Game-Theory-Based Clustering Scheme for Energy Balancing in Underwater Acoustic Sensor Networks

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***Abstract*—The underwater acoustic sensor network (UASN) is a specific deployment of Internet-of-Things (IoT) technology in the underwater environment, since energy constraints limit the lifetime of UASNs, effectively balancing the energy consumption of acoustic sensor nodes in UASNs is important to maximize the amount of information collected and to prolong the network lifetime. Node clustering is widely regarded as one of the most important energy-efficient schemes for UASNs. However, most existing clustering schemes focus on the cooperation-based election of cluster headers (CHs) in a centralized manner. Due to the limited energy capacity, acoustic sensor nodes are designed to save their own energy, hindering the realization of such cooperation. To address this issue in this article, game theory is applied to UASNs to balance network energy consumption and model acoustic sensor nodes as rational and selfish players. Specifically, a game-theory-based clustering (GTC) scheme for UASNs is developed. In the CH election phase, each node makes a decision in pursuit of a greater payoff based on the Nash equilibrium. An incentive mechanism is invented to induce nodes to make more beneficial collective decisions and plays a role in the CH rotation to effectively balance the energy consumption. Meanwhile, the network area is divided into nonuniform sectors to ensure the energy consumption of the CH is more evenly distributed. Simulation results show that the proposed GTC scheme can effectively balance network energy consumption and extend the network lifetime.**

***Index Terms*—Clustering, energy balancing, game theory, incentive mechanism, Internet of Things (IoT), underwater acoustic sensor networks (UASNs).**

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I. Introduction

APPROXIMATELY 70% of the surface of the Earth is occupied by water. Therefore, the exploration of marine resources and acquisition of underwater information in real time are key challenges that must be addressed to achieve a complete understanding of the marine world. Underwater acoustic sensor networks (UASNs) constitute a specific deployment of wireless sensor networks (WSNs). UASNs have wide application prospects in marine information collection, underwater resource exploration, underwater pollution monitoring, military detection, disaster prevention, etc. As a result, UASNs have attracted widespread attention in recent years [1]. UASNs are mainly composed of sink nodes and numerous underwater acoustic sensor nodes. The underwater acoustic sensor nodes are responsible for collecting information about the marine environment and forwarding the data to the sink nodes along specific routing paths. Underwater acoustic sensor nodes are generally powered by batteries with limited energy. In complex underwater environments, batteries are difficult to replace or charge, so energy constraints restrict the network lifetime [2]–[4]. Therefore, effectively balancing and reducing the energy consumption of the entire network is critical to prolong the network lifetime for UASNs.

Since most of the energy consumption is due to the data transmission and reception by sensor nodes, an optimized routing scheme is crucial for reducing the energy consumption [5], [6]. As an effective routing method, cluster routing divides the network nodes into several clusters, and each cluster selects a CH to receive and integrate the information sent by the other nodes in the cluster before forwarding. In traditional routing, nodes farther from the sink consume more energy. Clustering reduces the transmission distance of non-CH nodes, effectively reducing network energy consumption. However, if a node frequently acts as a CH, it will consume more energy than an ordinary node. Rapid depletion of the CH energy may lead to an energy hole and shortened network life. Therefore, the energy consumption between nodes must be balanced.

Most existing cluster-based routing algorithms are based on a hypothesis, that the nodes can cooperate well with each other. However, this assumption does not hold in practice. Due to the limited energy of nodes, cluster headers (CHs) are responsible for collecting, fusing, and forwarding data of nodes in a cluster, thereby consuming substantial amounts of consumed. In fact, nodes do not tend to act as CHs. However, if none of the nodes acts as a CH, many nodes may need to consume an excessive amount of energy for long-distance communication to the sinks, resulting in the death of a premature node. Therefore, it is of great significance to study the conflict and cooperation among nodes to reduce energy consumption [7]. The key issue is to explore the energy balance of acoustic sensor nodes in UASNs. Game theory provides a means of studying whether there is a most reasonable behavior scheme for the players in a game and determining how to find this scheme [8], [9]. In this article, we regard the nodes as rational players with their own preferences. We discuss how the selfish behavior of a single node affects energy consumption and network performance. Then, we propose a game-theory-based clustering (GTC) scheme to optimize the energy consumption and prolong the network lifetime. The main contributions of this work are summarized as follows.

1) We propose a GTC scheme to balance the network energy consumption in UASNs considering the acoustic sensor nodes as rational players with their own preferences. Each node makes a decision in pursuit of a greater payoff, while the CH election is performed based on the Nash equilibrium.
2) An incentive mechanism is designed to induce nodes to make more beneficial collective decisions and plays a role in the CH rotation to effectively balance the energy consumption.
3) The network is divided into nonuniform areas to simplify the network structure and balance the energy consumption of CHs.

