*Intelligent and Converged Networks* ISSN 2708-6240
2021, 2(3): 163−176 DOI: 10.23919/ICN.2021.0012

# Routing strategy of reducing energy consumption for underwater data collection

**Jiehong Wu*, Xichun Sun, Jinsong Wu, and Guangjie Han**

**Abstract:** Underwater Wireless Sensor Networks (UWSNs) are widely used in many fields, such as regular marine monitoring and disaster warning. However, UWSNs are still subject to various limitations and challenges: ocean interferences and noises are high, bandwidths are narrow, and propagation delays are high. Sensor batteries have limited energy and are difficult to be replaced or recharged. Accordingly, the design of routing protocols is one of the solutions to these problems. Aiming at reducing and balancing network energy consumption and effectively extending the life cycle of UWSNs, this paper proposes a Hierarchical Adaptive Energy-efficient Clustering Routing (HAECR) strategy. First, this strategy divides hierarchical regions based on the depth of the sensor node in a three-dimensional (3D) space. Second, sensor nodes form different competition radii based on their own relevant attributes and remaining energy. Nodes in the same layer compete freely to form clusters of different sizes. Finally, the transmission path between clusters is determined according to comprehensive factors, such as link quality, and then the optimal route is planned. The simulation experiment is conducted in the monitoring range of the 3D space. The simulation results prove that the HAECR clustering strategy is superior to LEACH and UCUBB in terms of balancing and reducing energy consumption, extending the network lifetime, and increasing the number of data transmissions.

**Key words:** underwater sensor network; balanced energy consumption; clustering scheme; energy efficiency

## 1 Introduction

The ocean occupies about two-thirds of the Earth's surface and plays an important role in maintaining human life. It is an important source of global development factors. Underwater Wireless Sensor Networks (UWSNs) are network systems used for underwater exploration of data information[1, 2], which are widely used in actual ocean observations to achieve interaction information between different observation devices. UWSNs mainly use sound waves for data communication. It is generally believed that optical and radio frequency communications are not feasible. This is mainly because optical signals are severely scattered and high-frequency radio signals are strongly absorbed due to high attenuation. Thus, the use of the above methods for long-distance transmission is difficult. However, the attenuation of underwater acoustic communication is relatively slow. Therefore, underwater acoustic communication is a typical physical layer technology in UWSNs[3].

In the real world, various technical means are used to place sensor nodes in the underwater target area in a uniform or random manner. By utilizing UWSNs,

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Manuscript received: 2021-04-07; revised: 2021-05-12; accepted: 2021-05-16

people can conduct research on marine environmental pollution, ocean current monitoring, microbial tracking, and assisted navigation[4]. As shown in Fig. 1 , the proposed network architecture includes a sink node floating on the surface of the sea, which communicates with the on-shore monitoring station via a microwave link, and with underwater sensor nodes via the acoustic wireless channel. The nodes in UWSNs finish the information transmission through a one-hop or multi-hop mechanism. The sink node performs data fusion for the collected information, and then sends the data to the land base station, satellite, or data processing center that is docked.

The battery energy of underwater sensor nodes is severely limited. The node’s battery cannot be easily charged or replaced in the ocean. Underwater acoustic communication technology has limited bandwidth capacity, high bit error rate, high and variable time delay, and high communication power. These reasons lead to the increased energy consumption of UWSNs[5]. Therefore, to save energy in a multi-hop UWSN, the selection of the best route to send data packets from the source node to the destination node is very important. This process requires the routing protocol to consider not only the energy consumption of a single node, but also the overall energy consumption of the entire network to achieve a balanced utilization of energy and extend the life of the network.

In this study, we focus on the balance of energy consumption and effectively extend the life cycle of UWSNs, and we propose a Hierarchical Adaptive Energy-efficient Clustering Routing strategy (HAECR). The simulation results of the proposed technique have revealed that HAECR achieves superior performance than other techniques with regard to the energy consumption balance and reduction, network life extension, and data transmission rate improvement. The main contributions of this study are listed as follows:

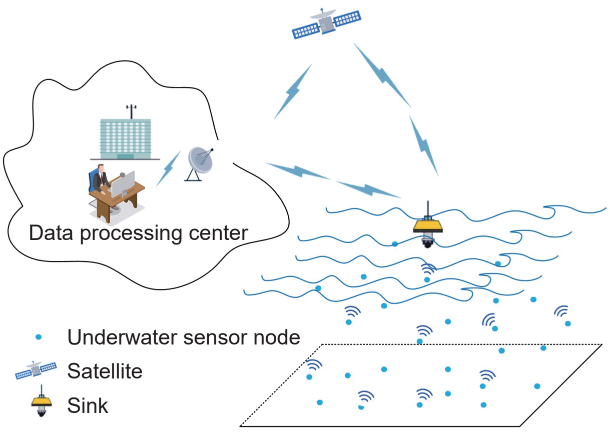


**Fig. 1 Structure of underwater sensor network.**

First, sensor nodes are modeled in layers and a three-dimensional (3D) space. All the sensor nodes in the first layer can act as relay nodes, transmitting the information of the Cluster Heads (CHs) of the upper layer to the sink, which helps reduce and balance the energy consumption.

Second, taking full advantage of the nodes’ location information and energy consumption, combined with the distance between the sensor node and the CH, this study designs a function for freely competing CH selection in the same layer. High-quality links can avoid the retransmission of information, reserve energy consumption, and increase delivery rates. The strategy fully considers the impact of link quality and remaining energy on the next hop selection function of the CH, and improves the lifetime of underwater wireless networks.

