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# Research on Underwater Sensor Network Adaptive Clustering Algorithm for Marine Environment Monitoring

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**Abstract:** In recent years, underwater environmental monitoring has primarily relied on monitoring systems based on underwater sensor networks (UWSNs). The underwater sensor node using a self-powered monitoring system has not been widely used because of the complicated design and high cost of its energy-harvesting device. Thus, the mobile monitoring nodes within UWSNs are typically powered by batteries with limited energy, and replacement on the seabed is challenging. As a result, optimizing the energy consumption of the mobile monitoring network is of significant importance. The clustering algorithm for UWSNs is acknowledged as a vital approach to balancing and reducing network energy consumption. Nevertheless, most existing clustering algorithms employ fixed schemes to balance the energy consumption among nodes, which are unable to dynamically adapt to changes in network topology and do not account for the complexities of the underwater channel environment, thus not aligning with the actual scenarios of marine environment monitoring. Consequently, this paper introduces an adaptive clustering algorithm for marine environment monitoring (MEMAC). The algorithm incorporates the multipath channel information of the underwater environment and the traffic weight between nodes into the probability model to calculate the probability of the node being elected as the cluster head (CH). The final calculated expected revenues are the user's revenues after participating in the game under the influence of the multipath effect, and the revenues of all users jointly determine the performance of the clustering algorithm proposed in this paper. When the energy consumption of the CH node is too much and needs to be rotated, MEMAC, through a CH rotation mechanism and a comprehensive analysis of the overall remaining energy of the network, further optimizes the CH selection strategy while ensuring network stability. Simulation results indicate that the network lifetime of the proposed MEMAC method is extended by 58.9% and 19.17% compared to the two latest clustering algorithms, the Game Theory-Based Clustering Scheme (GTC) and the Centralized Control-Based Clustering Scheme (CCCS), respectively. This demonstrates that the algorithm can achieve efficient energy utilization and notably enhance network performance.

**Keywords:** marine environment monitoring; game theory; energy balance; clustering algorithm



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## 1. Introduction

The real-time and effective collection of underwater environmental information is enabled via the marine environment monitoring system, which also provides early warnings for abnormal situations. It features advantages such as flexible deployment, high-level monitoring of real-time performance, and strong stability. Scattered and discontinuous monitoring data, as well as limited monitoring ranges, are drawbacks of traditional fixed underwater monitoring centers. Intelligent and multi-sensor integrated acoustic sensor networks [1] have been widely applied in the collection of marine environmental data [2]. However, the power supply for underwater mobile nodes, which are powered by batteries that are limited in energy and difficult to replace, leads to issues such as insufficient power supply, network lifespan reduction due to the death of individual nodes, imbalanced energy consumption, and interruptions in real-time monitoring [3,4].

In the context of large-scale UWSNs (underwater wireless sensor networks) used for marine environment monitoring, clustering has been recognized as an effective means of improving network energy management efficiency [5]. The division of UWSNs into different clusters and the use of cluster head (CH) nodes to schedule and transmit for cluster members are employed to reduce the energy consumption of both individual member nodes and the entire network. However, issues such as heavy loads on CH nodes have led to the application of game theory by many experts to the energy consumption optimization of acoustic clustering networks. A non-cooperative game-based UWSNs energy consumption balancing clustering scheme was proposed by Xing et al. [6], which optimizes the selection strategy of CH nodes to achieve a Nash equilibrium in energy consumption optimization and extend the network lifespan. Nevertheless, this scheme did not take into account the assessment of energy levels of ordinary nodes themselves, nor the significant control overhead of CH nodes.

The literature [7] has proposed a Centralized Control-Based Clustering Scheme (CCCS) for Energy Efficiency in Underwater Acoustic Sensor Networks. From a global point of view, the scheme establishes a centralized controller in the cluster to optimize the selection of relay nodes. However, the disadvantages of this algorithm and the differences between it and the proposed algorithm are as follows: Firstly, the CCCS will optimize the selection of CHs according to the collective behavior and interests and lack the evaluation of the node's own energy, resulting in the premature death of some nodes. The algorithm proposed in this paper balances the energy consumption between nodes through a non-cooperative game and prolonging the life cycle of nodes. Secondly, the centralized scheme has fewer application scenarios, which also increases the communication and control overhead of sink nodes. The CHs node in this paper only collects data of member nodes in the cluster, thus greatly reducing the control overhead of the cluster network. After collecting data, CHs first carry out data fusion and then forward it to the sink node through multi-hop. Thus, the communication and control overhead of the sink node is also reduced.

Moreover, the complex underwater multipath channel conditions are seldom incorporated into the node game competition model in existing clustering game algorithms, which results in the overall benefits of UWSNs being less applicable to actual underwater scenarios. Therefore, a game-theory-based UWSN adaptive clustering algorithm for marine environment monitoring is proposed in this paper. The main contributions of this paper are as follows:

1. In the environmental monitoring system design presented in this paper, power supply equipment is placed on underwater data vaults located on floating platforms at the surface, thereby providing power for underwater central nodes. This ensures that the energy of the central nodes remains unrestricted, enabling them to obtain information from all underwater nodes within their communication range, which in turn further ensures the clustering monitoring of a wide range of underwater mobile nodes.
2. A non-cooperative game-based adaptive clustering algorithm is proposed for the purpose of underwater mobile node clustering monitoring. In this algorithm, underwater node multipath channel information is incorporated into the game model, The expected return calculated by this game model is the return of users who participate in the game under the influence of the multipath effect, and the total return of all users jointly determines the performance of the clustering algorithm proposed in this paper to enhance the environmental adaptability of users during the game competition process.
3. In the MEMAC (Adaptive Clustering of Marine Environmental Monitoring) algorithm proposed in this paper, the determination of pre-cluster heads is initially performed according to a distributed non-cooperative game of nodes, followed by the calculation of the overall remaining energy value of the whole network to ultimately determine CH nodes. This approach allows for a comprehensive optimization of the strategy for CH competition.

4. In the algorithm, the remaining energy and traffic are incorporated as different game conditions into the calculation of the payoff function, which effectively balances the energy consumption. Furthermore, CH nodes are rotated in special cases to ensure network stability.

