of intersection between node  $i$  and its neighbors is. Namely, the larger  $r(i)$  indicates that the node  $i$  is more likely to become the cluster head.

(4) *Data Transmission Reliability*. Data transmission reliability is an important issue to be considered for QoS because any node failure or packet loss will cause a large amount of packet loss in data transmission. In this way, more reliable requirements of data gathering are put forward for network scenarios with data collection reliability. The cluster head as the leader of the cluster unit is responsible for forwarding and receiving data more often in the network of clustered data gathering. Therefore, the probability of a highly reliable node as the cluster head should be greater. The evaluation value of data transmission reliability is defined as follows:

$$R_i = \frac{B_{\text{ava}}(i)}{B_{\text{total}}(i)}, \quad (8)$$

in which  $B_{\text{ava}}(i)$  is the available buffer space for node  $i$  and  $B_{\text{total}}(i)$  is expressed as the total buffer space of node  $i$ . We can observe that the smaller the available space of the node's buffer is, the lower the reliability of node  $i$  is.

(5) *Number of Neighbor Nodes*. In the network initialization, the number of current neighbor nodes can be determined according to the information in the neighbor information table. In an underwater sensor network where nodes are randomly deployed, the sink will calculate the optimal number of cluster heads in each layer when the energy is the smallest based on the global information of the nodes to obtain the optimal number of cluster members. According to this information, the closer the number of neighbor nodes is to the optimal number of cluster members, the greater is the probability that the node will become the cluster head. The evaluation value of the number of neighbor nodes is defined as follows:

$$N = \frac{|N_i - N_o|}{N_o}, \quad (9)$$

in which  $N_i$  is the number of neighbor nodes of node  $i$  and  $N_o$  is the best number of cluster members.

(6) *Depth Factor*. The depth of the node will affect the possibility of the node becoming the cluster head. The data gathering algorithm proposed in this paper is suitable for large-scale hierarchical underwater sensor networks. Since the selection of cluster heads is carried out in the same layer, the depth factor  $D(i)$  is calculated as the ratio of the relative height of the current node in the layer to the height of the layer. The depth factor is defined as follows:

$$D(i) = \frac{l \times L_{ni} - h_i + d \times \text{mod}(n-1, l/d)}{l}, \quad (10)$$

in which  $l$  is the height of the layer;  $h_i$  is the current depth information of the node  $i$ ;  $d$  is the downward adjustment distance of each network layer; and  $L_{ni}$  is the network layer of the  $n$ th round of node  $i$ . The calculation equation is as follows:

$$L_{ni} = \lfloor \frac{h_i + l - d \times \text{mod}(n-1, l/d)}{l} \rfloor. \quad (11)$$

4.1.2. *Determining the Attribute Importance Degree of the Cluster Head ( $g$ )*. In the previous section, the comprehensive attribute evaluation value of a cluster head has been obtained. This section determines that the attribute importance degree ( $g$ ) of the comprehensive evaluation of cluster heads will be determined according to the fuzzy integral. To be consistent with the actual selection of cluster heads in underwater sensor networks, it is necessary to use the intuitionistic fuzzy AHP that is closer to human thinking to select cluster heads because it can represent the neutrality of the expert's scoring. DHCDGA uses the cluster head selection comprehensive evaluation hierarchical structure in Figure 3 and the fuzzy analytic hierarchy process proposed in [33] to obtain the attribute importance degree ( $g$ ) of the cluster head. Firstly, many experts are asked to compare the importance of the indicators in the criterion level and the subcriteria for the upper-level target level. Based on the opinions of experts, the distance of intuitionistic fuzzy complementary judgment is established, where the intuitionistic fuzzy complementary judgment matrix of all attributes of the second layer to the target layer is shown as follows:

$$L_1 - L_2 = \begin{bmatrix} 0.5 & (0.7, 0.9) & (0.8, 0.9) \\ (0.1, 0.3) & 0.5 & (0.7, 0.8) \\ (0.1, 0.2) & (0.2, 0.3) & 0.5 \end{bmatrix}. \quad (12)$$

The intuitionistic fuzzy complementary judgment matrix of the attributes of the third-level subcriteria layer to the attributes of the second-level criterion layer is shown as follows:

$$L_{21} - L_3 = \begin{bmatrix} 0.5 & (0.8, 0.9) & (0.5, 0.8) & (0.8, 0.9) \\ (0.1, 0.2) & 0.5 & (0.1, 0.2) & (0.6, 0.7) \\ (0.2, 0.5) & (0.8, 0.9) & 0.5 & (0.7, 0.8) \\ (0.1, 0.2) & (0.3, 0.4) & (0.2, 0.3) & 0.5 \end{bmatrix}, \quad (13)$$

$$L_{22} - L_3 = \begin{bmatrix} 0.5 & (0.5, 0.8) & (0.3, 0.7) \\ (0.2, 0.5) & 0.5 & (0.5, 0.6) \\ (0.3, 0.7) & (0.4, 0.5) & 0.5 \end{bmatrix}, \quad (14)$$

$$L_{23} - L_3 = \begin{bmatrix} 0.5 & (0.3, 0.5) & (0.5, 0.7) \\ (0.5, 0.7) & 0.5 & (0.4, 0.7) \\ (0.3, 0.5) & (0.3, 0.6) & 0.5 \end{bmatrix}. \quad (15)$$