Third, properly shutting down the node avoids the sudden death of the sensor node in the process of transmitting information due to insufficient energy, resulting in information error and loss. To demonstrate the effectiveness of the proposed routing strategy, we compared HAECR with the classic algorithm LEACH and the UCUBG algorithm. The results show that HAECR achieves superior performance than the other techniques with regard to the energy consumption balance and reduction, network life extension, and transmission data rate increase.

The rest of this paper is organized as follows: Section 2 introduces the related work of the existing routing protocols. Section 3 introduces the network model and energy consumption model of the underwater environment. Section 4 introduces the cluster formation model based on hierarchical topology control and the selection of CHs, considering the combination of multiple parameters to transfer information between

CHs. Section 5 provides the simulation experiment results and analyses. Section 6 summarizes and elaborates the paper.

## 2 Related work

UWSNs are currently a rapidly developing research field with broad research topics. Many unique features of UWSNs have a significant impact on sensor data acquisition and remote transmission. As one class of core underwater acoustic network technologies, routing algorithms have been considerably studied[6].

The Depth-Based Routing (DBR) protocol[7] mainly decides whether to forward data based on the depth information of the node itself and the previous hop. The Energy-Efficient Probabilistic Depth-Based Routing (EEPDBR)[8] algorithm is an improvement of the DBR. The key idea of the EEPDBR is to design an improved probabilistic DBR algorithm for reliable underwater data reporting to any surface sonobuoy, which takes the node's depth, residual energy, and forwarding number within its two-hop neighborhood into account.

In the Vector-Based Forwarding (VBF) protocol[9], each node knows the location of itself and the destination node in advance, and establishes a fixed vector pipeline from the source node to the destination node. The VBF adaptive algorithm estimates the neighborhood density and forwarding packets, low end-to-end delay, good sparse network efficiency, high energy consumption, and sensitivity to pipe radius. Pouryazdanpanah et al.[10] designed dual-sink VBF, which forms an optimal network topology by balancing the remaining energy and position information of the nodes, thereby improving the transmission efficiency of the network and extending the life of the network. Hop-by-Hop (HH) VBF[11] uses an HH virtual pipeline on the basis of VBF, which increases the dynamics of the pipeline. The introduction of redundant feedback technology enhances mobile robustness and locally improves the delivery success rate of sparse networks, but it also encounters the energy consumption problem.

Huang et al.[12] proposed an Energy-aware Dual-path Geographic Routing (EDGR) to better recover the routing in a network. EDGR exhibits a higher energy efficiency in WSNs over a variety of communication scenarios passing through routing holes. Ismail et al.[13] proposed a Reliable Path Selection and Opportunistic Routing (RPSOR) protocol for UWSNs. The RPSOR algorithm has good performance in terms of packet delivery rate and energy utilization. However, the energy consumption balance of nodes is not considered.

Due to the complex and changeable underwater environment, it is very difficult to replace or recharge the sensor node with a new battery. The network life cycle and energy consumption are the two main factors considered in the design of UWSNs. The clustering routing algorithm is one of the key technologies in WSNs, which directly affects the lifetime and energy utilization of sensor networks[14].

The well-known LEACH algorithm[15] uses a round-robin mechanism to campaign for the cluster leader based on the number of times that a node has been selected. The CH sends a single jump of member data in the cluster to the base station. Although it reduces the node energy consumption to a certain extent, it extends the network life cycle. The uneven distribution of CHs easily results in the premature death of CHs with too many members in the cluster and those far away from the base station. The LEACH-C algorithm[16] is an improvement of the LEACH clustering algorithm. Each sensor node sends its own information to the base station in the network during each iteration, and then calculates the average remaining energy in the network. The large remaining energy nodes are designated as CH nodes, but the distribution of CH nodes in this protocol is not very balanced. Lee and Cheng[17] proposed the fuzzy-logic-based clustering approach, which uses residual energy and predictable residual energy as input variables to calculate the chance of becoming a CH node, ignoring the node density. The hybrid energy-efficient distributed clustering protocol[18] sets the primary and secondary parameters in the network to the average energy consumption in the entire network to extend its life cycle. However, each node has to broadcast its own information to neighboring nodes in each round of clustering. These tasks are repeated, and the energy consumption in each round is also considerable. Aiming at balancing the energy consumption and prolonging the network life, the UCUBG algorithm, an uneven clustering algorithm for UWSNs[19], was proposed. The algorithm uses the average energy and node density to identify the CH layer and optimize the clustering process in order to achieve the goal of balancing the network energy consumption and extending the network life. However, obtaining the node density in practice involves knowing the location distribution information of nodes.

Li et al.[20] proposed a high-dimensional energy efficient clustering algorithm based on machine learning, which can select CH nodes in a high-dimensional space and help non-CH nodes to transmit data packets. The selection of CHs only considers the residual energy of nodes rather than comprehensive information. Krishnaswamy and Manvi[21] proposed a new method to form clusters using fuzzy clustering and Particle Swarm Optimization (PSO). This method analyzes the fitness function of the cluster and uses the PSO clustering method to determine the CH node. However, PSO needs to know the information of all nodes and repeatedly iterate to obtain the optimal clustering. In this process, there will be inevitable energy consumption.

Aiming at the energy problem of underwater sensor networks, we propose a hierarchical adaptive energy-saving cluster routing strategy to ensure the balance of energy consumption and effectively extend the life cycle of UWSNs. HAECR achieves a good energy utilization rate by controlling the selection of CH nodes, the clustering range, and the next hop selection of the CH in data packet transmission.

## 3 System description

UWSNs use sound waves for underwater communications. To compensate for underwater communications[22], nodes need to adopt more complex signal processing techniques, so that the energy required for signal processing in underwater acoustic communication is higher than that in terrestrial wireless communication. Therefore, the network environment and energy consumption model are introduced in this section to accurately simulate the underwater environment.