The rest of this paper is organized as follows: In Section 2, we mainly introduce the related research on clustering algorithms. In Section 3, we introduce the marine environment monitoring network model. In Section 4, we introduce the new MEMAC proposed in this paper in detail. Then, we compare the results through simulation experiments in Section 5 so as to verify the superiority of the algorithm in this paper, and finally, we share an outlook and summary in Section 6.

## 2. Related Work

Research on underwater environmental monitoring was begun in developed countries of Europe and America as early as the 20th century, with various monitoring instruments and equipment being designed. In 2009, NEPTUNE, which was established jointly by the United States and Canada, was officially launched. It is recognized as the world's largest cabled ocean observatory network, being capable of achieving gigabit-level bidirectional transmission communication monitoring. By June 2022, the Global Ocean Observing System (GOOS) had become the most comprehensive ocean observation system currently available, with its total number of observation devices exceeding 9000, providing reliable data for marine environmental protection and disaster early warning [8].

Currently, the increasing use of UWSNs (underwater wireless sensor networks) to achieve large-scale and flexible monitoring tasks in marine monitoring systems has led to growing attention and research on clustering algorithms for the large number of underwater nodes deployed in UWSNs. For example, the LEACH algorithm for balancing node energy consumption was first proposed by Heinzelman et al. [9], in which CH (cluster head) nodes are rotated to share their load through the setting of random numbers and thresholds, although this also leads to uneven energy consumption. A series of more efficient clustering algorithms have been proposed based on the LEACH algorithm, such as opportunistic particle swarm optimization [10], energy-saving scalable algorithm [11], and correlation clustering algorithm [12], which have significantly improved network performance. Furthermore, Zhang et al. [13] proposed a low-energy clustering method that non-uniformizes node density, which involves selecting pre-cluster heads through random number settings and determining the communication range based on their coverage lengths for CH election. This algorithm enhances the performance of UWSNs, but it also increases frequent interactions between nodes, leading to instability in the algorithm.

Fixed strategies are used in most of the above solutions to balance node energy consumption, and they are unable to dynamically adjust the node's own strategy to adapt to the constantly changing marine monitoring scenarios in a time-varying, complex underwater environment. As a result, some experts have begun to focus on establishing dynamic competition models between users through game theory to optimize network performance.

Yang et al. [14] proposed a game theory-based distributed multi-dimensional clustering protocol, which calculates the probability of Nash equilibrium based on the distance of nodes to CH and the degree of nodes and selects CH based on the size of the remaining energy. However, there is still significant room for improvement in energy consumption optimization with this algorithm. Subsequently, some scholars began to design utility functions using various strategies to enhance the overall performance of the network, such as repeated games [15], a dual-cluster head mechanism [16], and two-level management clustering [17], etc. However, these algorithms only consider the clustering performance of wireless networks in terrestrial environments, and they do not take into account the impact of complex underwater environments on game clustering. Therefore, they are not suitable for marine environments.

To address this issue, a multi-dimensional game-based underwater adaptive energy-saving clustering algorithm was proposed in the literature [18], which establishes a multi-

dimensional game model and increases the opportunity for historical CH nodes to compete for CH again, further optimizing the strategy for CH election. However, this algorithm takes less consideration of the state of the nodes themselves and environmental factors, resulting in weak applicability in real scenarios.

Based on the above analysis, it has been found that none of the existing algorithms have incorporated underwater channel state information into the establishment of the game clustering model, and as a result, they lack practicality for monitoring in complex marine environments.

### 3. Marine Environment Monitoring Network Model

As shown in Figure 1, the marine monitoring system constructed in this paper is composed of three main parts: the land-based shore station platform, the surface floating platforms, and the underwater data vaults along with the nearby central node area. The specific monitoring process is as follows: a notification of clustering initiation is broadcast by the central node connected to the underwater data vault to all mobile nodes within its communication range. Location information is then broadcast via the nodes to the network upon receiving this information. The clustering of all mobile nodes that receive the clustering notification is performed using the GTAC algorithm proposed in this paper. Within the clustered groups, data collected via ordinary member nodes is transmitted to the CH (cluster head) nodes. The CH nodes first fuse all the received data information and then, using CH nodes from other clusters as relays, transmit this information to the underwater central node through a multi-hop method.