The remainder of this article is organized as follows. Section II provides a review of the existing work. Section III discusses the system model and related assumptions. Section IV introduces the clustering game, utility function, and game optimization with an incentive mechanism. Section V presents the details of the GTC scheme. Section VI discusses the results of the simulation experiments conducted to verify the effectiveness of the GTC scheme. Finally, Section VII summarizes the conclusions.

II. Related Work

In recent years, cluster routing has been extensively studied in WSNs and UASNs. Heinzelman *et al.* [10] proposed a low-energy adaptive clustering hierarchy (LEACH) in WSNs. In LEACH, each node randomly selects a number; if the number is less than a preset threshold, the node becomes the CH. By means of a periodic CH rotation, LEACH allows each node to serve as a CH within a certain number of rounds to effectively balance the energy consumption. However, due to the randomness of the CH election, the cluster distribution may be uneven. Younis and Fahmy [11] proposed hybrid energy-efficient distributed clustering in WSNs, which adopts a CH rotation mechanism to determine the CH periodically based on primary and secondary parameters. The primary parameter is the residual energy, which is used for the CH election. A node with a larger residual energy is more likely to become a CH. The secondary parameter is the communication cost of the nodes, which is used to determine to which cluster the nodes within multiple clusters ultimately belong. Li *et al.* [12] proposed a novel distributed clustering scheme in WSNs, in which the cluster radius decreases as the distance to the sink increases and designed a mathematical method to solve the optimal cluster radius set.

To explore the effectiveness of the clustering scheme in an underwater environment, Khan *et al.* [13] proposed a multilayer energy-efficient scheme in UASNs that first divides the network hierarchically, where clustering occurs for all nodes at the same layer and then selects the appropriate CH according to the Bayesian probability and residual energy. Each CH selects a CH with a greater fitness value, a smaller hop count, and a smaller layer level as the next-hop forwarding node. Zou *et al.* [14] proposed a cluster-based adaptive routing (CBAR) scheme for UASNs to prolong the network lifetime. CBAR simplifies the transmission format of data packets, adopts two adaptive methods of dynamic routing updating and power control, and improves the lifetime of UASNs and the data transmission rate. To avoid the premature death of CH nodes due to an excessively large competition radius, Zou *et al.* [14] proposed an energy-efficient adaptive clustering routing for UASNs. In the CH election phase, the residual energy and transmission path of the node are considered. The routing method is selected according to the residual energy of the node in the data transfer stage. Huang *et al.* [16] proposed an improved *K*-means clustering algorithm by using the Elbow method and setting the distance threshold in the clustering phase. Ahmed *et al.* [17] introduced a two-level redundant transmission control scheme in cluster-based UASNs. In the data forwarding phase, the CH node and area head are used to remove the redundant data before forwarding to the next layer, thereby effectively reducing the energy consumption of UASNs.

To make the CH election more reasonable, the comprehensive factors of sensor nodes are further considered. Khan *et al.* [18] proposed a cluster depth-based routing (cDBR) in UASNs. In the CH election phase, each node randomly selects a number; if the number is not greater than a preset threshold and has not served as a CH, the node is selected as a candidate CH. Then, the candidate CH whose residual energy is less than the average remaining energy of all nodes exits the candidate CH set. The nodes in the candidate CH set, whose distances to other candidate CH nodes are all greater than the preset distance value become the CH nodes; otherwise, they are non-CH nodes. Hou *et al.* [19] proposed an energy-balanced unequal layering clustering scheme (EULC) in UASNs. In the CH election phase, each node calculates a CH election weight based on three factors: 1) the remaining energy; 2) node degree; and 3) distance to the sink. First, the candidate CH nodes are generated according to their own thresholds and judgment conditions. Then, all the candidate CH nodes broadcast CH competition messages within their competition radius. The candidate CH node with the largest election weight becomes the CH. The CH nodes broadcast the elected message within the competition radius, while the non-CH nodes in the same layer join the cluster after receiving the broadcast message.

Game theory is an effective tool for solving optimization problems [20] that can be used effectively to model the interactions between nodes in UASNs and has been utilized extensively in research for the optimization of WSN energy consumption. For instance, Abd *et al.* [21] proposed energy-balanced geographical routing using game theory to divide the area around the transmission node into a group of forwarding areas according to network density. Evolutionary game theory and classical game theory are utilized to determine the traffic and select forwarding nodes, respectively. Furthermore, Sengupta *et al.* [22] proposed a novel scheme using noncooperative game theory to solve power control problems. The Nash equilibrium was solved to design a distributed algorithm for optimal power control to achieve the best possible payoff of the nodes and improve the network lifetime. Lin *et al.* [23] studied the data transmission at sensor nodes using a game model in which each sensor pursues its maximum payoff to achieve energy balance and to prolong the network lifetime. These studies, however, are general investigations of energy consumption in WSNs; however, the UASN environment is unique, and the underwater acoustic communication model differs from that of general WSNs. In addition, the above models mainly address general routing problems in WSNs without considering clustering issues. This article explores the optimization of energy consumption in UASNs based on clustered routing and proposes a GTC scheme for energy balancing to effectively balance the energy consumption of underwater acoustic sensor nodes.