### 3.1 Network environment

This paper uses a static 3D underwater sensor network as the network model (Fig. 2). The network environment is assumed as follows:

(1) The underwater sensor nodes are fixed in a specific position through a manual deployment (anchored fixing method). Once the deployment is completed, the node slightly shakes in the area. We assume that a set of anchored sensor nodes $n=\{n_1,n_2,\ldots,n_N\}$ of a 3D static network are deployed in a 3D underwater space with side length $b$. The sink node is located in the center of the water surface in the network monitoring area. It has unlimited energy and can be communicated with sound waves and radio waves.

(2) The sensor nodes in the network are homogeneous. Each node has a unique Identification Number (ID). All nodes are in a half-duplex state, where the nodes cannot simultaneously send and receive data. The 3D position information of each sensor node is realized by a positioning algorithm or hardware unit using sound wave detection. Sensor nodes can perceive the monitoring space around themselves, and the perception model is Boolean perception.

(3) The link is symmetric, and the underwater sensor node can estimate the distance between the two parties

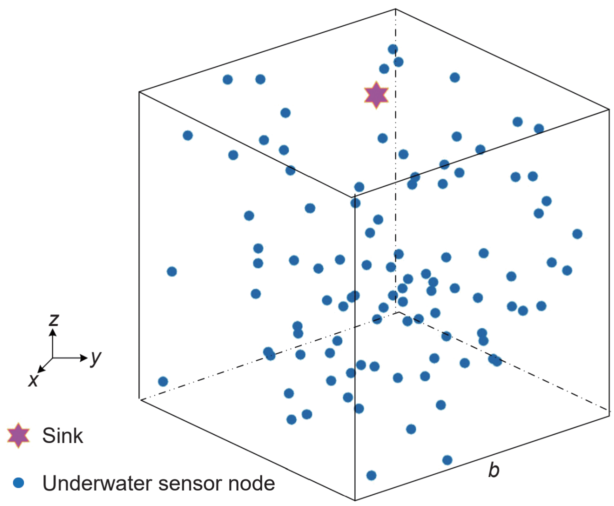


**Fig. 2 Network environment.**

based on the strength of the received signal.

### 3.2 Energy consumption model

The signal transmission loss of land-based sensor networks is related to the signal transmission distance $d$. However, due to the special situation of Underwater Acoustic Sensor Networks (UASNs), signal transmission loss is related to not only signal transmission distance but also transmission conditions, such as signal frequency.

In underwater acoustic communication, the channel model is empirical in nature that varies based on the underwater environment. This study adopts the classic underwater acoustic communication model[23] for modeling. The energy $E_{TX}$ consumed by the node to transmit a data packet of length $l$ can be expressed as

$$E_{TX}(l,d) = P_t l A(d) \tag{1}$$

where $P_t$ is the normal power of 1 bit data sent by the node and $A(d)$ is the attenuation of the transmission power with the transmission distance $d$, which is related to the transmission distance, working frequency, and data transmission method,

$$A(d) = d^k a^d \tag{2}$$

where $k$ is the energy spreading factor, which is related to the signal propagation conditions ($k$ = 1.5 in practical applications), and $a$ is the attenuation coefficient, which is determined by the absorption loss $\alpha(f)$,

$$a = 10^{\frac{\alpha(f)}{10}} \tag{3}$$

$$\alpha(f) = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f^2} + 2.75\times 10^4 f^2 + 0.003 \tag{4}$$

where $\alpha(f)$ is related to frequency, $f$ is the frequency of the carrier wave sound signal, and its unit is kHz, the unit of absorption coefficient $\alpha(f)$ is dB/m

From the perspective of the member node, when the transmission distance is $d$, the energy consumption of the $i$-th member node of the $s$-th cluster to send a packet of $l$ bits is $E_{T\_si}$. It can be expressed as

$$E_{T\_si}(l,d) = P_t l d^k a^d \tag{5}$$

Similarly, the energy $E_{R\_si}$ required for member nodes to receive l bit data packets is expressed as

$$E_{R\_si}(l,d) = P_r l \tag{6}$$

where $P_r$ is the normal power of 1 bit data received by the node. From the perspective of the CH node, the energy consumption of the head node of the $s$-th cluster receiving the $l$ bits data packet sent by $n$ member nodes is expressed as

$$E_{R\_sh}(l,d) = NP_r l \tag{7}$$

After the CH node collects the member node information, it aggregates the information received from all member nodes, and the energy consumed is expressed as

$$E_{DA\_sh}(l,d) = \eta P_\eta N l \tag{8}$$

where $\eta$ is the aggregation ratio and $P_\eta$ is the working power of the node during data aggregation. The energy consumed by the head node of the $s$-th cluster to send aggregated data is expressed as

$$E_{T\_sh}(l,d) = \eta N P_t l d^k a^d \tag{9}$$

## 4 Design of HAECR

The underwater 3D routing mechanism is used to control the depth of each node on the basis of a two-dimensional plane, so that the sensor nodes in a certain area are distributed at different ocean depths to obtain more information and build a 3D ocean network structure. This study divides the sensor nodes distributed in the underwater monitoring area into several clusters of different sizes, and each cluster is composed of a CH node and common member nodes. This section will introduce the routing algorithm from four aspects: the layering of nodes, CH election phase of nodes in the same layer, information transmission phase between clusters, and graceful shutdown of nodes. HAECR uses a topology reconstruction mechanism during operation. The topology is reconstructed every other cycle until the network reaches its maximum life cycle.