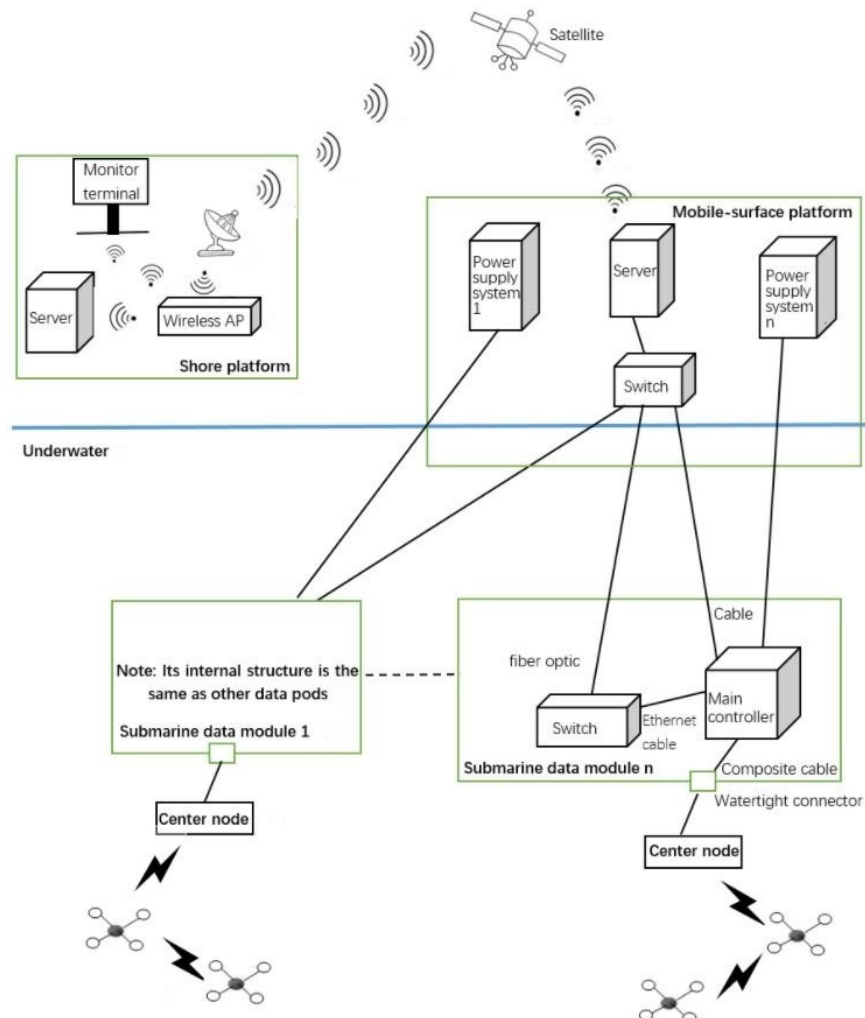


Figure 1. Marine environment monitoring network model.

Secondly, the collected analog signal data is converted into digital signals via the underwater central node and connected to the watertight connectors installed on the bulkhead of the data center through the submarine cable. The watertight connectors are then connected to the main control unit inside the data vault via the network-electrical composite cables within the vault. After the collected data are parsed according to the communication protocol, one end of the main control unit is connected to the power distribution system on the floating platform, providing continuous electrical power to the underwater central node. On the other end, it is connected to the switch inside the vault via network cables, converting the digital signals into optical signals and transmitting them via fiber-optic cables to the switch and server on the floating surface platform. The power supply system connected to the main control unit on the floating platform is numbered in a one-to-one correspondence with the underwater data vault where the main control unit is located. Data uploaded to the floating platform server are first stored and then transmitted to the land-based shore station monitoring area via wireless satellite communication.

Finally, the data information received by the shore station monitoring system is transmitted to the shore station server. The server integrates and processes the received data information and pushes it to the user monitoring terminals. The pushing process involves, on the one hand, the selection of appropriate communication protocols based on the data characteristics. On the other hand, information needed for the monitoring terminals, such as alarms and queries, is filtered out based on user requests.

Before the channel correlation analysis of underwater nodes, it is necessary to use existing algorithms [19] to locate underwater mobile nodes.

### 3.1. Channel Correlation of Underwater Nodes

In underwater acoustic communication, channel noise is very complicated; for instance, sea tides, wind waves, and ship activities will produce noise. In this paper, the noise of the underwater acoustic channel is uniformly represented as  $\sigma^2$ . At the same time, the attenuation of underwater acoustic channels is severe. If the absorption coefficient of the ocean is  $a(f)$ , the transmitting frequency is  $f$ , the distance of each user node is  $d(km)$ , and the underwater acoustic propagation coefficient is  $\epsilon$ . Then, the attenuation formula of the underwater acoustic channel can be expressed as follows:

$$A(d, f) = d^\epsilon [a_0(f)]^d \tag{1}$$

where the variable  $d$  km represents the distance between any two nodes,  $\epsilon$  represents the underwater acoustic propagation coefficient, and the ocean absorption coefficient  $a_0(f)$  can be expressed as [20]:

$$a_0(f) = 10^{0.011 \frac{f^2}{1+f^2} + 4.4 \frac{f^2}{4100+f^2} + 2.75 \times 10^{-5} f^2 + 3 \times 10^{-4}} \tag{2}$$

Suppose that the channel set of nodes  $i$  is  $h_i = [h_{i1}, h_{i2}, \dots, h_{iL}]$ , and  $L$  corresponds to the underwater path  $L$  in the channel response between user  $i$  and the CH node. Then, the channel response auto-correlation matrix of user  $i$  is  $R_{ii} = E\{h_i h_i^H\}$ . By decomposing the characteristic of the moment,  $R_{ii}$  can be further decomposed into

$$R_{ii} V_i = S V_i \tag{3}$$

If the sub-correlation matrix contains all paths, then the eigenvector  $V$  can represent the vector containing single path information [21], the eigenvalue  $S$  in the above formula is taken as the weight coefficient of  $V$ , and the multi-path information of node  $i$  can be expressed as follows:

$$R_i = \sum_{l=1}^L S_{iL} V_{iL} \tag{4}$$

Then, the channel correlation between user node  $i$  and node  $j$  can be expressed as follows:

$$E_{i,j} = \frac{E\{R_i^H R_j\}}{E\{R_i^H R_i\} \| E\{R_j^H R_j\}} \tag{5}$$

### 3.2. Node Flow Analysis

Suppose the traffic of node  $i$  is  $x$ , and its traffic weight coefficient is  $\theta \in (0,1)$ . Then, the weight generated via the traffic of node  $i$  can be expressed as follows:

$$y_i = \theta_i X(i) \tag{6}$$

In addition, according to the location information of nodes, assuming the total number of nodes in the cluster is  $n \in [1,N]$ , the distance  $d$  between node  $j$  and node  $i$  can be expressed as follows:

$$d_{i,j} = \sum_{n=1}^N \|n_i - n_j\| \tag{7}$$

Then, the traffic weight generated via node  $j$  to  $i$  can be expressed as follows:

$$y_{i,j} = \frac{\theta_j \theta_i X(i)}{d_{i,j}} \tag{8}$$

If node  $i$  is a common member node in the cluster, only the cluster head node communicates with it and generates the single node traffic of the above formula. However, if node  $i$  is a CH node, the member node  $j$  in the whole cluster will generate traffic to it. However, since some nodes may be in a dormant state at some time, it is assumed that the number of nodes communicating with CH is  $m$ . At this time, the sum,  $W$ , of the traffic weights generated via node  $i$  can be calculated as follows:

$$W = \theta_i X(i) + \sum_{j=1}^M \frac{\theta_j \theta_i X(i)}{m d_{i,j}} \tag{9}$$

It can be seen that, when the residual energy of node  $i$  is equal to or slightly less than  $j$ , if the sum of traffic weights,  $W$ , at node  $i$  is much larger than node  $j$ , it indicates that the location and communication state of node  $i$  are more suitable to be selected as a CH node, and the election of a CH node in the cluster cannot be determined solely according to the residual energy.