Furthermore, the fuzzy approximation judgment matrix of the abovementioned four matrices is obtained as follows:

$$F_{L1} = \begin{bmatrix} 0.5 & 0.875 & 0.889 \\ 0.125 & 0.5 & 0.778 \\ 0.111 & 0.222 & 0.5 \end{bmatrix}, \quad (16)$$

$$F_{L21} = \begin{bmatrix} 0.5 & 0.889 & 0.714 & 0.889 \\ 0.111 & 0.5 & 0.111 & 0.667 \\ 0.286 & 0.889 & 0.5 & 0.778 \\ 0.111 & 0.333 & 0.222 & 0.5 \end{bmatrix}, \quad (17)$$

$$F_{L22} = \begin{bmatrix} 0.5 & 0.714 & 0.5 \\ 0.286 & 0.5 & 0.556 \\ 0.5 & 0.444 & 0.5 \end{bmatrix}, \quad (18)$$

$$F_{L23} = \begin{bmatrix} 0.5 & 0.375 & 0.625 \\ 0.625 & 0.5 & 0.571 \\ 0.375 & 0.429 & 0.5 \end{bmatrix}. \quad (19)$$

Then, we realize Algorithm 1 in [33] by Matlab R2013 (b). The consistency test of the abovementioned four fuzzy complementary judgment matrices was performed, where  $\lambda = 0.5$ . After checking and adjusting the consistency of the matrix, a satisfactory consistency matrix is obtained as follows:

$$F'_{L1} = \begin{bmatrix} 0.5000 & 0.5521 & 0.5843 \\ 0.4479 & 0.5000 & 0.5464 \\ 0.4157 & 0.4536 & 0.5000 \end{bmatrix}, \quad (20)$$

$$F'_{L21} = \begin{bmatrix} 0.5000 & 0.8914 & 0.6512 & 0.9380 \\ 0.1086 & 0.5000 & 0.2466 & 0.5722 \\ 0.3488 & 0.7534 & 0.5000 & 0.7974 \\ 0.0620 & 0.4278 & 0.2026 & 0.5000 \end{bmatrix}, \quad (21)$$

$$F'_{L22} = \begin{bmatrix} 0.5000 & 0.5670 & 0.5132 \\ 0.4330 & 0.5000 & 0.4851 \\ 0.4868 & 0.5149 & 0.5000 \end{bmatrix}, \quad (22)$$

$$F'_{L23} = \begin{bmatrix} 0.5000 & 0.4516 & 0.5484 \\ 0.5484 & 0.5000 & 0.5710 \\ 0.4516 & 0.4290 & 0.5000 \end{bmatrix}. \quad (23)$$

Finally, the weight vector can be calculated by the (1) in [33]. After obtaining the satisfactory consistency matrix, the weight of all attributes in the second layer to the target layer can be obtained as  $W = (0.2879, 0.3352, 0.3769)$ . In the same way, the weights of the attributes subcriteria layer in the third level to the second level in the comprehensive hierarchy and the final combined weights of the attributes of the subcriteria layer in the third level relative to the elements of the target layer can be obtained. These weights are as shown in Table 1.

By the previous sections, the evaluation value ( $h$ ) of each attribute and its corresponding importance degree ( $g$ ) are obtained. Next, the overall evaluation value of the node can be obtained by the comprehensive evaluation hierarchical structure of the cluster head according to Figure 3. The process of calculating the overall evaluation value adopts the same tree structure as in [34]. Firstly, the attribute evaluation value is calculated from the leaf node. Then, the evaluation value of the previous layer can be obtained by the fuzzy integral to integrate the attribute evaluation value of the node and the weight of this layer. For instance, by the fuzzy integral, the evaluation value of the second layer L2 can be obtained by the evaluation value ( $h$ ) of the third layer L3 and the weight ( $g$ ) of the third layer. In the same way, by the fuzzy integral, the evaluation value of the first layer L1 can be obtained by the evaluation value ( $h$ ) of the second layer L2 and the weight ( $g$ ) of the second layer. By analogy, the evaluation value of the upper layer and the weight of this layer are calculated by fuzzy integral, and the comprehensive evaluation score of the node becoming the cluster head can be obtained.