### 4.1 Network layer

To reduce the necessary energy consumption, as shown in Fig. 3 , this study divides all underwater wireless sensor nodes into several relatively independent regions based on the depth interval $W$. The sensor node calculates its own layer number $L_i$ according to its depth information,

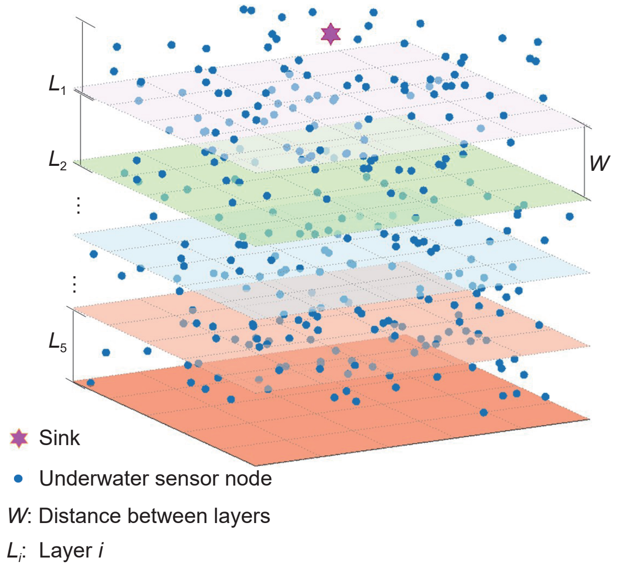


**Fig. 3 Layered graph.**

$$L_i = \left\lceil \frac{h_i}{W} \right\rceil \tag{10}$$

where $h_i$ is the depth at which the sensor node is placed. The set of nodes contained in each layer is $S_{L_i}$, i.e., $S_{L_i} = \forall n_i \in L_i$. The nodes of the first layer are not clustered. Other nodes freely compete for CHs in the layer they belong to.

In the node data transmission process, the CH node close to the sink node not only sends the data in the cluster area, but also forwards the data sent from other CH nodes. This process will cause the node close to the sink node to die too quickly, which is an important issue[24]. To alleviate this problem, the nodes of the first layer do not cluster, but directly transmit the collected information to the sink node. This method simplifies the network model while making energy consumption balanced.

## 4.2 Cluster head election

UASN nodes are randomly distributed, not requiring all nodes to participate in the CH election to save energy. Considering this point, in the CH election, nodes judge whether they participate in the competition for CHs based on their own remaining energy $E_i$ and the average remaining energy $\overline{E_l}$ of the current layer. $\overline{E_l}$ is calculated in the following:

$$\overline{E_l} = \frac{\sum\limits_{i=1,\, i\in S_{L_i}}^{m} E_i}{m} \tag{11}$$

where $m$ represents the number of members in the cluster. The node detects the information of surrounding nodes through the broadcast package. The broadcast package format is presented in Fig. 4.

Nodes with energy lower than the average energy of the same layer do not participate in the competition and directly serve as member nodes waiting for the CH broadcast package by the CH. The format of the CH broadcast package is shown in Fig. 4.

The sensor nodes participating in the competition for the CH adaptively adjust the cluster range according to information, such as energy and location. The clustering scope is mainly determined by the competition range of the CHs. Because of the existence of hot issues, this strategy tends to decrease the clustering range of the CH nodes in the layer close to the sink. The nodes in the first layer do not perform clustering and serve as optional relay nodes to transmit data packets sent by the CH of the upper layer. The initial competition range of the strategy definition layer proposed in this paper is shown in the following:

$$R_L = \begin{cases} 0, \ L_i = 1; \\ R, \ L_i = \dfrac{b}{D}; \\ R_{L+1} - r, \ \text{else} \end{cases} \tag{12}$$

where $r$ represents the clustering range decreasing by layer, and $D$ represents the monitoring area. $b/D$ is a constant, which represents the bottom layer of the monitoring area. The basic clustering range of the sensor nodes at the highest layer (the farthest layer from the sink) is the communication range $R$ of the node, and $R$ is a constant.

| Packet type | Node ID | Node layer | Node position | Residual energy |
|---|---|---|---|---|

(a) Broadcast package

| Packet type | Node ID | Node layer | *comp*($n_i$) |
|---|---|---|---|

(b) Competition package

| Packet type | Node ID | Node layer | Residual energy |
|---|---|---|---|

(c) CH broadcast package

| Packet type | CH ID | CH layer | Source ID | Next ID | Data |
|---|---|---|---|---|---|

(d) Data package

**Fig. 4 Packet format.**

After the basic layer range is determined, HAECR uses the depth of the sensor node and the projection distance $d'_{i,sink}$ to further determine the CH competition range $R$ of the node $n_i$. The plane parallel to the sea level where the underwater sensor node $n_i$ is located is $\varphi_i$. This plane is given in the following:

$$\varphi_i = \begin{cases} x_{\varphi_i} - x_{ni} + y_{\varphi_i} - y_{ni} = 0, \\ z_{\varphi_i} - z_{ni} = 0 \end{cases} \tag{13}$$

where $x$, $y$, and $z$ represent position coordinates.

As shown in Fig. 5, $d'_{i,sink}$ is the distance between the projection of the sink node on the plane $\varphi_i$ and the node $n_i$,

$$d'_{i,j} = \sqrt{(x_{ni} - x_{nj})^2 + (y_{ni} - y_{nj})^2} \tag{14}$$

$$R_{i,comp} = \left(\left(1 - \frac{d'_{i,sink}}{b}\right) + \left(\frac{1}{2} - \left|\frac{1}{2} + \frac{h_i}{W} - L_i\right|\right)\right) \times \frac{2}{3} R_L \tag{15}$$

where $R_{i,comp}$ represents the competition range of the node $n_i$. The closer the sensor nodes on the same layer are to the center, the greater the clustering range of nodes. Moreover, nodes with high energy have a large clustering range. The sensor nodes at the corners have a smaller clustering range. At the same time, nodes of different layers are distinguished by $R_L$ to ensure that the sensor nodes of higher layers have more member nodes.

