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Underwater Acoustic Cooperative Communication Network: A Stackelberg Game-based Power Control Method

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In underwater acoustic sensor networks (UASNs), power allocation is a critical challenge owing to the need to balance energy efficiency and communication quality. To address this issue, we propose a distributed power control algorithm based on a Stackelberg game integrated with a pricing mechanism. The approach incorporates residual energy awareness at relay nodes and employs multivariate data analysis, including channel gain and transmission cost, to achieve an effective trade-off between energy efficiency and cooperative performance. The interaction between source and relay nodes is modeled as a hierarchical game in which the source node, acting as the leader, minimizes its transmission and relay payment costs, while the relay nodes, as followers, dynamically adjust their power pricing to maximize revenue and reduce energy consumption. Optimal response strategies are derived using Lagrangian multipliers, and the existence and uniqueness of the Nash equilibrium are established. To adapt to time-varying channel conditions, a distributed iterative algorithm that relies only on local information is developed, thereby reducing signaling overhead and overall system cost. Simulation results demonstrate that the proposed method significantly improves the network lifetime, enhances the average transmission rate, and increases the energy efficiency of the nodes.

1. Introduction

Underwater acoustic communication networks (UACNs), which transmit information through acoustic signals, are being widely used in a variety of fields such as ocean exploration, target tracking, and marine environment monitoring.[1,2] As a fundamental infrastructure for underwater sensing systems, UACNs support the acquisition and transmission of sensor data in highly dynamic and energy-constrained environments. In recent years, significant progress has been made in UACN technology. For example, Pelekanakis and Cazzanti successfully solved the challenge of high spectral efficiency under bit error rate (BER) and signal-to-noise ratio (SNR) constraints.[3] In addition, Li *et al.* introduced cooperative relay nodes to reduce end-to-end delay under bandwidth-limited conditions.[4]

However, as communication distances and transmission frequencies increase, acoustic signal attenuation becomes more severe, significantly limiting the effective communication range of

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sensor nodes. In addition, multi-node contention for channel access often leads to instability in network performance.[5,6] While cooperative communication has been proposed to improve bandwidth utilization and mitigate multipath fading,[7] it introduces additional energy consumption, making power control a key issue. Several solutions have been proposed to optimize power allocation. Wang *et al.* designed a joint relay selection and power allocation method to reduce energy consumption,[8] and Wang *et al.* proposed a novel distributed coordination algorithm based on reinforcement learning to effectively solve the power control and interference problems in UACNs.[9]

Game theory, as an effective mathematical tool, has been widely used in the field of resource allocation.[10–12] For example, Li *et al.* proposed a joint power and frequency allocation scheme based on game theory to derive the power and frequency allocation relationship among nodes, which significantly improves the SNR.[11] Rasti *et al.* introduced a power control mechanism based on the Stackelberg game and proposed a power augmentation control algorithm that reduces the system interference.[12] However, most existing works either neglect the energy balance among nodes or fail to incorporate energy awareness into their pricing strategies. This imbalance may shorten network lifetime and reduce sensing reliability. Some studies have explored the use of pricing models to incorporate interference as a resource,[13,14] but energy-aware pricing in a Stackelberg game framework remains underexplored.

To address these limitations, in this paper, we propose an energy-aware Stackelberg game-based power control algorithm tailored for UACNs. The model defines the source node as a leader and relay nodes as followers within a pricing-based interaction framework. Importantly, the utility function incorporates each node's residual energy, allowing for the dynamic adjustment of power and pricing strategies while maintaining network cooperation. This design improves both energy efficiency and network lifetime, which are essential for the sustainable operation of underwater sensing networks.

To demonstrate the practical effectiveness of the proposed model under realistic network conditions, we introduce two comparative energy management schemes for validation: the energy retention coefficient method (ERCM) and the energy uncorrelation coefficient method (EUCM). The ERCM integrates residual energy into the utility function, guiding relay nodes to dynamically adjust their transmission behavior based on energy status. The method of designing the utility function with the power cost coefficient as a constant (i.e., EUCM) is described in detail in Refs. 15–17. These two schemes are compared through simulations to evaluate the impact of energy-aware design on system performance, including network lifetime, transmission rate, and energy efficiency. The novelty of this work lies in several key aspects:

A dynamic pricing mechanism based on a Stackelberg game is proposed, in which relay nodes adjust their power prices according to their residual energy levels, aiming to balance individual energy consumption and extend overall network lifetime.