## 4.2. Establishment of the Cluster Topology

**4.2.1. Cluster Head Broadcast Time.** In this section, the mapping relationship between the comprehensive evaluation value and cluster head broadcast time is illustrated. The cluster head broadcast timing method of the final cluster head adopts the method in [16]. Its core is to map the comprehensive evaluation score of the candidate cluster head to trigger the message of being a cluster head on the timeline. The time for publishing the competing cluster head message is shown in (24). Its purpose is to broadcast the message *FIN\_CH\_MES* for the cluster leader election quickly with high comprehensive evaluation scores.

$$T_i = \gamma \times (1 - CS_i) \times T_{ini}, \quad (24)$$

in which  $\gamma$  is a random number from 0.8 to 1;  $CS_i$  represents the comprehensive evaluation score calculated by the hierarchical fuzzy integral; and  $T_{ini}$  is the preset clustering time.

**4.2.2. Competition Radius of the Cluster Head.** After the cluster head is selected, the node needs to broadcast the

TABLE 1: Weights based on intuitionistic fuzzy AHP ( $g$ ).

Attribute	$L_{21}$	$L_{22}$	$L_{23}$	Weights
	0.2879	0.3352	0.3769	
$L_{31}$	0.0866	0.3066	0.3333	0.2533
$L_{32}$	0.3454	0.0000	0.0000	0.0994
$L_{33}$	0.1833	0.3606	0.2935	0.2843
$L_{34}$	0.0000	0.3328	0.0000	0.1116
$L_{35}$	0.3846	0.0000	0.0000	0.1107
$L_{36}$	0.0000	0.0000	0.3731	0.1406

message in the range of the cluster head competition radius. Hence, clusters closer to the sink have the smaller cluster size, and clusters farther from the sink have the larger cluster size. The specific regulations are as follows.

We set that the network layer  $i$  starts from 0 and is numbered with increasing from the top to bottom. In the initial stage of the network, the NO.0 layer does not exist, and the network number starts from 1. The network number starts from 1. After that, the 0th layer of the network is within the communication range of Sink, so the 0th layer is required to not cluster and send data directly to Sink. The cluster head at other levels needs determination of its level according to (10), and then, the cluster head competition radius is determined by the following equation:

$$CH(i).cr = CH(i).br + level(j) \times initial\_range, \quad (25)$$

in which  $CH(i).cr$  is the competition radius of the cluster head  $i$ ;  $CH(i).br$  is the broadcast radius of the cluster head  $i$ ;  $level(j)$  is the number of layers; and  $initial\_range$  is the initial range value. From (25), it can be seen that the larger the cluster head is, the larger the competition radius is.

**4.2.3. Cluster Topology Formation.** In cluster topology formation, if a node loses the opportunity to become the cluster head, it will join a cluster as a common member node. In joining a cluster, there are two very important parameters, namely, the distance from the node to the cluster head and the density of the cluster head. If there is more than one cluster head in the communication range of a node, the node will calculate the score of joining each cluster head node according to the following equation:

$$Sort_{CH} = \alpha \cdot distance_{itoCH} + \beta \cdot Density_{CH}, \quad (\alpha + \beta = 1). \quad (26)$$

The node's decision to join which cluster head mainly depends on its lower score. Then, this node sends a message *JOIN\_CH\_MES* to the cluster head with the lowest score to join it. The cluster topology formation of other rounds is similar to this process. Algorithm 1 shows the pseudocode of the member nodes joining the cluster unit.

**4.3. Data Transmission.** After establishing cluster topology, the nodes begin to transmit data steadily. When the energy value of a node is lower than the threshold  $E_0$ , it means that the node is dead, and then, the network starts to reconstruct.

Input: the distance between node  $i$  to CH; the density of CH;  
Output: cluster topology

- (1) **for** each node  $i$  ( $i$  is not CH)
- (2) Receive message with the distance between node  $i$  to CH; the density of CH
- (3) Calculate  $\text{Sort}_{\text{CH}} = \alpha \cdot \text{distance}_{i\text{toCH}} + \beta \cdot \text{Density}_{\text{CH}}$
- (4) Select Min ( $\text{Sort}_{\text{CH}}$ )
- (5) Send request message  $\text{JOIN\_CH\_MES}$  to the CH which has the minimum score.
- (6) **end for**

ALGORITHM 1: Cluster topology formation.