The competition factor of the CH is affected by the distance through the sink and the remaining energy of the sensor nodes. The sensor nodes closer to the sink in the same layer have more possibilities to compete to become CHs. The competition factor $comp\ (n_i)$ is defined in the following:

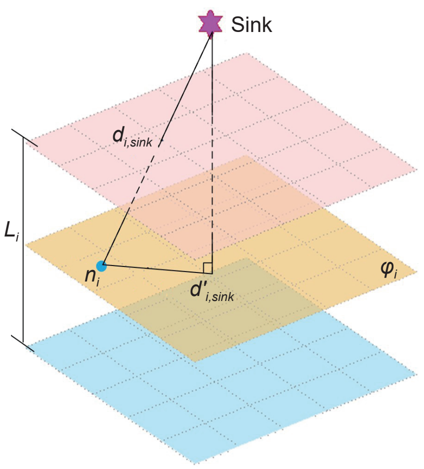


**Fig. 5 Influencing factors of the competition scope.**

$$d_{i,j} = \sqrt{(x_{ni} - x_{nj})^2 + (y_{ni} - y_{nj})^2 + (z_{ni} - z_{nj})^2} \tag{16}$$

$$\begin{cases} d_{max} = \max\limits_{i \in S_{Li}} (d_{i,sink}), \\ d_{min} = \min\limits_{i \in S_{Li}} (d_{i,sink}) \end{cases} \tag{17}$$

$$comp\ (n_i) = \alpha\left(\frac{d_{max} - d_{i,sink}}{d_{max} - d_{min}}\right) + \beta\left(1 - \cos\left(\frac{\pi}{2} \times \frac{E_i}{E_0}\right)\right) \tag{18}$$

$$T = \frac{R}{v} \tag{19}$$

where $d_{min}$ represents the distance of the node closest to the sink among all underwater sensor nodes in the same layer, and $d_{max}$ is the distance of the node farthest. $\alpha$ and $\beta$ are the influence factors, and $\alpha + \beta = 1$. $E_i$ represents the remaining energy of the node, and $E_0$ represents the initial energy of the node.

The sensor nodes participating in the competition calculate their own competition factor $comp(n_i)$ according to the remaining energy $E_i$, broadcast the competition package within the competition range $R_{i,comp}$, and wait for a period of time $T$. If node $n_i$ receives competition packets from other nodes within time $T$, then the received competition factor is greater than the local competition factor. The competition packet with the highest competition factor is stored locally. Node $n_i$ is a member waiting for the CH broadcast package. Otherwise, the node itself becomes the CH and broadcasts the selected package. When the energy of the CH drops by 10%, the election of CHs is performed again. We further explained this concept in Algorithm 1.

### 4.3 Data transfer

The member nodes in the cluster use a single-hop communication method to transmit information to the CH node when the underwater sensor node is transmitting data packets. The CH node will perform data fusion on the information collected from the member nodes. Data integration through multi-hop fashion is performed between the CHs. In every other cycle, the topology is reconstructed until the network reaches its maximum life cycle. The data packet format

**Algorithm 1 Competitive election of cluster head nodes**

1: **for** every node $n_i$ **do**
3: **if** $L_i \neq 1$ and $E_i > \overline{E_l}$ **then**
4: Calculate the scope of competition $R_{i,comp}$;
5: Calculate the competition factor $comp\ (n_i)$;
6: Broadcast competition package, and wait for a period of time $T$;
7: **if** $comp\left(n_j\right) > comp\ (n_i)$ in the data packet received within $T$ **then**
8: Wait for the CH broadcast package of $n_j$;
9: **if** $n_i$ does not receive CH broadcast package **then**
10: $n_i$ broadcasts CH broadcast package in the $R_{i,comp}$;
11: **else**
12: $n_i$ broadcasts CH broadcast package in the $R_{i,comp}$;

is shown in Fig. 4.

The transmission of the CH data packet is performed across layers. The next hop candidate of the CH of the current layer is the elected CH of the upper layer. The next hop candidates of the CH of the second layer are all undead sensor nodes of the first layer. The next hop selection function is mainly affected by two factors: the remaining energy of the next hop node and the link quality $M_{i,j}$ from the current node to the next hop node. $M_{i,j}$ is determined by the degree of the node and the Euclidean distance between two nodes,

$$M_{i,j} = \left(\frac{N_j}{\bar{N}} - c\frac{d_{i,j}}{\sqrt{2b^2+4W^2}} + 1\right) \tag{20}$$

where $N_j$ represents the degree of the node and $\bar{N}$ represents the average degree of the CH nodes in the same layer. $c$ is the distance influence factor, with a value between 0 and 1. The purpose of this method is to normalize the distance. The next hop selection function is in the following:

$$next\left(n_{i,j}\right) = (1-\gamma)M_{i,j} + \gamma\left(1-\cos\left(\frac{\pi}{2}\times\frac{E_j}{E_0}\right)\right) \tag{21}$$

The CH $n_i$ selects the node $n_j$ with the largest next value among the candidates as the next hop.

The data packet transmission between clusters is shown in Fig. 6. The space between the two planes is one layer. Data packets are transmitted between two adjacent layers. The CH node selects one of the candidate nodes to send the data packet until the second layer. All surviving nodes from the first layer can be candidates for the relay nodes of the second

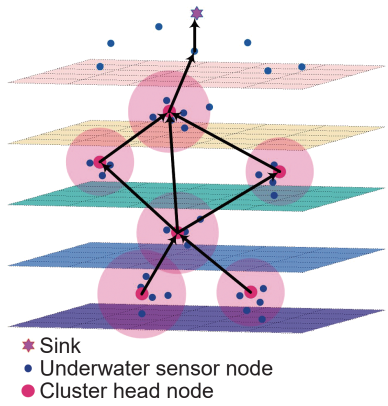


**Fig. 6 Data transfer between clusters.**

layer CH and transmit data packets to the sink. Except for the CH nodes on the fifth layer, other CHs also receive data packets sent to them by their member nodes while transmitting data between clusters. To alleviate hot issues, the clustering range of nodes is related to the location, remaining energy, and layer.