III. System Model

A. Network Model

The network considered in this article is a 3-D UASN, as shown in Fig. 1. Acoustic sensor nodes are randomly deployed in the underwater 3-D cube as the network area. Without loss of generality, a sink node is deployed in the middle of the upper surface of the cube network area. We assume that the UASN has the following characteristics.

1) Regardless of the node mobility, all sensor nodes are static with their position information available. All nodes have a unique ID and the same initial energy.
2) All sensor nodes can be ordinary nodes or CH nodes and can integrate data and adjust the transmission power automatically according to communication distance.
3) The sink node energy is not limited, and the sink node has the ability to communicate with all sensor nodes wirelessly.
4) The communication links between nodes are reliable and symmetrical. Any node can derive the distance to the transmitting node from the received signal strength and transmission power.

B. UASN Energy Consumption Model

According to Sozer *et al.* [24], the energy consumption of a data packet with l bits sent by the acoustic sensor node can be calculated using

$$E_{\text{sent}}(l, d) = P_0 \cdot A(d) \cdot T \tag{1}$$

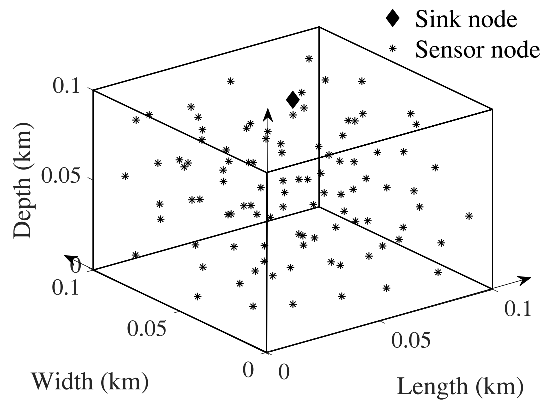

Fig. 1. Three-dimensional UASN structure.

where P_0 is the receiving power level of the node. $A(d)$ is the power attenuation coefficient related to distance, and T is the time required to transmit a data packet with l bits.

In the underwater environment, $A(d)$ can be determined by

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

where k is the energy spreading factor. c denotes the power attenuation parameter and is given by

$$c = 10^{\partial(f)/10} \tag{3}$$

where $\partial(f)$ is the acoustic signal absorption coefficient and f is the acoustic signal frequency. $\partial(f)$ can be calculated using

$$\partial\ (f) = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f^2} + \frac{2.75f^2}{10000} + 0.003. \tag{4}$$

The energy consumption of a data packet with l bits received and integrated by the acoustic sensor node can be calculated using

$$E_{\text{received}}(l) = l \cdot E_1 \tag{5}$$

and

$$E_{\text{integated}}(l) = l \cdot E_2 \tag{6}$$

where E_1 and E_2 denote the energy consumed to process and fuse 1 b of data, respectively.

IV. Clustering Game

In this section, we introduce the use of game theory to model the CH election process in UASN cluster routing. According to the UASN behavior characteristics, we consider a game with n nodes as $G = \{S_1, \ldots, S_n; U_1, \ldots, U_n\}$. All the optional strategies for each node constitute the set of strategy spaces $S_1, \ldots, S_n$. The payoff of node i is denoted as U_i, which is a multivariate function of the strategies of the nodes [25].

We assume that acoustic sensor nodes are rational players with their own preferences. A sensor node always makes decisions in pursuit of a greater payoff. Each node has two strategy choices: D or ND, where D means that the node declares itself as a CH and ND means that the node does not declare itself as a CH. Due to the limited energy capacity of nodes and the fact that CHs are responsible for collecting, integrating, and forwarding data, more energy is consumed by the CHs. Thus, rationally, each node prefers the ND strategy. However, if no node acts as the CH, the data of all the other nodes cannot be forwarded effectively, wasting the node energy and preventing the network from operating normally. Therefore, each node must consider the strategies that other nodes may adopt before making a decision.

A. Utility Function

The utility function of any node n_i can be expressed as $U_i(S_i, S_{-i})$, where S_{-i} represents the strategy set of all nodes except node n_i. When node n_i chooses strategy D, the payoff when the data are successfully forwarded can be calculated as

$$U_i(D, S_{-i}) = E_i^{\text{residual}} - C_i \tag{7}$$

where E_i^{residual} denotes the residual energy of node n_i. C_i represents the cost of node n_i, as a CH and can be evaluated using

$$C_i = E_{\text{received}}(l) + E_{\text{intergrated}}(l) + E_{\text{forward}}(\eta l, d) \tag{8}$$

which includes the energy consumption of receiving data from a node in the cluster $E_{\text{received}}(l)$, integrating data $E_{\text{integrated}}(l)$, and forwarding data $E_{\text{forward}}(\eta l, d)$. Here, ηl is the data packet size and η is the integrate ratio. Equation (8) indicates that the cost of a node which serves as a CH depends on the account of nodes and the distance from the node to the sink.