### 3.3. UWSN Energy Consumption Model

Since the rate  $v$  of the underwater acoustic channel is 1500 m/s [22–24], the transmission delay,  $T(K)$ , of  $K$ -bit packets under  $v$  is as follows:

$$T(K) = \frac{K}{v} \tag{10}$$

According to the underwater channel attenuation formula in Section 3.1 and the distance formula in Section 3.2, the energy consumption of sending  $K$ -bit data from node  $j$  far away from node  $i$ ,  $d$  m can be expressed as follows:

$$E_{i,j}^{\text{sent}}(k, d) = P \times T(K) \times A(d, f) \tag{11}$$

where, P is the received power of the node if the ordinary nodes that are active can be represented as ON. Then, the total amount of data received via CH node is as follows:

$$K_{total}^{rec} = K_{CH} + \sum_{j=1}^K K_{ON_{i,j}} \tag{12}$$

where  $K_{ON_{ij}}$  represents the data packet received via the ON node, and  $K_{CH}$  represents the amount of data that the CH node itself can perceive. If the transducer of the CH node is set to  $R_x$  mode, then the energy consumption of the CH node when receiving data is the same; therefore, the energy consumption of node CH to receive K-bit data can be expressed as follows:

$$E_{rec} = K_{total}^{rec} e_{rec} \tag{13}$$

where  $e_{rec}$  represents the energy consumption of receiving data per unit bit. Similarly, the energy consumed via data fusion when node i acts as CH is as follows:

$$E_{integ} = K_{total}^{rec} e_{integ} \tag{14}$$

where  $e_{integ}$  indicates the energy consumption per bit of data fusion.

#### 4. MEMAC Algorithm Design

##### 4.1. UWSN Game Clustering

This model is mainly used to realize the process of selecting CH nodes through game clustering. First, the user node is defined as the set of competitors in the game as  $N = \{N_1, N_2, \dots, N_n\}$ .  $S = \{S_1, S_2, \dots, S_n\}$  is the strategy set of node competition.  $U = \{U_1, U_2, \dots, U_n\}$  is the set of revenue functions of user nodes under different policies.

When the available policy space of each node is  $S = \{PCH, NCH\}$ , PCH indicates the node that claims to be the pre-cluster head, and NCH indicates the node that selects the non-cluster head policy.

Assuming that node j is other nodes except i, when both nodes i and j choose strategy NCH, clustering fails, and the total revenue in the network is 0. To wit,

$$U_i(S_i, S_j) = 0 \tag{15}$$

When node i selects strategy PCH, its income function is as follows:

$$U_i(S_i, S_j) = R_{ii}e^{-\varphi} (E_i^{res} - C_i^{PCH} + \beta W) \tag{16}$$

where  $C_i$  represents the cost when the node selects the PCH strategy,  $R_{ii}$  is the multipath information of node i, and  $E_i^{res}$  is the remaining energy of node i,  $\beta$  is the adjustment coefficient of the traffic weight W, and  $\beta W$  represents the income reward for nodes with a significant traffic weight. The purpose is to encourage nodes with a greater traffic weight to be elected as cluster heads with a greater probability.  $R_{ii}e^{-\varphi}$  represents the parameter that regulates user revenues under multipath conditions.

When node i selects the PCH policy, the cost  $C_i^{PCH}$  can be further expressed as follows:

$$C_i^{PCH} = E_{rec} + E_{integ} + E_{sent} \tag{17}$$

When node i chooses NCH, and node j chooses the PCH strategy, the payoff can be expressed as follows:

$$U_i(S_i, S_j) = (2 - R_{ii}e^{-\varphi})(E_i^{res} - C_i^{ON} + \gamma_i) \tag{18}$$

When node i selects the NCH strategy, the cost,  $C_i^{ON}$ , only includes the energy consumption of data transmission, which is far lower than the cost of clustering. Therefore,

the penalty factor  $\gamma_i$  is added here to make user nodes compete for cluster heads with a fairer probability. The specific calculation method is as follows:

$$r_i = bC_i^{PCH} \frac{E_i^{res}}{E_j^{max}} \tag{19}$$

where  $b$  is the adjustment factor, and the specific value of the cost,  $C_i^{ON}$ , is as follows:

$$C_i^{ON} = E_{sent} \tag{20}$$

In a round of the game, if only the node with the maximum remaining energy is considered the cluster head without considering the traffic between nodes, nodes with less traffic can be elected as the CH. For example, when the node with the maximum remaining energy but less traffic, node  $i$ , chooses the PCH strategy, there exists a node,  $j$ , with the maximum traffic, whose remaining energy is slightly less than that of node  $i$ , but its traffic is much greater than that of node  $i$ . In this case, if node  $j$  chooses the NCH strategy, the node  $i$  with less traffic, but which acts as the CH, will require a greater scheduling cost to complete data transmission, resulting in a decrease in overall network performance. Therefore, this paper incorporates the traffic weight of nodes as part of the reward value in the payoff function, allowing nodes with slightly less energy than node  $i$  but the greatest traffic weight, such as node  $j$ , to be elected as cluster heads with a higher probability and thereby enhancing the performance of the network.

Furthermore, in the formula for the penalty factor,  $r_i$ , as  $E_i^{res}$  approaches  $E_j^{max}$ , the penalty increases, making it more likely for node  $i$  to select the PCH strategy due to the penalty and thereby balancing the energy consumption of the nodes. The algorithm involves node  $i$  continuously engaging in a game between the PCH and NCH strategies until convergence is achieved.

#### 4.2. Analysis of Game Probabilities

Since pure-strategy Nash equilibria can lead to local optimal solutions, it is necessary to consider the equilibrium states of mixed strategies. In this paper, the choice of Nash equilibrium probabilities for different strategies within the probability distribution  $P_R = P_a, P_b$  of multipath channel information is permitted to adapt to the complex underwater multipath channels while ensuring a Nash equilibrium in the global state.