### 4.4 Low-energy node shutdown

The sudden death of a node during the collection and transmission of information results in incorrect data transmission or transmission failure. Accordingly, this work proposes that, when the energy of the node is less than a certain threshold (0.02 J), the node within the transmission range broadcasts the news of its own death and gracefully shuts down.

## 5 Performance and discussion

In this section, the results of HAECR are assessed and contrasted with those of LEACH and UUCBG. The implementation of the proposed scheme was performed by utilizing MATLAB version R2019b. A similar number of nodes was utilized during all simulations for all the three schemes (i.e., LEACH, UUCBG, and HAECR). In the 3D surveillance area, 500 nodes were randomly deployed. For every node, the initial energy was 5 J. The transmission range of the underwater sensor node was 100 m. The sink was arranged in the center of the water surface and utilized for the collection of data from sensor nodes. The detailed parameters are listed in Table 1.

### 5.1 HAECR simulation verification

We conducted simulation experiments for the proposed

**Table 1 Parameters for simulation.**

| Variable | Parameter | Value |
|---|---|---|
| $D$ | Dimensions of network | 500×500×500 m$^3$ |
| $(x_s, y_s, z_s)$ | Sink node location | (250, 250, 0) |
| $N$ | Number of sensor nodes | 500 |
| $E_0$ | Initial energy of node | 5 J |
| $f$ | Acoustic frequency | 10 kHz |
| $R$ | Transmission range | 100 m |
| $v$ | Velocity of acoustic waves | 1500 m/s |
| $\eta$ | Data aggregation ratio | 0.2 |
| $P_t$ | Power sent by sensor node | 5 nJ/bit |
| $P_\eta$ | Aggregate power of sensor node | 5 nJ/bit |
| $P_r$ | Power received by sensor node | 5 nJ/bit |
| $l_b$ | Broadcast packet size | 32 bit |
| $l_d$ | Average data packet size | 1024 bit |
| $\alpha, \beta, \gamma$ | Factors in objective function | [0, 1] |

strategy and analyzed HAECR from the following aspects.

### 5.1.1 Energy consumption

Figure 7 shows the influence of weighting factor $\gamma$ on the average energy consumption of sensor nodes in the network. As shown in Fig. 7, when $\gamma = 0.2$, the energy consumption of the overall network is relatively balanced. Especially in the later stage of the network, with the decrease in node energy, the link quality was more fully considered. In the initial stage of the network, as shown in Fig. 8, when $\gamma = 0.8$, the energy consumption is less because more attention is paid to the influence of energy.

### 5.1.2 Network lifetime

As a general rule, a node is considered to be dead or alive depending on the energy it contains. If the energy

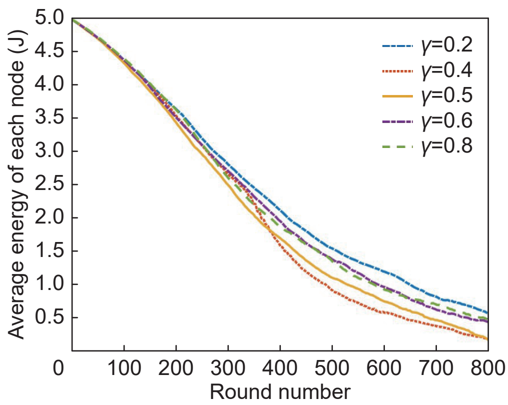


**Fig. 7 Effect of $\gamma$ on the average remaining energy in 800 rounds.**

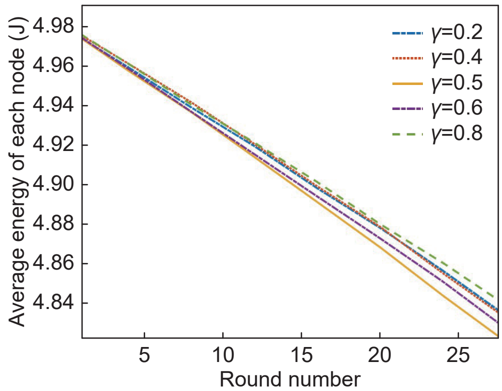


**Fig. 8 Effect of $\gamma$ on the average remaining energy in 25 rounds.**

of the node reduces to 0, then it is considered a dead node. Simultaneously, in the network, if the count of dead nodes exceeds a cut of value, then the entire network is measured to be deceased. In this study, the time from when the network starts to run until the number of surviving nodes is less than 20% of the total number of nodes is called the life cycle of the network.

Figures 9 and 10 show the influence of weighting factor $\alpha$ on the first dead node and network lifetime, respectively. The weighting factor $\alpha$ reflects the importance of node location to CH election. With the increase of $\alpha$, the nodes tend to choose the sensor nodes that are closer to the sink nodes in the same layer and higher than the average energy of the nodes in the same layer as the CHs.

Therefore, according to the experimental results, with the decrease of $\alpha$, the network lifetime gradually increases, whereas the number of the first dead node gradually decreases.