Multiple decision-making parameters are integrated into the utility function using a multivariate modeling approach. These parameters include channel gain, SNR, energy level, and transmission cost. This integration enables more adaptive and energy-aware power control.

A distributed iterative algorithm is designed, allowing each node to make decisions based solely on local information, which reduces signaling overhead and enhances scalability.

These innovations set our method apart from traditional game-theoretic schemes by addressing energy awareness and adaptability, making it more suitable for practical deployment in energy-limited underwater environments.

2. System Model and Problem Formulation

2.1 Network and channel models

Figure 1 gives a collaborative UACN, which consists of N relay nodes, a source node S, a target node D, and a surface base station. The source node is responsible for collecting marine environment data, and the relay node forwards this information to the target node. The target node then transmits the information to the surface base station to realize the real-time monitoring and data transmission of the marine environment. It is assumed that each communication link is independent of each other and there exists a direct link from the source node to the target node with no interference between channels. In addition, the relay nodes work in amplify-and-forward (AF) mode, and the collaborative transmission of the system is divided into two-time intervals executed sequentially.

In the first time slot, the source node S broadcasts a message to the target node D and all the relay nodes, at which time the SNR at the target node D and the relay nodes are, respectively,

$$\gamma_{s,d} = \frac{P_s h_{s,d}}{N(f)\Delta f}, \tag{1}$$

$$\gamma_{s,i} = \frac{P_s h_{s,i}}{N(f)\Delta f}, \tag{2}$$

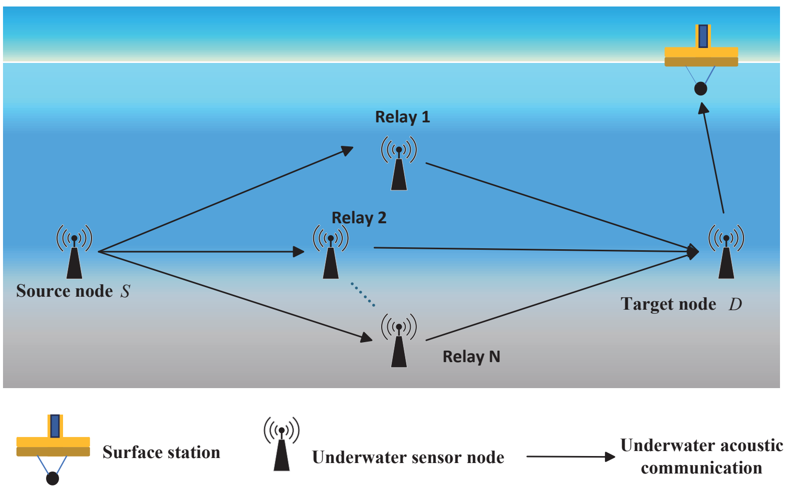


Fig. 1. (color online) Network model.

where P_s is the transmission power of the source node, and $h_{s,d}$ and $h_{s,i}$ denote the channel gains from the source node to node *D* and relay node *i*, respectively. $N(f)\Delta f$ corresponds to the hydroacoustic channel noise at each node, and its calculation can be referred to in Ref. 18.

In the second time slot, the relay node amplifies and forwards the received signal to the target node *D*. The SNR at node *D* is then given by

$$\gamma_{i,d} = \frac{P_i h_{i,d}}{N(f)\Delta f}, \tag{3}$$

where P_i is the transmission power of relay *i* and $h_{i,d}$ is the channel gain for the link from relay *i* to node *D*.