The probability distribution  $P_R$  can be expressed as follows:

$$P_R = \begin{cases} R = R_1(P_a^1, P_b^1) \\ R = R_2(P_a^2, P_b^2) \\ \dots\dots\dots \\ R = R_n(P_a^n, P_b^n) \end{cases} \tag{21}$$

where  $P_a^1$  is the probability that node  $i$  selects policy PCH under multipath channel  $R_1$ , and  $P_b^1$  is the probability that node  $i$  selects policy NCH under multipath channel  $R_1$ . Further, the expected utility of node  $i$  choosing PCH strategy can be expressed as follows:

$$U_i^{expect}(S_i = PCH) = Re^{-\varphi} (E_i^{res} - C_i^{PCH} + \beta W) \tag{22}$$

Similarly, the expected utility of node  $i$  choosing the NCH strategy can be expressed as follows:

$$\begin{aligned} U_i^{expect}(S_i = NCH) &= (2 - R_i e^{-\varphi})(E_i^{res} - C_i^{ON} \\ &\quad - \gamma_i) \left(1 - (1 - P_a^i)^{N-1}\right) \end{aligned} \tag{23}$$



Since each node has the same expectation for selecting PCH and NCH policies, we get the following:

$$U_i^{\text{expect}} (S_i = PCH) = U_i^{\text{expect}} (S_i = NCH) \tag{24}$$

When it is combined with Formulas (22)–(24) above, we can get the following:

$$P_a^i = 1 - \left( 1 - \frac{(E_i^{\text{res}} - C_i^{\text{PCH}} + \beta W)}{(2 - R_i e^{-\varphi})(E_i^{\text{res}} - C_i^{\text{ON}} - \gamma_i)} \right)^{N-1} \tag{25}$$

Let  $(2 - R_i e^{-\varphi})$  in the above equation =  $\epsilon$ ,  $(E_i^{\text{res}} - C_i^{\text{PCH}} + \beta W) = \omega_1$ ,  $(E_i^{\text{res}} - C_i^{\text{ON}} + \gamma_i) = \omega_2$ ; then,

$$P_a^i = 1 - \left( 1 - \frac{\omega_1}{\epsilon \omega_2} \right)^{N-1} \tag{26}$$

From Formula (26), the probability of node i choosing NCH can be obtained:

$$P_b^i = 1 - P_a^i = \left( 1 - \frac{\omega_1}{\epsilon \omega_2} \right)^{N-1} \tag{27}$$

In sum, all nodes can obtain the probability of choosing the PCH or NCH strategy under the condition of equal expected probability through their own multipath channel state information, that is, the state of Nash equilibrium in which no node has the motivation to change strategies.

#### 4.3. Design and Implementation of Clustering Protocol

The overall flow of the clustering algorithm in this paper is shown in Algorithm 1, and the steps are as follows:

1. Initialize the network, set the distance range, D, of the cluster, and start the clustering notification based on the central node.
2. Using Formulas (3) and (4), the multipath channel information R of node i is calculated. The traffic weight  $y_{ij}$  when node i is an ordinary ON node and the total traffic weight W when node i is a CH node are calculated by combining Formulas (6)–(9).
3. By combining Formulas (11)–(15), the revenue  $U_i$  of node i participating in the game is obtained. Substitute Formulas (4), (9) and (15) into Formula (22) to find the expected revenue of user i as a PCH node.
4. Node i is used as PCH and NCH, respectively, whether their expected revenues are equal or not. If yes, node i is added to the set of PCH; otherwise, add node i to the set of ON.
5. With the probability  $P_a^i$  calculated via Formula (26), PCH nodes are elected, as well as a set,  $S_{PCH} = \{PCH_1, PCH_2, \dots, PCH_n\}$ . If the relation  $RAN_i < P_a^i$  is not satisfied, then the node i sets itself as an ordinary node.
6. All nodes in the  $S_{PCH}$  set participate in the CH node competition, and the node with the lowest  $T_i$  value in the set is selected as the CH node.
7. When the probability calculated via Formula (26) is zero, it is determined whether to rotate CH nodes according to Formula (31). If yes, node rotation is carried out.
8. If the formula is not met, go back to Step 6, and start from Step 6.
9. Every time a clustering period, T, is reached, new clustering is performed.

The detailed process is as follows:

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**Algorithm 1** MEMAC algorithm

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**Input:** Dataset  $S_{PCH} = \{PCH_1, PCH_2, \dots, PCH_n\}$ , the random number  $RAN_i$ , total underwater noise  $\sigma^2$ , the node traffic weight  $W$ , the adjustment coefficients  $\theta_1$  and  $\theta_2$ .

- 1: Using Formulas (3) and (4), the multipath channel information  $R$  of node  $i$  is calculated.
- 2: The traffic weight  $y_{ij}$  when node  $i$  is an ordinary ON node and the total traffic weight  $W$  when node  $i$  is a CH node are calculated by combining Formulas (6)–(9).
- 3: By combining Formulas (11)–(15), the revenue  $U_i$  of node  $i$  participating in the game is obtained.
- 4: Substitute Formulas (4), (9) and (15) into Formula (22) to find the expected revenue of user  $i$  as a PCH node.
- 5: **for**  $i \in [1, N]$  **do**
- 6:     **if**  $U_i^{\text{expect}}(S_i = PCH) = U_i^{\text{expect}}(S_i = NCH)$  **then**  $S_i \in S_{PCH}$
- 7:     **else**  $S_i \in S_{ON}$
- 8:     **end if**
- 9: **end for**
- 10: Initialize the distance,  $D$ , between two CHs.
- 11: Use Formula (26) to calculate the  $P_a^i$
- 12: **for**  $i \in [1, N]$  **do**
- 13:     **if**  $RAN_i < P_a^i$  **then**  $S_i = PCH$
- 14:     **else**  $S_i = ON$
- 15:     **end if**
- 16:     **if**  $S_i = PCH$  **then**  $S_i \in S_{PCH}$
- 17:     **end if**
- 18:     Use Formula (31) to calculate the  $T_i$
- 19:     **if**  $T_i < T_j$  and  $S_i \in S_{PCH}$  **then**  $S_i = CH$
- 20:     **else** Repeat steps 16-19
- 21:     **end if**
- 22:     **if**  $S_i = CH$  and  $\delta_1 \left( \frac{E_i^{\text{res}}}{E_i^{\text{max}}} \right) + \delta_2 \left( \frac{W_i}{W_j} \right) > 1$  **then** CH rotation
- 23:     **else** Repeat steps 11-22
- 24:     **end if**
- 25: **end for**