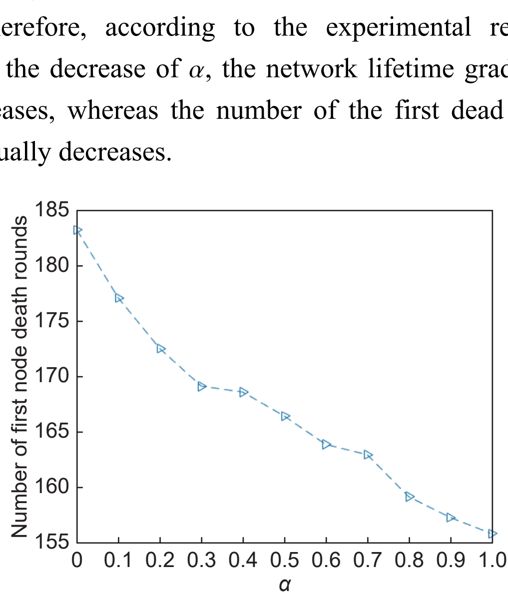


**Fig. 9 Impact of $\alpha$ on the first dead node.**

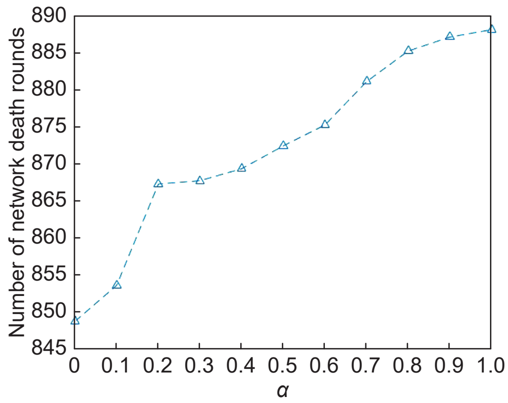


**Fig. 10 Impact of $\alpha$ on the network lifetime.**

### 5.1.3 Cluster distribution

To alleviate the hot issues, the nodes in the first layer were not clustered to prevent the sensor near the sink node from dying too fast. For nodes of other layers, they freely compete in the same layer. Figure 11 shows node clustering at 160 rounds.

To clearly show the topology of information transmission between clusters, Fig. 12 hides the member nodes in the cluster that are not in the first layer. The sensor node in the first layer transmits the information between clusters as the relay node from the lower CH node to the sink node. This method can alleviate the hot issues to a certain extent.

Table 2 shows the rounds of the first death in the first layer of the network and the rounds when all the nodes of the first layer die in the first layer of the network with and without clustering. In both cases, the first dead node in the entire network appears in the first layer. For the case where the first-layer node of the HAECR protocol do not participate in the clustering, the first node in the network is dead in 149 rounds. When the first-layer nodes are also clustered, the first dead node appears in 74 rounds. This outcome is attributed to the sensors close to the sink node that is needed to act as a relay node to receive and transmit the information sent by the CH. The frequent transmission will quickly consume the energy consumption of nodes, leading to changes in the network topology, which is not conducive to reducing the total energy consumption of the network. Therefore, in the case of clustering in 497 rounds, all the nodes of the first layer are dead.

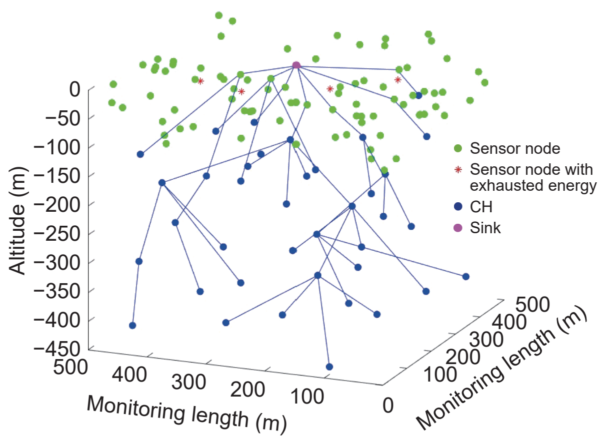


**Fig. 11 Topology of information transmission in the cluster.**

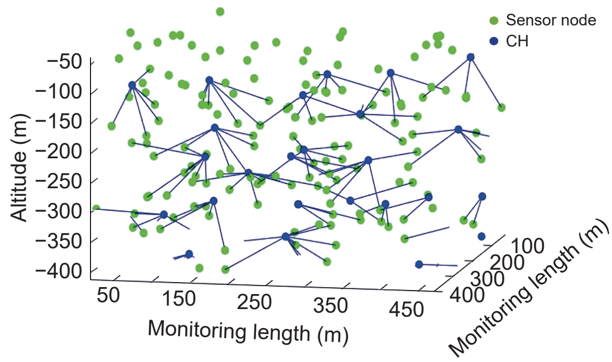


**Fig. 12 Topology of information transmission between clusters.**

**Table 2 Lifetime of the first-layer nodes.**

| Different situation | Round number | |
|---|---|---|
| | First node die | Last node die |
| Clustering | 74 | 497 |
| Non-clustering | 149 | 832 |

### 5.1.4 Death distribution of hierarchical nodes

The number of dead nodes in different layers can be used as a measure of the energy balance of the clustering strategy. As shown in Fig. 13, the sensor nodes in the first layer are the first to die, and the mortality rate is higher than that in other layers. This outcome is mainly because they are relay nodes when transmitting between clusters. They not only need to transmit the information they have collected, but also transmit the packets brought by the CHs in the high layer. The energy consumption of the fifth layer of the sensor network is high because the clustering range is large and the energy consumption of the CH node is