When all nodes choose strategy ND, the payoff of each node is 0. When node n_i chooses strategy ND and at least one node chooses strategy D, the payoff of node n_i can be determined using

$$U_i(\text{ND}, S_{-i}) = E_i^{\text{residual}} - E_{\text{forward}}\big(l, d_{i,\text{CH}}\big). \tag{9}$$

In this case, node n_i acts as a normal node to forward data to the CH, so the energy consumed by transmitting data to the CH node must be considered. From (9), we can see that the closer the node n_i is to CH, the higher the payoff. In other words, if the shorter the distance between the CH and other nodes in a cluster, the greater the payoff of each node in the cluster.

In a game round, if all nodes choose strategy ND, the payoff of each node is 0. If m nodes choose strategy D, the payoff of these m nodes can be calculated by (7), and the payoff of the other $n - m$ nodes is calculated by (9). Each node determines its strategy based on selfish considerations to save its own energy. Finally, the game maintains an equilibrium state: a node chooses strategy D, while the other $n-1$ nodes choose strategy ND, and there are n Nash equilibria. It can be seen from the set of n equalization strategies that at least one of the n nodes chooses strategy D; thus, the CH election is realized.

Although the CH election is achieved, the payoffs of different nodes when forwarding data successfully and the cost of serving as a CH vary. The total payoffs for the nodes in the n different equilibrium strategy sets are different, so the game result is not guaranteed to be optimal. In other words, the rational pursuit of maximizing personal interests does not necessarily lead to the overall optimal state.

B. Game Optimization With Incentive Mechanism

The above results show that the Nash equilibrium analysis may not completely solve a game problem. Since the existence of a Nash equilibrium is not equivalent to uniqueness, further analysis should be performed based on the Nash equilibrium analysis. In multiple Nash equilibria, there is an equilibrium strategy set $S^\wedge = \{S_1^\wedge, \ldots, S_n^\wedge\}$ that makes the following formula true:

$$S^\wedge = \arg\max \sum_{i=1}^{n} U_i(S). \tag{10}$$

Suppose that the set of Nash equilibrium strategies after a game round is $S^* = \{\text{ND}, \ldots, D, \text{ND}, \ldots, \text{ND}\}$. Among all possible Nash equilibria, there is an equilibrium strategy set $S^\wedge = \{\text{ND}, \ldots, \text{ND}, D, \ldots, \text{ND}\}$ that satisfies (10), and our goal is to optimize the game results from S^* to $S^\wedge$. From the strategy set S^* to $S^\wedge$, the nodes that need to change strategies are n_{i-1} and n_i. Since $U_{i-1}(S^\wedge) > U_{i-1}(S^*)$, node n_{i-1} is motivated to change its strategy actively under the premise that node n_i changes its strategy. However, $U_i(S^\wedge) < U_i(S^*)$, and node n_i has no motivation to change its strategy. To address this problem, we propose an incentive mechanism to induce nodes to take more beneficial collective actions to achieve an ideal equilibrium state. Suppose node n_i makes strategic changes in a given round with an incentive value π_i, which can be expressed as follows:

$$\pi_i = \left\lceil \frac{C_i}{\sigma \cdot E_{\text{forward}}(1, d)} \right\rceil \tag{11}$$

where C_i is the cost of node n_i as the CH. σ is the average number of bits of data that need to be forwarded per round when node n_i does not serve as a CH, and $E_{\text{forward}}(1, d)$ is the energy consumed by node n_i in forwarding 1 b of data to a node at distance d. The incentive value π_i represents the number of rounds corresponding to the cost of node n_i serving as the CH compared to that when node n_i is a normal node. If node n_i is willing to change its strategy and serve as a CH, it will receive an incentive value. Then, the node is not allowed to participate in the game for the next π_i rounds, during which other nodes serve as CHs to forward data. This incentive mechanism can induce nodes to make more beneficial collective decisions to play the role of a CH in rotation, effectively balancing node energy consumption.

V. GTC Scheme

Each node decides whether to act as the CH in pursuit of greater benefits, which may cause an uneven CH node distribution. To avoid such imbalance, we divide the entire UASN area into different layers. The layer spacing of each layer can be calculated by

$$\text{LS}_k = \text{LS}_{k-1} + \Delta\ \text{LS}, \text{LS}_1 = R_0 \tag{12}$$

where ΔLS is the preset layer spacing increment and R_0 is the initial node communication radius. Then, the vertical range of the ith layer is

$$\left(H-\sum_{j=1}^{i}\mathrm{LS}_j, H-\sum_{j=1}^{i-1}\mathrm{LS}_j\right] \quad (13)$$

where H is the coordinate height of the network area. Each node calculates its own layer level L_i by comparing its depth and the vertical area range of each layer. In this way, the network model can be simplified, and the energy consumption of the CH can be more balanced.