In the data transmission phase, each cluster member node periodically gathers data from the sensing area and transmits the data to its cluster head according to TDMA timing allocated by the cluster head to avoid message collision in the same cluster. When all the data of the cluster members are transmitted to the cluster head, the cluster head will fuse the data and transmit the fused data packets to Sink. Therefore, data transmission can be divided into two stages: intracluster communication and intercluster communication. Cluster members sense the data in the gathering environment and transfer the gathered data to their cluster head. This process is intracluster communication. Direct transmission is adopted to simplify the communication between member nodes and cluster heads. In intercluster transmission, a multihop inter layer routing algorithm is proposed. The cluster head with a large layer number is transmitted to the smaller layer number and, finally, to Sink. This can not only ensure the direction of data transmission but also prevent the generation of routing loops. Before selecting the next-hop node, the cluster head or node  $i$  calculates the set of neighbor nodes in the upper layer according to the location information of the sink and establishes a table of neighbor nodes, including node ID, node depth, sink location, current remaining energy, and the number of neighbor nodes. The cluster head  $i$  calculates the routing cost of its upper neighbor nodes and selects the next-hop node of the cluster head with the lowest routing cost. When the cluster head  $j$  is selected as the next-hop node, the relay node of the next-hop is selected according to the depth information. The cost function is shown as follows:

$$\text{cost}(i, j) = \alpha \frac{d_{j\text{-Sink}}}{d_{i\text{-Sink}}} + \beta \frac{\bar{E}_{\text{above-Nei}}(i)}{E_{\text{residual}}(\text{CH}_j)} + \gamma \frac{\bar{N}_{\text{above-Nei}}(i)}{N(\text{CH}_j)}, \quad (27)$$

in which  $d_{i\text{-Sink}}$  is represented as the depth information of the node  $i$ ;  $d_{j\text{-Sink}}$  is the depth information of the upper neighbor node  $j$ ;  $\bar{E}_{\text{above-Nei}}(i)$  is the average residual energy of the neighbor nodes in the upper layer of the node  $i$ ;  $E_{\text{residual}}(N_j)$  is the current residual energy of the cluster head  $j$ ;  $\bar{N}_{\text{above-Nei}}(i)$  denotes the average number of neighbor nodes in the upper layer of the node  $i$ ; and  $N(\text{CH}_j)$  is the number of neighbors of the node  $j$ .  $\alpha$ ,  $\beta$ , and  $\gamma$  are weighted coefficients, and the sum of the three weighting coefficients is 1. The cluster head or node  $i$  selects the node whose cost function is the least among its neighbors, namely,  $k = \text{armincost}(i, j)$ .

When designing this cost function, a relay node closer to the sink may be selected in the first term of (27). Since the transmission range of the node is fixed in this paper, choosing a relay node closer to the sink can reduce the number of relays and reduce the energy consumption of the node.

In the second term, the node with higher remaining energy may be selected as the next-hop relay node. Because the energy of the underwater sensor network is limited, it consumes energy during transmitting data, receiving data, or selecting cluster heads. Therefore, the residual energy of the node is the main factor in selecting the relay node.

In the third term, the node with more neighbor nodes may be selected as the next-hop relay node. This factor is considered because the nodes are randomly deployed in this paper, namely, some nodes are deployed densely and some nodes are deployed sparsely. When the nodes are dense, the selected next-hop relay nodes are more scattered, and the energy consumption is more balanced. When the nodes are sparse, the selected next-hop relay nodes are more concentrated. This brings the nodes with the largest energy consumption to appear prematurely, which shortens the network lifetime.

It is worth noting that if there are multiple same minimum routing costs in the neighbor node table toward the water surface, a node is selected randomly as the next-hop relay node. If the set of neighbor nodes of the upper level of the cluster head  $i$  is empty, the fallback mechanism in [14] is adopted. Namely, this node is deleted from the neighbor information table, and the node with the second smallest cost function in the upper-level neighbor node set of  $\text{CH}_i$  is reselected as the next-hop relay node.

## 5. DHCDGA Theoretical Analysis

**Proposition 1.** *The message complexity of DHCDGA is  $O(N)$  in the clustering phase, where  $N$  is the number of sensor nodes in the network.*

*Proof.* Because the energy consumption of sending messages is much greater than that of receiving messages, the complexity of sending messages as the message complexity of DHCDGA is discussed only in the clustering phase. Firstly, in the initialization phase,  $N$  sensor nodes broadcast initialization messages and establish the neighbor table of the nodes. Furthermore, DHCDGA is executed in each layer

to form clustering topology. Because three communications are required between nodes, the total number of messages sent is  $N + N + N$ . Otherwise, assuming that  $M$  nodes in the network become the final cluster heads,  $M$  nodes broadcast, at least,  $FIN\_CH\_MES$  messages. There are  $(N - M)$  non-cluster heads, and they broadcast  $(N - M)$   $JOIN\_CH\_MES$  messages to the cluster head with the smallest score to construct a clustering topology. In summary, the total message overhead is  $4N + M + (N - M)$ . Therefore, the message complexity is  $O(N)$  in the clustering phase.  $\square$

**Proposition 2.** *In DHCDGA,  $(2K + l/d_1 - 1)$  hops are required, at most, for any data packet transmitted to Sink, where  $K = \lfloor D/l \rfloor$ ,  $D$  is the area radius of the underwater sensor network;  $l$  is the width of the layer; and  $d_1$  is the average distance of a hop in the first layer.*

*Proof.* Assuming that the node  $S_i$  is located in the  $K$ th layer, the node in its cluster has one cluster head. There are two transmission methods for a data packet transmitted from the  $K$ th layer to the Sink. Namely, the second layer to the  $K$ th layer is clustered, and the flat multihop transmission mode is used in the first layer.