Finally, the target node *D* receives the information from the source and relay nodes using the maximum combined ratio (MRC) and finally obtains the end-to-end SNR, which can be expressed as[19]

$$\gamma_{s,i,d} = \frac{\gamma_{s,i}\gamma_{i,d}}{\gamma_{s,i} + \gamma_{i,d} + 1}. \tag{4}$$

To simplify the calculation, assuming that each link noise is σ^2, the SNR at the target node *D* can be expressed as

$$\gamma(P) = \gamma_{s,d} + \sum_i^N \gamma_{s,i,d} = \frac{P_s h_{s,d}}{\sigma^2} + \sum_i^N \frac{P_s P_i h_{s,i} h_{i,d}}{\left(P_i h_{i,d} + P_s h_{s,i} + \sigma^2\right)\sigma^2}, \tag{5}$$

where $P = \{P_s, P_1, P_2, ..., P_N\}$ is the power set of the source and relay nodes. Additionally, when the signal with the transmit frequency *f* is transmitted over a distance *d*, the channel gain *h* in Eq. (5) is expressed as[20]

$$h = A_0^{-1} d^{-k} \alpha(f)^{-d}, \tag{6}$$

where A_0 denotes the normalization factor and *k* is the diffusion coefficient, with the usual value set to $k = 1.5$. In addition, the absorption coefficient $\alpha(f)$ can be expressed as

$$10\log\alpha(f) = \frac{0.11 f^2}{1+f^2} + \frac{44 f^2}{4100+f^2} + 2.75\times10^{-4} f^2 + 0.003. \tag{7}$$

2.2 Problem formulation

The Stackelberg game is a type of non-cooperative game with a two-layer structure, which can be used in this paper to jointly optimize the utility among nodes. The source node, as the leader, acts first to determine the amount of relay power purchased; the relay node, as the follower, chooses the optimal power price strategy to maximize its utility gain according to the amount of power purchased by the source node.

Assuming γ_{th} is the SNR threshold, the service quality of the source node S is guaranteed when $\gamma(P) \geq \gamma_{th}$ at target node D. At this time, the optimization objective of the source node can be expressed as

$$\begin{gathered} \min U_s = v_s P_s + \sum_{i=1}^{N} v_i P_i \\ \text{s.t. } P_s > 0, P_i > 0, \gamma(P) \geq \gamma_{th}, \end{gathered} \tag{8}$$

where U_s is the utility function of the source node, and v_s and v_i represent the unit power prices of the node S and the relay node, respectively.

The revenue of relay node i consists of the reward paid by node S for purchasing power and the transmission cost. Therefore, the optimization problem for relay node i can be expressed as

$$\begin{gathered} \max U_i = \left(v_i - \frac{m_i}{\beta_i} \right) P_i \\ \text{s.t. } v_i > 0, i \in \{1, 2, \ldots, N\}, \end{gathered} \tag{9}$$

where m_i is the power cost price of relay node i, $\beta_i = E_{total} - E_t/E_{total}$ represents the remaining energy percentage of the relay node i, and E_{total} and E_t denote the total energy and the energy consumed at a given moment, respectively.

The proposed model leverages multivariate data analysis by integrating several parameters into the power control decision process. The utility functions are formulated as functions of channel gain, SNR, transmission cost, energy consumption, residual energy level, and dynamic power pricing. These variables interact within the Stackelberg game framework, allowing nodes to make energy-aware decisions under varying environmental and network conditions. Such a multivariate design enhances the responsiveness and robustness of the power allocation mechanism.

3. Stackelberg Game Solution and Equilibrium Analysis

3.1 Sub-game for the leader

To solve the optimal set of transmit power P^*, we first fix the source node power P_s. We employ the Karush–Kuhn–Tucker (KKT) conditions, which are a set of first-order necessary conditions for optimality in nonlinear programming with inequality and equality constraints. These conditions extend the method of Lagrange multipliers by incorporating both the primal and dual variables. Thus, considering the Lagrange multipliers λ, the Lagrange function can be expressed as

$$L(P,\lambda)=v_sP_s+\sum_{i}^{N}v_iP_i-\lambda\left(\gamma(P)-\gamma_{th}\right). \tag{10}$$

The optimization problem (8) under KKT conditions can be expressed as

$$\begin{cases}\dfrac{\partial L(P,\lambda)}{\partial P_i}=0,\\ \gamma(P)\geq\gamma_{th},\\ \lambda\geq 0,\\ \lambda(\gamma(P)-\gamma_{th})=0.\end{cases} \tag{11}$$