**Output:** The CH node is user  $i$  (or the CH node is user  $j$ )

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4.3.1. Network Initialization

Assume that the communication radius of the node is  $R$ , the distance between two CH nodes is  $D$ , and the length, width, and height of the entire network are, respectively,  $L$ ,  $W$ , and  $H$ ;  $g(0.5,1)$  is a gradient coefficient. If the overlap between clusters is allowed at most for  $1/4$  of the parts, the distance can be set as follows:

$$D \geq (1 + g)R \tag{28}$$

After that, the central node broadcasts a notification to the whole network to start clustering, and then each node in the cluster starts to exchange relevant status information with its neighbor nodes, including node ID, node location, and the energy,  $E_{\text{neigh}}$ , consumed via the neighbor nodes in the interaction process.

4.3.2. PCH Selection

Node  $i$  determines whether user  $i$  is selected as PCH, according to the probability  $P_a^i$ , calculated according to its own multipath information,  $R_{ii}$ . The specific process is as follows: First, the node generates a random number,  $RAN_i$ , through a random function, and then it judges whether the relation  $RAN_i < P_a^i$  is established. If it is,  $i$  selects the PCH strategy; otherwise, the NCH strategy is selected. Finally, all nodes elected as PCH form a set containing preselected cluster heads,  $S_{PCH} = \{PCH_1, PCH_2 \dots PCH_n\}$ .

### 4.3.3. CH Competition

In the formed  $S_{PCH}$  set, the optimal PCH is selected by estimating the energy consumption and the state of the global network. The specific process is as follows: First, each competing  $PCH_i$  broadcasts a short control packet,  $PCO_i$ , which includes the node ID, the node identification  $PCH_i$ , the priority of the node selected as CH, and the estimated total energy consumption of the network at this time. Here, when node  $i$  competes for the CH status, the total energy consumption of the entire cluster network can be estimated as follows:

$$\zeta_i = \mu \left( \mathbf{1} - \frac{C_i^{PCH} + \sum_{j=1, j \neq i}^{N-1} C_j^{on}}{NE} \right) \quad (29)$$

where  $N$  is the total number of nodes in the network,  $E$  is the initial energy of nodes,  $\mu$  is the weight coefficient,  $\zeta_i$  is the weight of the estimated residual energy consumption of the network, and the maximum distance in the whole cluster can be expressed as follows:

$$d_{max} = \left( L^2 + W^2 + (1 + g)^2 R^2 \right)^{\frac{1}{2}} \quad (30)$$

Then, when node  $i$  claims to be node CH, the time required to wait for confirmation from other nodes after broadcasting  $PCO_i$  packets can be calculated as follows:

$$T_i = \eta \frac{d_{max}}{v} (1 - \zeta_i) \quad (31)$$

where  $v = 1500$  m/s is the propagation speed of the underwater acoustic signal, and  $\eta$  is the time adjustment coefficient. It can be seen that, when the total residual energy weight,  $\zeta_i$ , in the network is larger, the time required for node  $i$  to wait for all other member nodes to confirm that it is a CH node is shorter so as to ensure that the node with the most residual energy can compete and be elected as a CH node at the fastest speed.

### 4.3.4. CH Rotation

When the probability calculated via the formula is zero, CH rotation is required for this node. In this case, the conditions for CH rotation are set as follows:

$$\delta_1 \left( \frac{E_i^{res}}{E_j^{max}} \right) + \delta_2 \left( \frac{W_i}{W_j} \right) > 1 \quad (32)$$

where  $\theta_1$  and  $\theta_2$  are the adjustment coefficients. When the above formula is established, it means that the sum of the specific gravity of another node,  $j$ , in the residual energy and flow begins to be greater than that of the current CH node,  $i$ ; that is, node  $j$  is more suitable as the cluster head node.

## 5. Simulation and Performance Analysis

In this chapter, the simulation of the MEMAC algorithm proposed in this paper is carried out using the ns-3 simulator. The network scenario depicted in Figure 2 is used as an example of an area covered by a central node. where the nodes are systematically grouped into multiple clusters, with nodes of identical color signifying their affiliation to the same cluster. In this network area, Sink node is the central node, apart from the central node, the total number of nodes is set to 30. All nodes are randomly and uniformly distributed within a  $6000 \times 6000 \times 6000$  m three-dimensional space. The position coordinates of the central node at the seabed are (3000, 3000, 3000). Each node is equipped with its own node ID and location information, and a weight coefficient for node traffic ranging from 0 to 1 is included. The initial energy,  $E_1$ , of the node is set to 100 nj/bit. The gradient control coefficient for the inter-cluster distance is set to  $g(0.5,1)$ . The length of the data packets is 1024 bits, and the length of the control packets for campaigning for CH nodes is 150 bits. The operational data rate of the nodes is maintained at 1 kbps. The transmission power of the nodes can be

adjusted between 1 W and 30 W to meet different communication requirements within and between clusters. A single simulation run lasts for 15,000 s. The repetitions with different seeds are set to 2000. In this simulation experiment, a collision avoidance MAC (DC-MAC) protocol in the literature [25] was adopted to carry out CH scheduling and transmission. The complete parameter settings are detailed in Table 1.

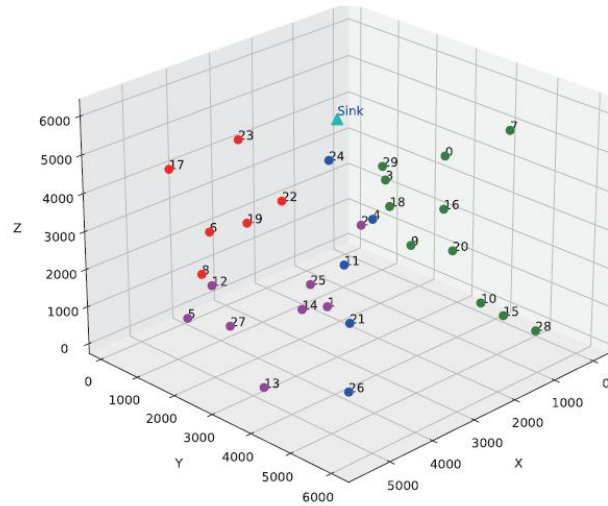


Figure 2. Network topology scene simulation.