We take the sink as the initiator of the game and execute the entire game process. Compared with underwater acoustic sensor nodes, the sink node usually has higher computing power, greater storage capacity, and almost unlimited energy. Meanwhile, the overhead of sending information between nodes is reduced considerably.

A. CH Election

After the network is initialized, the sink broadcasts a message indicating the start of the game. Each node receiving the message calculates the distance between the sink node and its own level according to the received signal strength and then sends a packet that participates in game $M_i(ID_i, L_i, E_i^{\text{residual}})$ to the sink, where ID_i is the number of nodes n_i, L_i is the layer level of node n_i, and E_i^{residual} is the residual energy of node n_i. After receiving all the game participation packages, the sink divides the set of players according to the layer level, and all nodes at the same level constitute a set of players. The sink executes the game process for each set of players, and each node selects a strategy for each round out of selfish considerations to save its own energy. The resulting Nash equilibrium strategy set is $S^* = \{s_1, \ldots, s_n\}$. If S^*satisfies (10), then the node that chooses strategy D in S^* acts as the CH; otherwise, an incentive value is given to the node that needs to change strategies to optimize S^* to $S^\wedge$, and the node that chooses strategy D in $S^\wedge$ acts as the CH.

B. Cluster Formation

The node that chooses strategy D in the optimal equilibrium strategy of each set of players is elected as the CH. The sink broadcast the IDs of the CHs elected at each layer. These nodes act as CH nodes for the layer, and other nodes in the same layer join the cluster as non-CH nodes. The non-CH nodes transmit data packets to the CHs in the same layer. Each CH is responsible for collecting and integrating data packets and sending these data packets to the CH in the adjacent upper layer. Finally, the CH node at the top layer sends the data to the sink.

VI. Simulation Results

To verify the performance of the GTC scheme, we use MATLAB to compare the GTC method with the LEACH, cDBR, and EULC approaches. Table I lists the simulation parameters.

TABLE I
Simulation Parameters

Parameters	Value
Network dimensions	100 m × 100 m × 100 m
Number of nodes	100
Sink location	(50,50,100)
Data packet size	2000 bits
Broadcast packet size	200 bits
Initial energy	0.5 J
P_0	3 mW
k	1.5
f	10 kHz
E_1	50 nJ/bit
E_2	5 nJ/bit
η	0.5
R_0	20 m

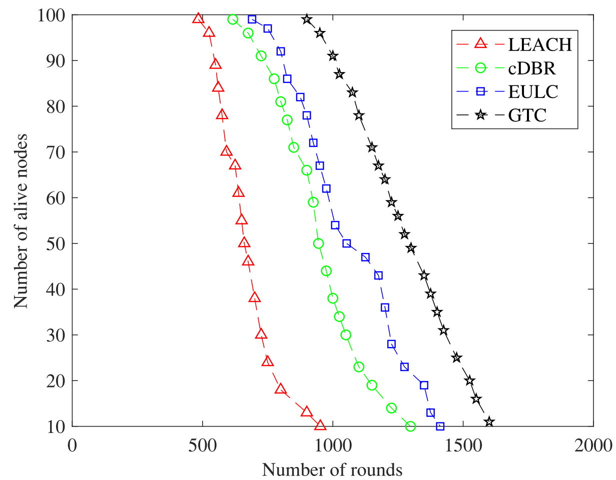

Fig. 2. Number of alive nodes.

Network lifetime is an important indicator of performance in clustered routing. Fig. 2 shows the change in the number of live nodes in the network with the number of simulation rounds. The GTC method substantially improves the network lifetime compared to the LEACH, cDBR, and EULC approaches. The death of the first node and the death of 90% of the nodes occur later than in the other schemes. The death of the first node occurs in rounds 484, 616, 690, and 900 when the LEACH, cDBR, EULC, and GTC approaches are used, respectively. Thus, the death of the first node in GTC occurs 186%, 146%, and 130% later than in the LEACH, cDBR, and EULC schemes, respectively. Therefore, the GTC effectively reduces network energy consumption.