The optimal power allocation strategy for the relay i node, derived from the first term of Eq. (11), can be expressed as

$$P_i^*=\sqrt{\frac{\lambda h_{s,i}P_s\left(h_{s,i}P_s+\sigma^2\right)}{v_ig_{i,d}\sigma^2}}-\frac{P_sh_{s,i}+\sigma^2}{h_{i,d}}. \tag{12}$$

Under the exact fulfillment of the minimum SNR threshold, the relationship is given by

$$\gamma(P)=\frac{P_sh_{s,d}}{\sigma^2}+\sum_{i=1}^{N}\frac{P_sP_ih_{i,d}h_{s,i}}{\left(P_ih_{i,d}+P_sh_{s,i}+\sigma^2\right)\sigma^2}=\gamma_{th}. \tag{13}$$

According to Eqs. (12) and (13), we obtain

$$\sqrt{\lambda}=\frac{\sigma^2P_s\sum_{i}^{N}h_{s,i}\sqrt{v_i/h_{i,d}}}{P_sh_{s,d}-\sigma^2\gamma_{th}+P_s\sum_{i=1}^{N}h_{s,i}}. \tag{14}$$

From Eqs. (12) and (14), the optimal transmit power of relay i can be obtained and expressed as

$$P_i^*=\frac{A_iP_s^2}{(DP_s-\sigma^2\gamma_{th})\sqrt{v_i}}\sum_{n=1}^{N}A_n\sqrt{v_n}-B_iP_s, \tag{15}$$

where $D=h_{s,d}+\sum_{i}^{N}h_{s,i}$, $A_i=h_{s,i}/\sqrt{h_{i,d}}$, $B_i=h_{s,i}/h_{i,d}$.

Bringing Eq. (15) into Eq. (8) can re-express the optimization problem as

$$\min_{\gamma(P)\geq\gamma_{th}} U_s = P_s\left(v_s - \sum_{i=1}^{N} v_i B_i\right) + \frac{P_s^{\,2}}{DP_s - \sigma^2\gamma_{th}}\left(\sum_{i=1}^{N} A_i\sqrt{v_i}\right)^2, \tag{16}$$

for the function $f(x) = ax + b/x + c$, $x > 0$, has a unique minimum point, which is the global minimum. Thus, Eq. (16) has a globally unique minimum at $P_s > 0$. Taking the derivative with respect to P_s for Eq. (16) and making it zero, the optimal transmit power at the node S can be obtained after solving the equation as

$$P_s^* = \frac{\sigma^2\gamma_{th}}{D} + \frac{\sigma^2\gamma_{th}H}{D\sqrt{H^2 - DI}}. \tag{17}$$

Finally, the optimal transmit power of the relay node can be obtained by bringing Eq. (17) into Eq. (15) as

$$P_i^* = \frac{\sigma^2\gamma_{th}\left(\sqrt{H^2 - DI} + H\right)}{D\sqrt{H^2 - DI}}\left[\frac{A_i\left(\sqrt{H^2 - DI} + H\right)}{D\sqrt{v_{r_i}}} - B_i\right], \tag{18}$$

where $H = \sum_{i}^{N} A_i\sqrt{v_i}$, $I = \sum_{i}^{N} B_i v_i - v_s$, $H^2 - DI > 0$.

3.2 Sub-game for the follower

The optimal transmit power of the source and relay nodes has been solved in the previous section; therefore, Eq. (18) can be brought into Eq. (9) to re-obtain the optimization problem representation as

$$\max U_i = \left(v_i - \frac{m_i}{\beta_i}\right)P_i^*$$
$$\text{s.t. } v_i > 0, i \in \{1, 2, \ldots, N\}. \tag{19}$$

When the transmit power of the source node and the amount of power purchased are certain, by taking the derivative of U_i with respect to v_i and making it zero, the optimal power price of the relay node is expressed as

$$v_i^* = \frac{m_i}{\beta_i} - P_i^* \bigg/ \frac{\partial P_i^*}{\partial v_i}. \tag{20}$$

3.3 Game equilibrium analysis

In this subsection, we will analyze and prove that the set of optimal solutions $P^* = \{P_s^*, P_1^*, P_2^*, \ldots, P_N^*\}$ and the optimal power price v_i^* are the Nash equilibrium (NE) points of the game.