Table 1. Simulation parameter.

Parameter	Value
Network size	6000 × 6000 × 6000 (m)
Sink location	(3000, 3000, 3000)
Node size	30
Transmission rate	1 kbps
$f$	10 kHz
$E_1$	100 nJ/bit
Transmitter power	1 to 30 w
$g$	0.5 to 1
$\eta$	0.65
$\delta_1, \delta_2$	0 to 1
$\mu$	0.46
Simulation time	15,000 s

The performance of the MEMAC algorithm proposed in this paper is verified by comparing it with three representative algorithms in the field: LEACH [9], CCCS [7], and GTC [6].

### 5.1. Comparison of the Lifespan of a Network

Network lifetime is considered one of the key metrics for assessing the effectiveness of clustering algorithms, and it is gauged according to the time until the first node within a cluster dies post-clustering. As depicted in Figure 3, the first node deaths for the four algorithms, LEACH, GTC, CCCS, and MEMAC, occurred at rounds 484, 900, 1200, and 1430, respectively. The reason for this is that the MEMAC algorithm employs a multipath channel information model, an environment-adaptive CH competition mechanism, a traffic weight model, a residual energy-balancing mechanism, and a CH rotation mechanism, comprehensively, and it takes into account the overall remaining energy of the network to comprehensively decide on the election of CH nodes, thereby delaying the occurrence of node death to the latest possible time. Compared to the other three algorithms, the network lifetime was extended by 195.5%, 58.9%, and 19.17%, respectively, which effectively balances

the energy consumption among nodes. However, between rounds 1300 and 1400, there was a significant increase in the death rate of nodes within the MEMAC algorithm’s cluster, indicating that there may be a short period during which the algorithm cannot balance all nodes in the network.

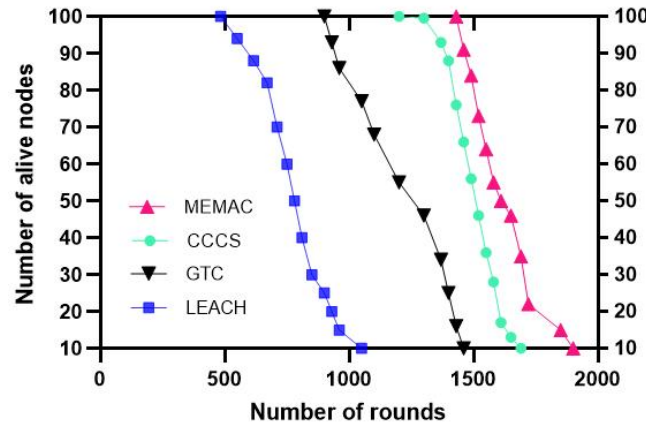


Figure 3. Performance comparison of four algorithms in terms of network lifetime.

As can be seen from the curve changes of CCCS in Figure 3, most nodes in the algorithm began to die after 1369 simulation rounds, and only a few nodes died between the 1200th and 1369th rounds. This is because CCCS’s centralized control mechanism evaluates the node’s own energy, resulting in the premature deaths of very few nodes.

It can be seen that the energy consumption of a single node is a decisive factor in the length of the network lifetime. The premature exhaustion of the energy of a single node in the CCCS algorithm greatly shortens its lifetime. As can be seen from the greatly increased number of continuous simulation rounds of nodes, the algorithm can optimize the overall energy consumption of its underwater mobile network. The MEMAC proposed in this paper not only draws on the advantages of the CCCS algorithm for centralized control in each cluster but also fully considers the energy benefits of each node from the perspective of the whole network, thus achieving higher efficiency than CCCS.

Figure 4 presents a comparison of the number of simulation rounds for these algorithms when the proportion of node deaths reaches 1%, 30%, 50%, and 80%. The larger the number of simulation rounds, the longer the network life is at various stages of remaining node numbers. It is observed that the network lifetime of the MEMAC algorithm, irrespective of the proportion of remaining live nodes, exceeds that of the other three protocols. Consequently, it is determined that the MEMAC algorithm clearly outperforms the other three algorithms in prolonging the overall average network lifetime.

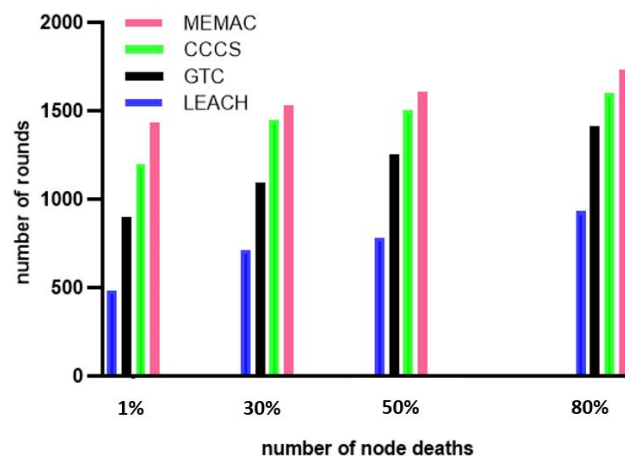


Figure 4. Simulation rounds corresponding to different node death ratios.

### 5.2. Comparison of Average Residual Energy at Node

From Figure 5, it is evident that a slower decline in the average residual energy consumption is exhibited by the MEMAC algorithm proposed in this paper when compared to the other three algorithms. Moreover, the nodes undergo a significantly greater number of rounds when the energy is ultimately depleted, indicating that the longest energy usage time is also shown via this algorithm. This is due to the incorporation of multipath channel information of underwater nodes into the model of inter-node competitive games via the MEMAC algorithm, which enhances the adaptability of the nodes during the clustering process in complex underwater environments.