Fig. 3 shows the variation in the average residual energy as the simulation proceeds. Clearly, the average residual energy for LEACH decreases at the highest rate. The average residual energy approaches zero earlier than in other schemes. The curve slopes corresponding to the cDBR and EULC methods are close to each other, and the residual energy of each round is greater than that in LEACH. In the CH election phase, the cDBR and EULC approaches take into account the residual energy and the distance to the sink, which is more reasonable than the CH election by the LEACH scheme based on random numbers and set thresholds. The node residual energy in each round of GTC is higher than that for LEACH, cDBR, and EULC. The reasons for this fact are clear. First, since the CH election occurs at the sink in the GTC game process, some of

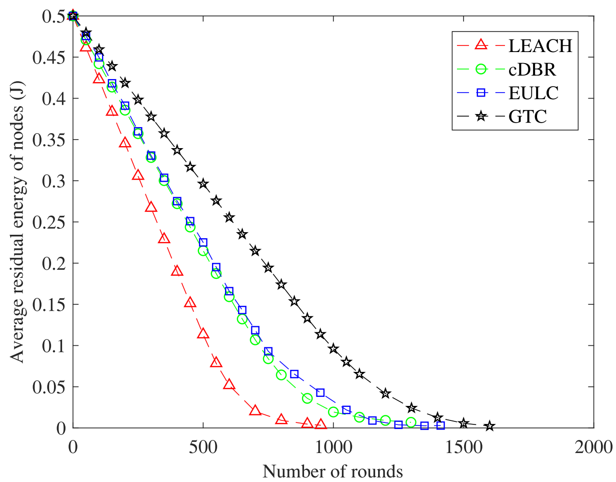

Fig. 3. Average residual energy of nodes.

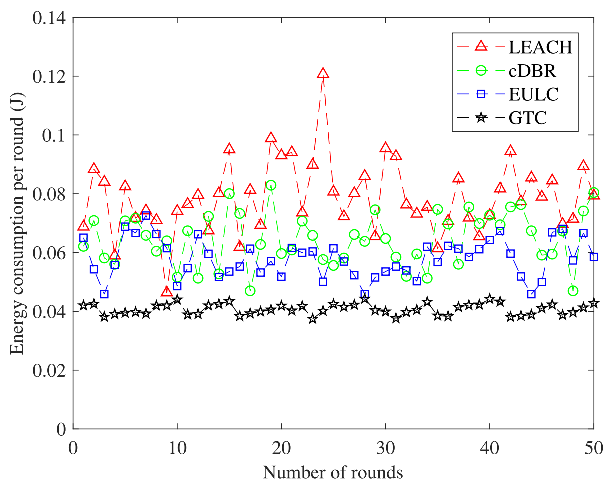

Fig. 4. Energy consumption per round.

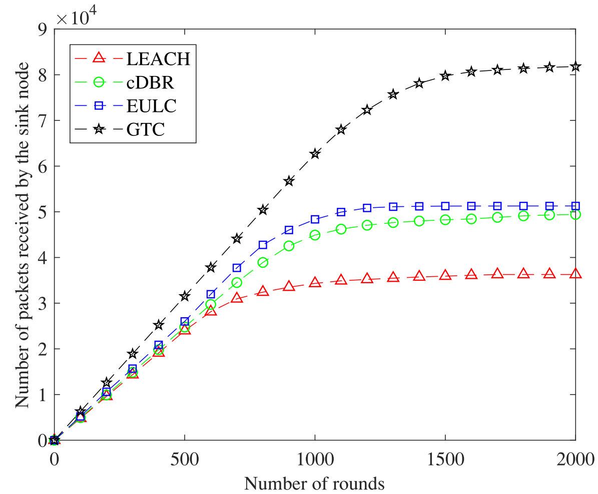

Fig. 5. Number of packets received by the sink node.

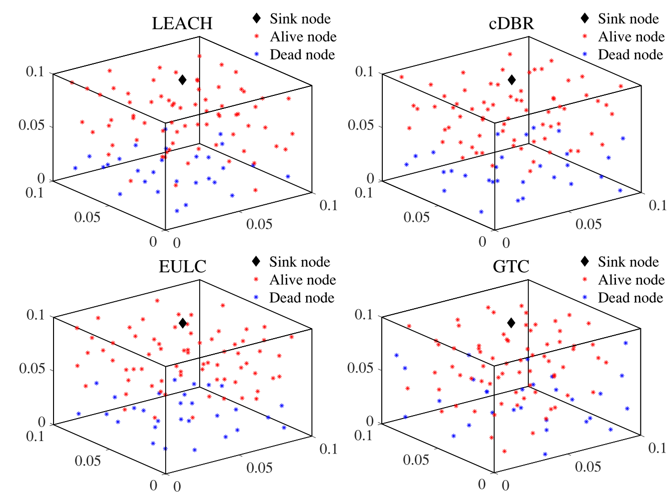

Fig. 6. Node distribution when 30% of the nodes have died.

the energy consumed by sending information between nodes can be reduced (e.g., sending the CH election message and broadcasting the messages of acting as the CH). Furthermore, each node, as a rational and selfish player, decides whether to act as a CH in pursuit of increasing its own profits, which reduces the energy consumption of each node in each round.