Theorem 1: The transmission power of the source node and the relay node power set $P^* = \{P_s^*, P_1^*, P_2^*, \ldots, P_N^*\}$, along with the relay node power price $v_i^* (i \in 1, 2, \ldots, N)$, form the NE point of the Stackelberg game.

Property 1: When the relay node power price is fixed, there exists a unique optimal power set P^* that satisfies the following equation for the optimization problem (8):

$$U_s(P^*) = \underset{\gamma(P) \geq \gamma_{th}}{\arg\min} U_s(P). \tag{21}$$

Proof: Since the objective function in Eq. (8) is a linear combination of P_s, P_i, it is a convex function. For the concavity verification of the constraints, we define the auxiliary functions $y_1(P_s) = 1/P_s$ and $y_2(P_i) = 1/P_i$, both of which are convex (with non-negative second-order derivatives). The composite function $y_3(P_s, P_i) = h_{i,d} y_1(P_s) + h_{s,i} y_2(P_i) + 2y_1(P_s)y_2(P_i)$ is constructed, and since the two auxiliary functions are convex and the composite function is a linear combination of convex functions, $y_3(P_s, P_i)$ is also convex. In addition, the SNR function $\gamma(P)$ is expressed as

$$\gamma(P) = \frac{P_s h_{s,d}}{\sigma^2} + \sum_{i}^{N} \frac{h_{s,i} h_{i,d} y_3(P_s, P_i)^{-1}}{\sigma^2}. \tag{22}$$

Since $1/y_3(P_s, P_i)$ is the inverse of a convex function, it is a concave function, and hence, its linear combination $\gamma(P)$ remains concave. Since the constraint term $\gamma(P) \geq \gamma_{th}$ is the lower-level set of the concave function, it constitutes a convex set. The minimum value of the convex objective function on the convex constraint set exists and is unique, so there is a unique global optimal solution. Thus, for all feasible power sets P, the unique optimal power set P^* satisfies $U_s(P^*) \leq U_s(P)$ and Property 1 holds.

Property 2: When the power prices of other relay nodes are fixed, the optimal transmission power P_i^* of the relay decreases as the unit power price v_i^* increases.

Proof: By taking the partial derivatives of P_i^* and P_s^* with respect to v_i, we can derive the following expression:

$$\frac{\partial P_i^*}{\partial v_i} = -\sigma^2 \gamma_{th} \frac{\left(B_i H - A_i I / \sqrt{v_i}\right)^2}{2H\left(H^2 - DI\right)^{3/2}} - \sigma^2 \gamma_{th} \frac{A_i \left(H + \sqrt{H^2 - DI}\right)^2}{2D^2 H v_i^{3/2} \sqrt{H^2 - DI}} \sum_{j=1, j \neq i}^{N} A_j \sqrt{v_j}. \tag{23}$$

From Eq. (23), we know that $\partial P_i^* / \partial v_i < 0$. Therefore, the optimal transmission power P_i^* of the relay decreases as the unit power price v_i increases, thus proving Property 2.

Property 3: The utility function U_i is concave with respect to the power price v_i. The node power price represents the weight of the resource cost required by the relay node to forward the data in the game model, and its value is dynamically adjusted by the amount of power sold and energy reserve. When other relay nodes' prices are fixed, its transmission power can be derived from Eq. (18).

Proof: Since P_i^* and the utility function U_i are continuous functions of v_i, the second-order partial derivative of U_i with respect to v_i can be expressed by Eq. (24). Therefore, U_i is a concave function with respect to the power price v_i. Furthermore, for the relay node, there exists an optimal power price $v_i^* > 0$ that satisfies $U_i^*(v_i^*) > U_i(v_i)$.