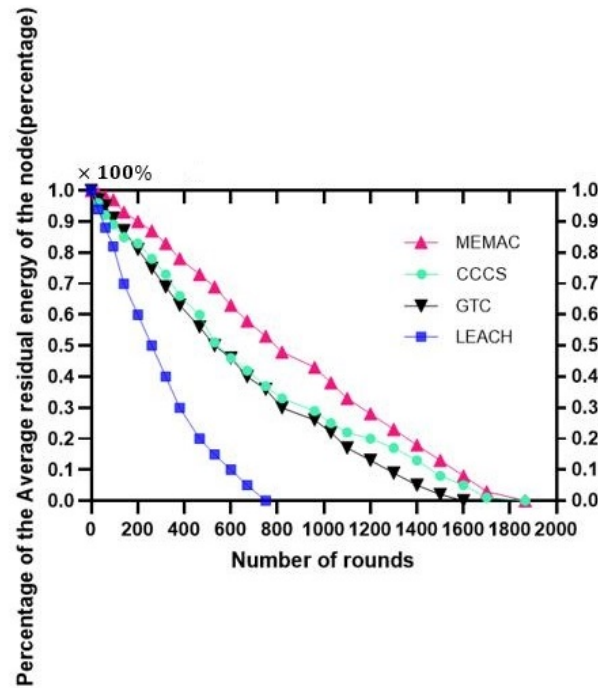
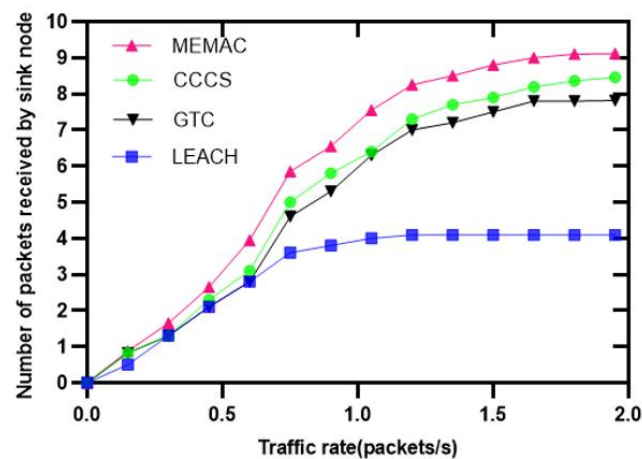


Figure 5. Comparison of average residual energy in nodes.

The average energy consumption curve of the CCCS and GTC algorithm has little difference in the decline rate, which is because CHs nodes of CCCS and GTC adopt the practice of centralized control of the data transmission of network nodes in their clusters. And the curve decline rate of these two algorithms is slower than that of the classical LEACH protocol, which is due to the randomness of CHs' selection in the LEACH algorithm. In the initial 150 rounds of simulation, the average energy consumption of the GTC algorithm decreased at a slower rate than that of the CCCS algorithm because the centralized control overhead of CCCS was greater than that of GTC, thus consuming more energy. However, with the increase in the number of simulation rounds, CCCS consumed less energy than GTC. CCCS reduces the communication costs required for centralized control. However, a faster average energy consumption decline rate is shown for the CCCS protocol than the MEMAC algorithm proposed in this paper within the underwater model.

### 5.3. Comparison of Total Data Received via Central Node

As shown in Figure 6, with the increase in network load, a higher total data reception at the central node is achieved using the MEMAC algorithm compared to the other three algorithms. This is due to the incorporation of the traffic weight of nodes as a reward value into the model for selecting the PCH strategy via the algorithm, which accelerates its convergence to the Nash equilibrium. This enables more data to be received within the same time frame.



**Figure 6.** Comparison of the total data received by the central node.

Additionally, the total remaining energy in the network is taken as a constraint in the CH competition for the algorithm, which factors this into the strategy for CH election. This approach leads to an increase in the overall network lifespan and the time for receiving data packets, thereby further increasing the total amount of data that can be received via the central node.

## 6. Conclusions

In the field of real-time marine environment monitoring, mobile node monitoring based on UWSNs is recognized as an efficient monitoring method today. However, the user nodes in UWSNs, being powered via batteries, lead to significant energy consumption and difficulty in replacement. Hence, the MEMAC algorithm is proposed in this paper. Firstly, a method is designed via the algorithm to place the power distribution system of underwater data warehouses on the floating surface platforms, allowing the power system to provide continuous electricity to underwater central nodes while being easy to maintain. This enables the uninterrupted acquisition of marine information collected via other mobile underwater nodes through clustering and better aggregation of this information. Secondly, the traffic weights of underwater nodes are proportionally adjusted via the MEMAC algorithm proposed in this paper and used as rewards for the node-selection PCH strategy, allowing for more rational participation in PCH competition. The channel state information of nodes is also introduced into the game model for PCH competition via the algorithm, thereby enhancing the environmental adaptability of the clustering algorithm. Lastly, the overall energy consumption level of the network is introduced to optimize the strategy for CH competition, and the setting of CH rotation thresholds via the algorithm ensures the overall stability of the network.

Simulation experiments have demonstrated that the algorithm proposed in this paper is outperformed by none of the three classical algorithms, LEACH, CCCS, or GTC, in terms of the network lifespan, the average residual energy of nodes, and the total amount of data received via the central node. Thus, while network stability is ensured, the adaptability of node clustering is improved, and the overall performance of the network is optimized.

In future work, the DC-MAC protocol based on game theory in the literature [25] will be further improved, and the scheduling strategy for the CH node in the MAC protocol will be optimized according to the communication distance between nodes so as to avoid the collision between underwater mobile nodes and CHs. In addition, the communication method adopted in this paper is mainly underwater acoustic communication. The articles “Underwater Moving Object Detection Using Superficial Electromagnetic Flow Velometer Array-Based Artificial Lateral Line System [26]” and “An optical system for suppression of laser echo energy from the water surface on single-band bathymetric “LiDAR””, [27] other

communication media, like optical systems' relevant technologies and methods, and future work will also increase attention and improve research.

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