Fig. 4 shows the single-round energy consumption of the four schemes. Clearly, the LEACH scheme has the highest single-round energy consumption and the largest change in energy consumption. Since CH election via LEACH entails a certain level of randomness, the number of CH nodes per round is unstable, and the cluster distribution is uneven, resulting in a large change in energy consumption per round. When selecting CH nodes, the cDBR approach considers the residual energies of the candidate CH nodes and the distance between candidate CH nodes, which are more uniformly distributed than those in LEACH. Meanwhile, the EULC scheme comprehensively considers the node residual energy, node degree, and distance to the sink, resulting in a small energy consumption fluctuation between rounds. The GTC approach models nodes as rational decision makers who pursue greater payoffs. Its utility function considers the node residual energy and the actual cost of acting as a CH. Since the incentive mechanism induces nodes to make more beneficial collective decisions and plays a role in the CH rotation, it can effectively balance the node energy. GTC has the smallest energy consumption in each round and fluctuation range, indicating that the energy consumption is more balanced.

Fig. 5 illustrates the number of data packets successfully received by the sink. Clearly, the sink receives the most data packets when the GTC scheme is applied, indicating that the GTC scheme improves the network utilization and the data transmission efficiency between CH nodes.

Figs. 6–8 show the node distributions of the four schemes when 30%, 50%, and 90% of the nodes have died, where red and blue indicate live and dead nodes, respectively. Fig. 6 shows the node distribution when 30% of the nodes have died. The dead nodes in LEACH are concentrated in the bottom area far from the sink because although the LEACH scheme adopts the CH rotation to balance the energy consumption between nodes, since the CH and sink nodes communicate via single-hop communication, a CH node farther from the sink consumes more energy. The dead nodes in cDBR are

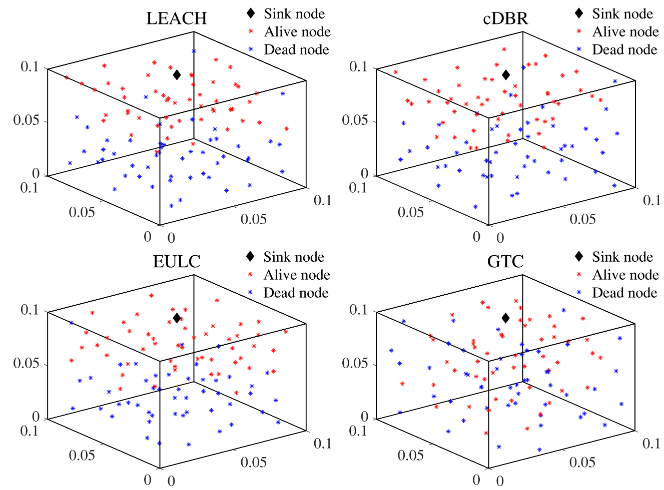

Fig. 7. Node distribution when 50% of the nodes have died.

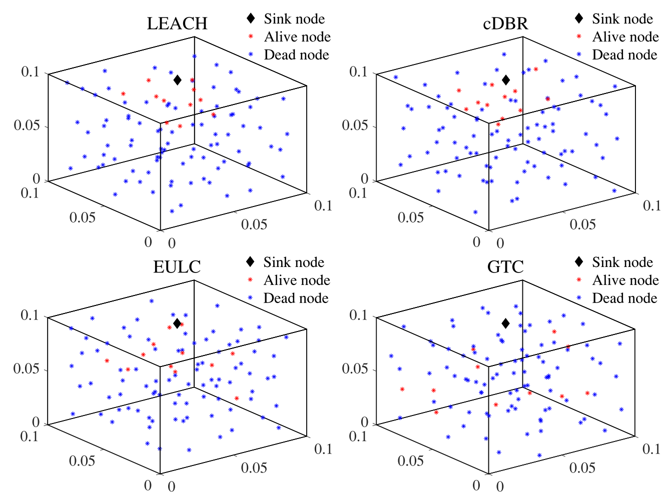

Fig. 8. Node distribution when 90% of the nodes have died.

distributed mainly near the bottom with a few in the middle. Although cDBR intercluster communication is performed over multihops, the selection of the next-hop node considers only the depth, causing some CH nodes to consume more energy. Since the EULC scheme adopts nonuniform layering and considers the node depth and node residual energy when selecting the next-hop node, slightly more dead nodes are observed in the middle layers. The dead nodes are evenly distributed throughout the network area in the GTC scheme, indicating that the energy consumption of the nodes is balanced. Fig. 7 depicts the node distribution when 50% of the nodes have died. The dead nodes in the LEACH, cDBR, and EULC schemes are distributed more densely in the lower half of the area and less in the upper half, while the dead nodes in the GTC scheme are more evenly distributed throughout the area. Finally, Fig. 8 presents the node distribution when 90% of the nodes have died. The live nodes in the LEACH, cDBR, and EULC schemes are mainly concentrated near the sink, indicating that nodes farther from the sink are more likely to die. Meanwhile, for the GTC scheme,