By Property 1 and Property 3, it can be concluded that Theorem 1 holds.

$$\frac{\partial^2 U_i}{\partial v_i^2} = -\frac{A_i P_s^2\left(\frac{v_i}{4}+\frac{3m_i}{4\beta_i}\right)}{\left(DP_s-\sigma^2\gamma_{th}\right)v_i^{5/2}}\sum_{j=1,j\neq i}^{N} A_j\sqrt{v_i} < 0. \tag{24}$$

3.4 Stackelberg game iterative algorithm

In the iterative process of the algorithm, the source node first determines the amount of power to be purchased from the relay node. The relay node updates the power price on the basis of the quantity of power purchased and feeds the updated power price back to the source node, which adjusts its power purchase strategy based on the power price. After collaborative communication is completed, the relay node gains revenue by selling power, while the source node pays the cost required to realize collaborative communication. On the basis of the above description, we summarize the specific implementation process of the proposed algorithm as Algorithm 1.

Algorithm 1
Distributed Stackelberg Game-based Power Control Algorithm with Price Mechanism.

Initialize relay node energy E_{total} and transmitting node power $P_s(0)$;
Initialize relay node power price information $v_i(0)$, power $P_i(0)$, and remaining energy percentage $\beta_i(0)$;
Set $t = 0$, the maximum number of iterations is $t_{max} = 25$;
For $t = 1{:}t_{max}$
    For $t = 1{:}N$
        Receive the transmission power P_s and the purchased power quantity P_i;
        Calculate the remaining energy percentage β_i;
        if $\beta_i \geq 0.1$:
            The relay node assists in communication by calculating the relay power P_i and the power price v_i using Eqs. (18) and (20);
        else:
            set $P_i = 0$, the remaining energy of the relay is insufficient;
        The transmitter node receives the power price feedback from the relay and calculates the power P_s using Eq. (17);
        Calculate the energy consumption E_t of the node;
    End For
End For
return $P^*(t_{max}) = \left\{P_s^*(t_{max}), P_i^*(t_{max})\right\}, v_i^*(t_{max}), i \in \{1,...,N\}$;

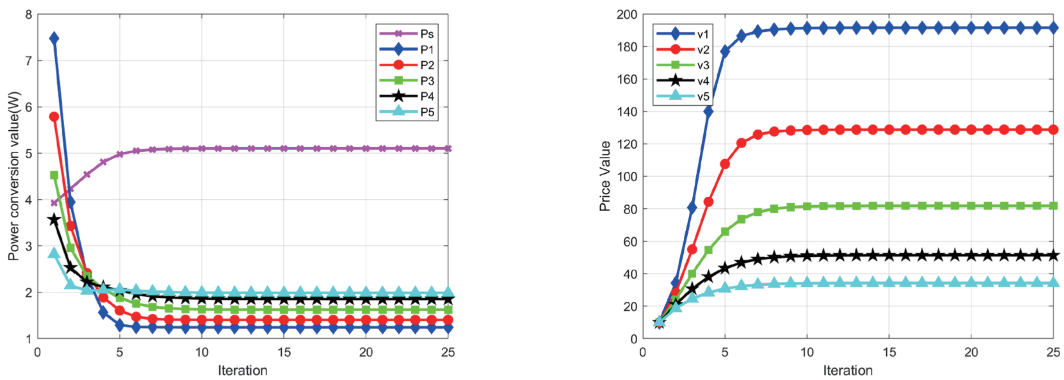
4. Simulation Results and Analysis

In this section, we evaluate the performance of the proposed distributed Stackelberg game power control algorithm based on the price mechanism through numerical simulations. The experiments are conducted in a 3 km target underwater region distributed with a source node, multiple collaborative relay nodes, and a target node. In the operation of the communication network, considering the random nonstationarity of underwater signals, we introduce a variable φ to reflect the impact of underwater uncertainty on the channel. Specifically, $\varphi = h\vartheta$, where ϑ follows a Rayleigh distribution with a mean of 0.1. Thus, in the numerical simulations, the gain of the underwater acoustic channel is modeled as $h + \varphi$. Additionally, the duration of each data slot is set to 0.2 s. Throughout the collaborative communication process, it is assumed that when the remaining energy of a relay node falls below 10% of its initial energy, the relay will exit the collaboration. Other system parameters are listed in Table 1.