Firstly, the number of transmission hops is calculated from the  $K$ th layer to the second layer. The data packet of node  $S_i$  is transmitted to its cluster head, and the cluster head is transmitted to the cluster head in the  $(K - 1)$  layer after data fusion. Keeping this way, data packets are transmitted until the second layer. Therefore, the number of hops for data packets of  $(2K - 1)$  nodes is  $(2K - 2)$  in data transmission.

Secondly, the number of hops is calculated for flat multihop transmission in the first layer. When data packets are transmitted from the second layer to the first layer, different transmission methods will be used. In the first layer, the flat multihop data transmission is used, and the number of hops for the data packet transmitted to the sink is  $l/d_1$ . Another hop is from CH in the second level to the nodes in the first layer.

Accordingly,  $(2K + l/d_1 - 1)$  hops are required, at most, for any data packet transmitted to the sink in DHCDGA.  $\square$

**Proposition 3.** *When the cluster head transmits data to Sink, there is no routing loop.*

*Proof.* Proof by contradiction is adopted for Property 3. We assume that there is a routing loop  $\{CH_1, CH_2, \dots, CH_K, CH_1\}$ .  $D_i$  represents the depth of  $CH_i$ . According to the network model in this paper, the depth  $D_{i-1}$  of  $CH_{i-1}$  is shorter than  $D_i$ , namely,  $D_1 < D_2 < \dots < D_L < D_1$ . However, the depth  $D_L$  of the node  $CH_L$  is longer than the depth  $D_1$  of the cluster head  $CH_1$ . This contradicts the actual situation. Accordingly, it is guaranteed that no routing loop will occur when the cluster head transmits data to Sink.  $\square$

## 6. Simulation

**6.1. Simulation Scenarios and Parameter Setting.** The simulation environment is the Intel Pentium dual-core processor (2.2 GHz), 2G memory, and the experimental platform is Matlab R2013 (b). To analyze the effectiveness of DHCDGA, three clustering data gathering algorithms, DHCDGA, NULCPR, and LEACH-Coverage-U, are implemented.

We analyze and compare the six performances of three clustering data gathering algorithms whose network lifetime, the number of alive nodes, the average remaining energy, the number of cluster heads, coverage ratio of the network, and the total amount of data are received by Sink. In the simulation, 1000 sensor nodes are randomly deployed in  $100\text{ m} \times 100\text{ m} \times 100\text{ m}$  of the underwater three-dimensional monitoring area  $A$ . The coordinates of the sink are (50, 50, 100) (m). For calculating the coverage ratio, area  $A$  is divided into  $100 \times 100 \times 100$  small cubes, and the size of each cube is  $1\text{ m} \times 1\text{ m} \times 1\text{ m}$ . The simulation result is the average of twenty experiments, and other parameters are shown in Table 2.

**6.2. Network Lifetime.** The network lifetime of three data gathering algorithms is shown in Figure 4. FDT (First node Died Time) is the time when the node is dead first in the network. LDT (Last node Died Time) is the time when the last node is dead in the network. FDT is one of the most important indicators investigated by underwater sensor network data gathering algorithms. However, when the first node died in the network, if the node has strong coverage, it will not have a great impact on the data gathering of the whole network. Therefore, it is not enough to observe only FDT but also LDT of three clustering algorithms.

As shown in Figure 4, we can observe that the FDT of the Leach-coverage-U algorithm appears the earliest, while the LDT appears at the latest. This result can be explained by the fact that Leach-coverage-U transmits data from CH to the sink by a single hop in the data transmission phase. The cluster head consumes more energy.

Otherwise, in Leach-coverage-U, the cluster structure must be rebuilt in each round. The message is expensive and consumes a lot of energy. Therefore, the FDT of the lease-coverage-U algorithm appears the earliest. Also, single-hop data transmission will bring that the nodes far away from the sink are not able to transmit data to the sink due to insufficient transmission range until their energy is exhausted. Hence, the LDT of Leach-coverage-U appears the latest. NULCPR and DHCDGA are unequal clustering data gathering algorithms. The FDT of DHCDGA is about 18.71% longer than that of NULCPR. The LDT of DHCDGA is about 15.38% longer than that of NULCPR. This result can be explained by the fact that the multihop routing path constructed takes into account factors such as residual energy, depth, and the number of neighbor nodes during the data transmission. But, NULCPR only focuses on the distance between cluster heads.

TABLE 2: Simulation parameters.