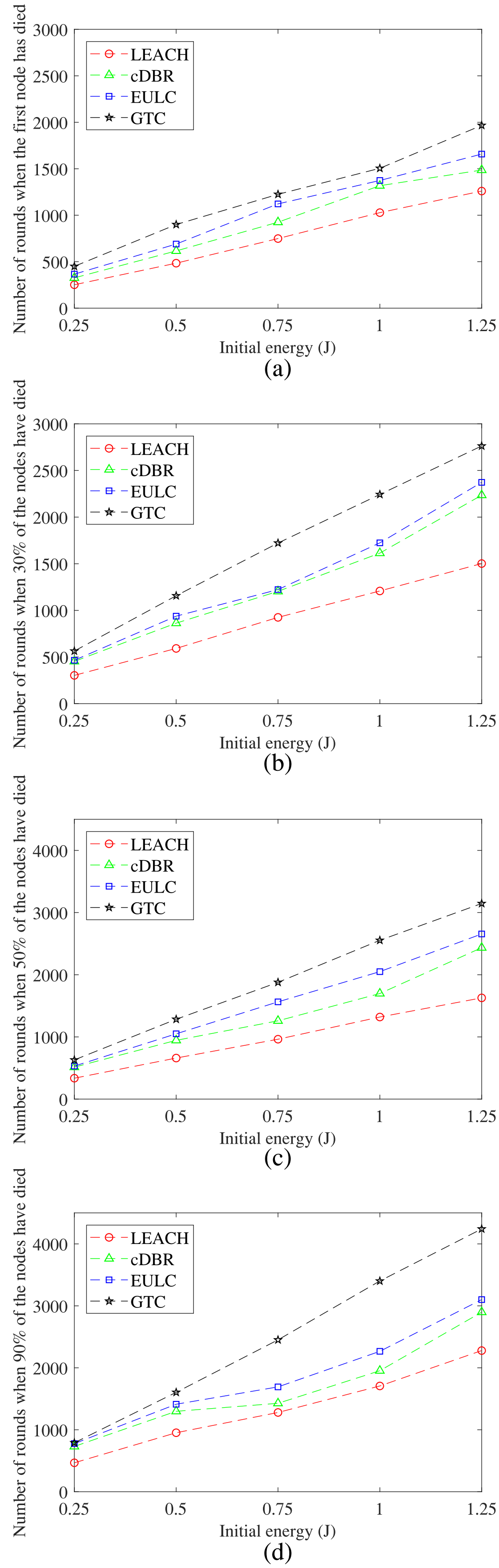

Fig. 9. Round number at which the first node has died (a) and 30% (b), 50% (c), and 90% (d) of the nodes have died under different initial energy conditions.

some of the living nodes are far from the sink node, indicating that the GTC scheme can effectively balance the energy consumption.

Fig. 9 shows the rounds, when the first node has died and 30%, 50%, and 90% of the nodes have died under different initial energy conditions. The rounds at which different proportions of nodes have died are later for the GTC scheme than the other three schemes. As the initial node energy increases, the round at which different proportions of nodes have died also increases. The utility function of the GTC scheme comprehensively considers the residual energy and the actual cost of acting as a CH, making the CH node election more reasonable. The incentive mechanism plays a role in the CH rotation to optimize the equilibrium strategy, alleviating the hot-spot problem in which some CH nodes die prematurely because they frequently serve as CHs and effectively balancing the energy consumption.

VII. Conclusion

Energy constraints are a critical issue limiting the lifetimes of UASNs. Hence, balancing and reducing the energy consumption of the entire network and effectively prolonging the network lifetime are key challenges for UASNs. To address this issue, this article has proposed a GTC scheme to balance energy in UASNs, by which acoustic sensor nodes are modeled as rational and selfish players. In the CH election phase, each node makes a decision to pursue a greater payoff, and the goal of the CH election is achieved by solving the Nash equilibrium. An incentive mechanism is utilized to optimize the equilibrium by encouraging nodes to make more beneficial collective decisions and plays a role in the CH rotation to effectively balance the node energy consumption. In addition, the entire game process occurs at the sink, which can reduce the energy consumed by sending information between the nodes. Furthermore, the entire network is divided into uniform areas to ensure that the CH nodes are more evenly distributed. Simulation results show that the GTC scheme is superior to the LEACH, cDBR, and EULC methods in terms of network lifetime and can effectively balance network energy consumption. In future work, to further reduce the overall energy consumption of clusters, a stable combination can be formed among intracluster nodes to maximize their payoff.

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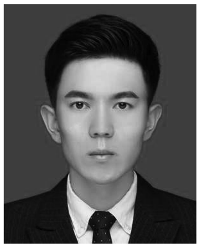

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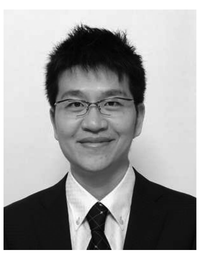

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