In the underwater multisensor node distributed algorithm application scenario, whether the NE solution can be obtained quickly is the key to evaluating the convergence of the algorithm. Figure 2 shows the convergences of the node power set with power price in the case of five relay nodes simultaneously.

Table 1
Simulation parameters.

Parameter	Symbol	Value
System bandwidth	W	1 MHz
Propagation coefficient	k	1.5
Carrier frequency	f	20 kHz
SNR threshold	γ_{th}	0.1
Background noise	σ^2	1.5×10^{-7} W
Initial energy	E_{total}	50 J
Relay cost	m_i	10



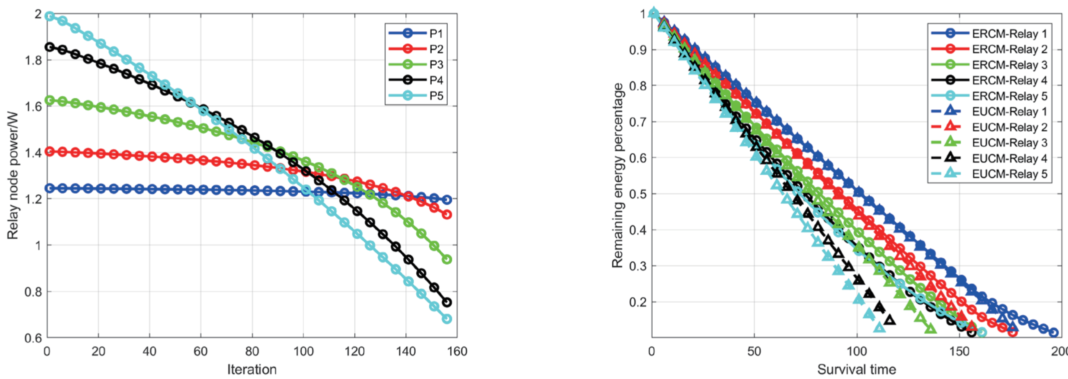
(a) (b)

Fig. 2. (color online) Convergences of (a) power and (b) power price.

Figure 2(a) illustrates the convergence process of the node power set, where at the initial moment, there is a difference in the amount of power purchased by the source node from each relay due to the different channel conditions in which the relay nodes are located. In addition, the transmission power of all nodes converges rapidly in a short period of time, which indicates that the nodes reach an equilibrium state after fewer information interactions. Figure 2(b) shows that the power price of relay nodes can converge rapidly; for the relay with a higher power price, the source node buys less power quantity, which verifies the game relationship between nodes and the effectiveness of the algorithm.

To further validate the dynamic adaptation under the consideration of node energy constraints, we analyze the correlation between the transmission power, survival time, and residual energy of the relay nodes. Figure 3(a) illustrates that the relay node's transmit power gradually decreases as the number of collaborative transmissions increases. This trend results from declining residual energy due to accumulated transmission tasks. As energy depletes, the cost of forwarding increases, prompting relay nodes to raise power prices and reduce the amount of power sold to balance overall energy consumption.

Figure 3(b) shows the variation of the survival time of each relay node under the ERCM and EUCM methods, and Table 2 shows the survival times of specific nodes. Under ERCM, the survival curves flatten gradually, indicating more balanced energy consumption and avoiding



(a) (b)

Fig. 3. (color online) (a) Power and (b) survival time.

Table 2
Node survival times for ERCM and EUCM.

Relay node	Survival time (s)	
	ERCM	EUCM
1	196.3	174.5
2	176.8	156.9
3	161.5	136
4	158	116.7
5	163.6	111