Parameters	Value
Node throughput	0.25 (kB/s)
The initial energy of the node	20 J
Lowest receiving power ( $P_o$ )	3 (mW)
Size of a data packet ( $l$ )	4000 (bits)
Communication radius ( $R$ )	600 (m)
Sense radius	15 (m)
Carrier frequency ( $f$ )	10 (kHz)
Energy diffusion	1.5 (K)
Energy consumption of data fusion	5 (nJ/bit)
Maximum offset distance of node ( $r$ )	10 (m)
Initial radius	10 (m)

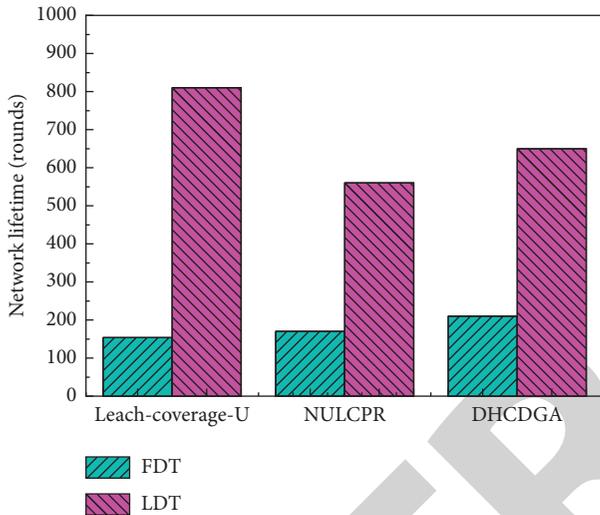


FIGURE 4: Network lifetime.

6.3. *Number of Alive Nodes.* The number of alive nodes represents the change in the number of nodes with energy from the beginning of work to the exhaustion of energy. This indicator is to examine the stability of the data gathering algorithm. The number of alive nodes for the three data gathering algorithms is shown in Figure 5.

As shown in Figure 5, the stability of DHCDGA is slightly better than that of Leach-coverage-U and NULCPR. Although DHCDGA occurs FDT, the number of alive nodes decreases linearly until all the nodes die instead of the network split causing the data gathering function paralysis. Since the message timing mechanism adopted by both DHCDGA and NULCPR replaces the message negotiation mechanism of Leach-coverage-U, energy consumption in the clustering phase is less than Leach-coverage-U. Otherwise, NULCPR only focuses on the factor of distance in selecting CH and data transmission; however, DHCDGA integrates multiple attributes for cluster head selection and routing path construction so that it is more suitable for underwater sensor networks with nonuniform node distribution. In summary, DHCDGA has better stability than the other two data gathering algorithms.

6.4. *Average Residual Energy of the Network.* The average residual energy of the network is the ratio of the current

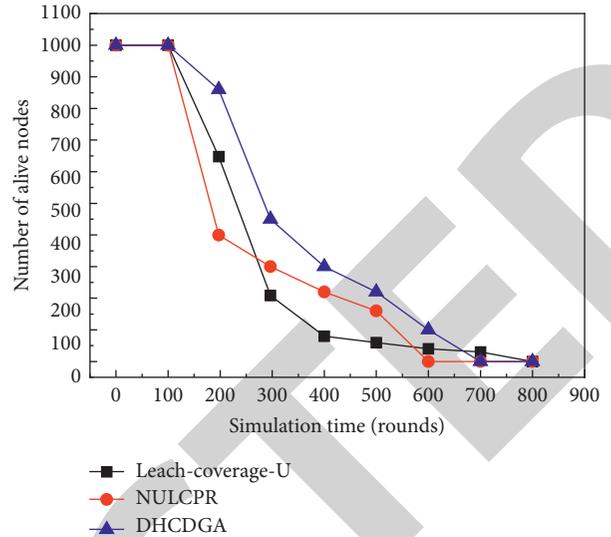


FIGURE 5: Number of alive nodes.

residual energy of each node in each round to the total number of nodes, which mainly examines the balance of energy consumption. The average residual energy of the three data gathering algorithms is shown in Figure 6.

As shown in Figure 6, DHCDGA consumes less energy than NULCPR. This result can be explained by the fact that DHCDGA considers six factors in CH selection when network forms cluster topology. These are results in the cluster structure more uniform and reasonable when nodes join in cluster units. Meanwhile, the intermultihop route algorithm takes into account factors such as the residual energy, depth information, and the number of neighbor nodes in the interdata transmission, which makes the selection of the next-hop relay node more reasonable and reduces energy consumption.

Otherwise, the nodes of Leach-coverage-U that is an equal size cluster algorithm have a less average remaining energy because the equally clustered data gathering algorithm does not use an effective balance mechanism for reducing energy consumption. The data gathering algorithm with equal cluster size may produce clusters with only one CH and no member nodes, which leads to an unbalanced node load and huge differences in energy consumption. Besides, Leach-coverage-U may cause CHs to be concentrated in certain areas. More edge nodes are generated, which is a result when all CHs are not within their communication range. Long-distance communication is required between edge nodes and sink, which increases energy consumption.