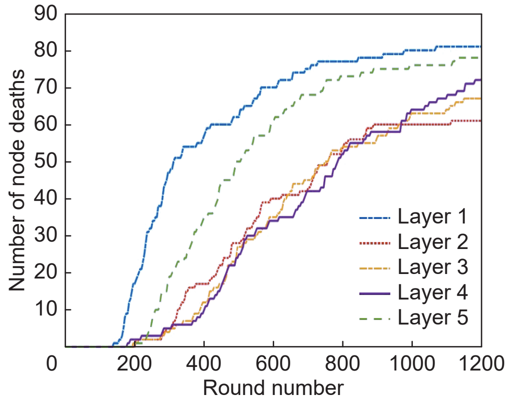


**Fig. 13 Death distribution of hierarchical nodes.**

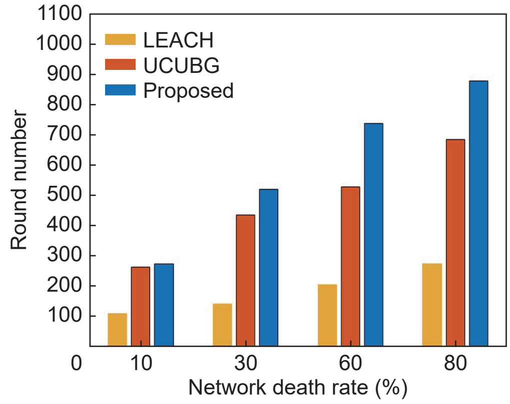


**Fig. 15 Network lifetime comparison.**

high, so the nodes easily die.

Therefore, the HAECR strategy reduces the competition range of the basic CH with a decrease in the number of layers. The first layer is not clustered to alleviate the mortality of the first-layer nodes. After 400 rounds, the mortality of nodes in each layer gradually approaches.

### 5.2 Comparative experiment

Our proposed strategy is compared with the LEACH and UCUBG algorithms to verify the superiority of HAECR in terms of energy consumption balance and network lifetime extension.

#### 5.2.1 Nodes and network survival periods

Figures 14 and 15 show the node survival periods for the respective algorithms, with Fig. 14 showing the decrease in the number of surviving nodes as the number of turns increase and Fig. 15 showing the 10%, 30%, 60%, and 80% node deaths of the three different routing schemes in the arbitrary topology. For LEACH, UCUBG, and HAECR, the first node dies at the 81st, 144th, and 149th turns, respectively.

In LEACH, the energy consumption increased because distant CHs directly communicate with the sink node. In UCUBG, the selection of the CH takes into account the remaining energy and density of the node, which makes the node distribution uniform. In HAECR, the selection of CHs makes full use of node location information, and considers the node energy, distance to the sink node, and quality of the communication link, so the CHs are evenly distributed and the energy consumption is balanced.

#### 5.2.2 Packets received by the sink node

Figure 16 shows the number of packets received by the sink node under the three different clustering algorithms. Among the three clustering algorithms, HAECR and UCUBG received significantly more data

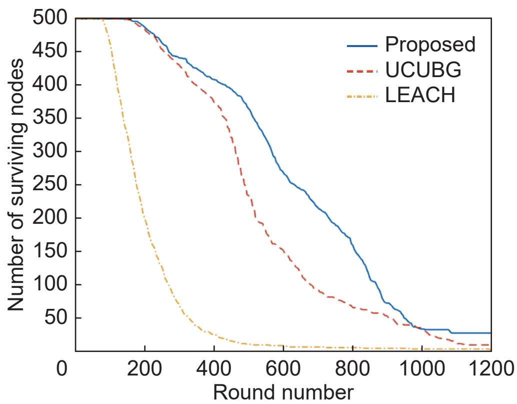


**Fig. 14 Changes in the number of surviving nodes during the data transmission of the underwater sensor network.**

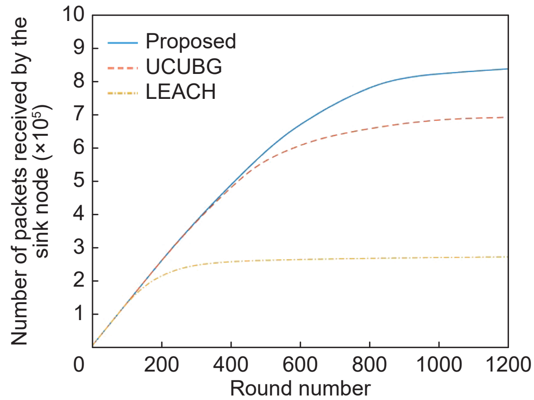


**Fig. 16 Number of packets received by the sink node during the data transmission of the underwater sensor network.**

packets than LEACH. Among them, HAECR received the most data packets, indicating that HAECR can effectively improve network energy utilization. The reason is that in the proposed method HAECR, when selecting CHs, the energy of sensor nodes and the position information in the 3D situation are fully utilized. During the transmission of information between clusters, link quality is also taken into consideration. The possibility of an effective operation of the network is ensured, and more data messages are delivered to the sink.

## 6 Conclusion

This paper proposes an energy-efficient underwater sensor network hierarchical clustering strategy in 3D environments. This strategy uses layering, where the nodes in the first layer are not clustered, and the sensor nodes of other layers compete freely for clustering in the same layer. Thus, it alleviates the hotspot problem and enables efficient use of energy in underwater sensor networks. Moreover, we have further optimized the uneven transmission load of CHs based on the position of the CHs relative to the base station and layer information.

Simultaneously, a comprehensive routing transmission method is constructed by taking the link quality into consideration. The simulation results demonstrate that HAECR can effectively alleviate hot issues, balance energy consumption, and extend the network life cycle. Hence, HAECR is an energy-efficient clustering strategy.

In future works, we will comprehensively consider network environment factors, such as the impact of ocean currents and marine biological activities, network communication delays, algorithm interference, and collusion issues, to more realistically simulate the ecological environment of shallow seawater. Aiming at the problems of high bit error rate and time scalability in underwater acoustic communication, a bio-friendly cluster routing algorithm is also designed to improve the reliability of data transmission in networks.

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