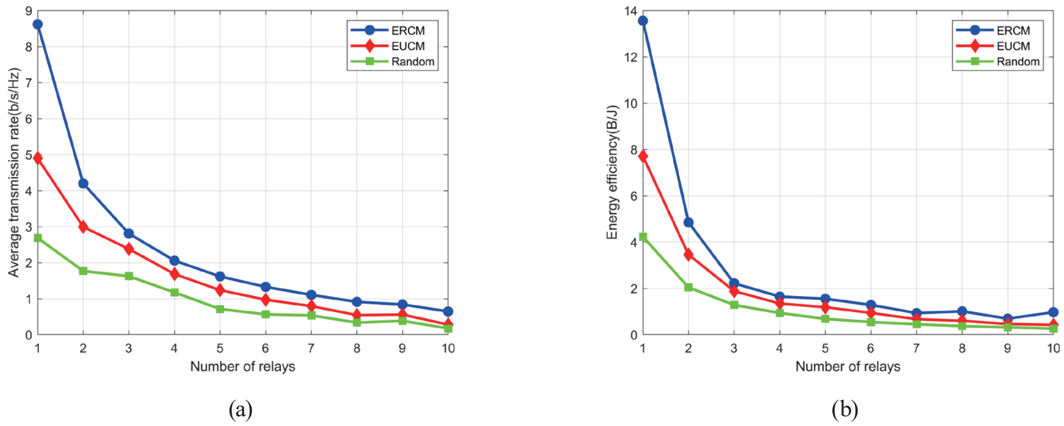


Fig. 4. (color online) (a) Average transmission rate and (b) node energy efficiency.

the premature failure of nodes. As a result, the network lifetime is extended. Specifically, the first node failure occurs at 161.5 s under ERCM, compared with 111 s under EUCM, representing a 45.45% improvement in network lifetime.

We analyze the effect of relay node quantity on transmission rate and node energy efficiency. The average network transmission rate is $\overline{R} = \sum_{i=1}^{N} \log_2(1+\gamma_{s,i,d}) / NT$, where N represents the number of relays and T denotes the transmission duration. The energy efficiency of a node is given by $\eta_i = sum(R_i)/0.9E_{total}$, where $sum(R_i)$ represents the total data transmission of the relay node throughout its life cycle.

Figure 4(a) presents the impact of relay node count on the network's average transmission rate. As the number of relay nodes increases, all methods experience performance degradation owing to the rising power acquisition cost for the source node. Notably, the ERCM method consistently maintains a higher performance than both EUCM and the stochastic strategy. At five relay nodes, ERCM achieves an average transmission rate of 1.61 b/s/Hz, which is 28.49% higher than that of EUCM and 100.77% higher than that of the stochastic method. Over the full range of relay nodes from 2 to 10, ERCM shows a decrease of 84.67%, whereas EUCM and the stochastic method exhibit more severe drops of 90.64 and 90.74%, respectively. These results demonstrate ERCM's effectiveness in preserving transmission performance under network scaling by dynamically adjusting power strategies based on residual energy.

Figure 4(b) further confirms the advantage of the ERCM method in terms of node energy efficiency (in B/J). At five relay nodes, ERCM achieves 1.553 B/J, representing improvements of 30.83 and 126.91% over EUCM and the stochastic method, respectively. When the number of relays increases from 2 to 10, ERCM's energy efficiency drops by 80%, from 4.851 to 0.972 B/J. In comparison, EUCM and the stochastic method decrease by 87.7 and 87.1%, respectively. Although all methods show declining trends with increasing relay count, ERCM exhibits a significantly lower rate of degradation. This can be attributed to its dynamic energy-aware power control strategy, which adjusts each node's transmission power based on its residual energy, thereby optimizing the energy distribution throughout the network's life cycle.

5. Conclusions

In this paper, we proposed a distributed power control algorithm based on the Stackelberg game to address optimal power allocation in UACNs with energy-constrained nodes. By modeling the interaction between source and relay nodes within a hierarchical game and introducing residual energy awareness, the proposed method achieves balanced energy consumption and enhanced cooperative performance. Simulation results demonstrated that, compared with the conventional EUCM method, the proposed ERCM improves network lifetime by 45.45%, average transmission rate by 28.49%, and energy efficiency by 30.83%. The proposed approach successfully integrates multivariate decision factors into the game-theoretic power control framework, enhancing adaptability to dynamic underwater environments. In addition, the algorithm requires only local information and operates without centralized control, making it suitable for practical deployment in underwater sensor networks.

Nevertheless, the current evaluation is limited to static network topologies and ideal channel conditions. Future work will focus on extending the algorithm to dynamic underwater environments with node mobility and incorporating machine learning techniques for relay selection and power optimization under uncertain channel states, further enhancing adaptability and intelligence.

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