6.5. *Number of Cluster Heads.* The number of cluster heads is the total number of cluster heads in the network in different simulation times. This indicator is mainly to investigate the stability of the clustering algorithm in the data gathering algorithm. The number of cluster heads with changes in network time is shown in Figure 7.

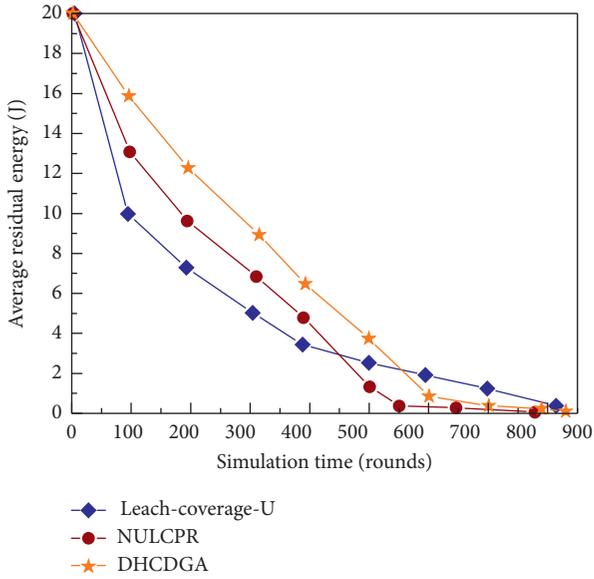


FIGURE 6: Average residual energy.

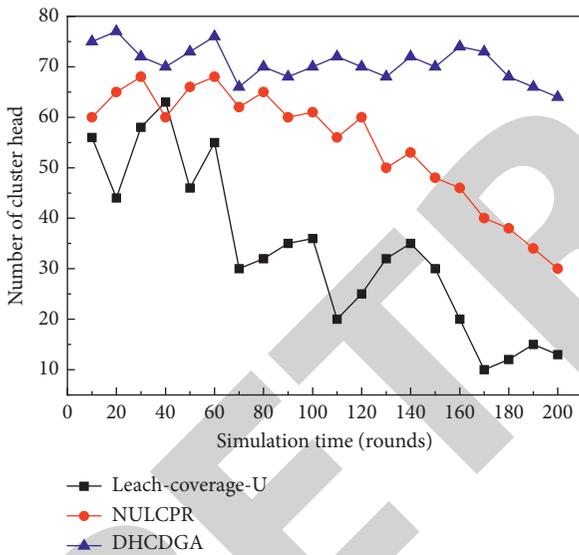


FIGURE 7: Number of cluster heads.

As shown in Figure 7, compared with NULCPR and Leach-coverage-U, the number of CH for DHCDGA is relatively stable. Because the number of CHs in the DHCDGA mainly depends on the number of neighbor nodes of CH<sub>i</sub>'s every layer, network coverage, and other information, the cluster head competition radius of each layer is relatively fixed.

Therefore, the number of cluster heads in the DHCDGA does not change significantly, so its clustering algorithm has a better stability. NULCPR algorithm is the data gathering algorithm with coverage preservation. After around, there are no nodes to die, so the network topology has not changed so that the coverage redundancy of each node has not changed. NULCPR can continue to keep the cluster topology of the previous round, and the number of CH is relatively

stable. However, the number of CHs fluctuates sharply for Leach-coverage-U since Leach-coverage-U is a random clustering data collection algorithm. Cluster topology must be rebuilt in each round, and candidate CHs will be randomly assigned according to the proportion of alive nodes, which will generate a cluster with a single node. Accordingly, the number of CHs in Leach-coverage-U fluctuates sharply.

**6.6. Network Coverage Ratio.** Network coverage refers to the percentage of the total area of the node gathering range to the entire network area. The network coverage ratio for three data gathering algorithms is shown in Figure 8. Because the coverage ratio is closely related to the number of alive nodes, Figures 5 and 8 are observed together.

As shown in Figures 5 and 8, comparing with NULCPR and Leach-coverage-U, DHCDGA has certain advantages. Furthermore, the coverage ratio decreases approximately linearly after occurring FDT of three data gathering algorithms. Besides, there is no network fragmentation caused by the simultaneous death of a large number of nodes. The coverage rate of the NULCPR algorithm is higher than that of Leach-coverage-U.

As shown in Figure 5, Leach-coverage-U has more alive nodes than NULCPR before the network runs 265 rounds. Leach-coverage-U and NULCPR have the same alive nodes in the 265th round. As shown in Figure 8, in the 265th round, although Leach-coverage-U has more alive nodes at this time, the coverage ratio of NULCPR is about 8.62% higher than the Leach-coverage-U. At the same time, the coverage ratio of DHCDGA is about 39% higher than that of the Leach-coverage-U. Assuming that the expected coverage ratio of the monitoring area is about 70%, the number of running rounds that meet the requirements for Leach-coverage-U, NULCPR, and DHCDGA is about 212 rounds, 253 rounds, and 384 rounds, respectively. Compared with Leach-coverage-U, the network lifetime of NULCPR and DHCDGA has been prolonged by about 41 and 172 rounds, respectively.

**6.7. Total Amount of Data Received by Sink.** The total amount of data received by the sink refers to the total amount of data received by the sink in each round. The total amount of data received by the sink for three algorithms is shown in Figure 9.

As shown in Figure 9, The data packets received by the sink for three data gathering algorithms increase steadily as the running time increases. Near the end of the simulation, the slope of the curve gradually decreases, which is caused by the continuous death of nodes as time increases.

Besides, the total amount of data received by the sink for DHCDGA is more than that received by the other two algorithms, since DHCDGA considers the reliability of data gathering in CHs selection. Otherwise, neither NULCPR nor Leach-coverage-U considers the reliability of data collection, and NULCPR receives more data than Leach-coverage-U. Because NULCPR is a data gathering algorithm with unequal cluster size, Leach-coverage-U is a data gathering algorithm with equal cluster size. The network lifetime of an unequal clustering algorithm is longer than that of an equal

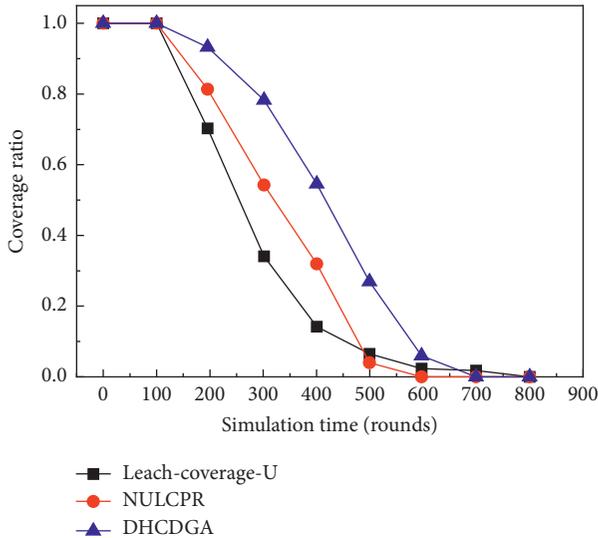


FIGURE 8: Network coverage ratio.

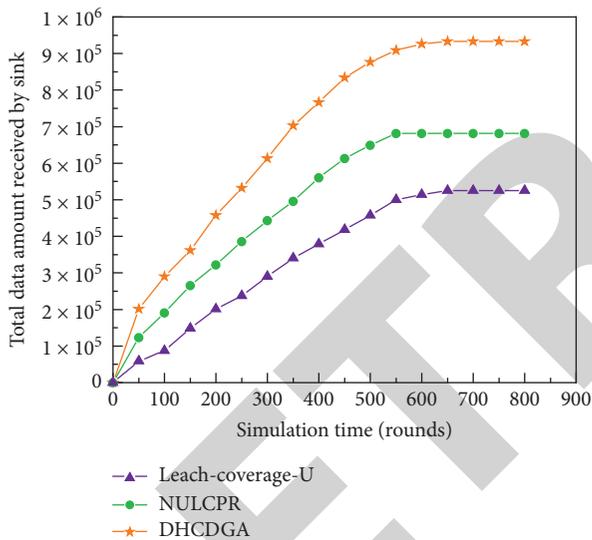


FIGURE 9: Total amount of data received by sink.

clustering algorithm. Therefore, NULCPR receives more data than Leach-coverage-U.

## 7. Conclusions

In this paper, a dynamic hierarchical 3D underwater sensor network clustering data gathering algorithm based on multiple criteria decision making is proposed. Firstly, the entire monitoring network is divided into layers. For selecting a cluster head in each layer, multiple criteria decision making of an intuitionistic fuzzy AHP and hierarchical fuzzy integration is adopted. Furthermore, a sorting algorithm is used to form a clustering topology algorithm to solve the problem that there is the only node in one cluster. Then, an energy-balanced routing algorithm between clusters is proposed according to the residual energy of the node,

the depth, and the number of neighbor nodes. Finally, the simulation results show that DHCDGA can not only effectively balance the energy consumption of the network and prolong the network lifetime but also improve network coverage and data gathering reliability.

Although DHCDGA shows good performances, it does not focus on fault tolerance, security, and other application scenarios in underwater sensor networks. We will study clustering technology in a more comprehensive application scenario in the underwater sensor network.

## Data Availability

The data used to support the findings of this study are included in the article.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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