Hunting Task Allocation for Heterogeneous Multi-AUV Formation Target Hunting in IoUT: A Game-Theoretic Approach

Meiyan Zhang, Hao Chen, and Wenyu Cai

***Abstract*—As one of the important tools for exploring the ocean, multiple autonomous underwater vehicles (multi-AUVs) system can complete complex tasks in complex Internet of Underwater Things. Collaborative target search, as a typical application of multiple autonomous underwater vehicle (AUV) systems, has been applied in the fields of territorial sea security and marine biology research. Among them, hunting task allocation is a key issue determining the effective application of multiple AUV systems. Therefore, this article proposes a hunting task assignment framework based on contract network (CN) to assign hunting tasks. In the investigated framework, the tenderee AUV (TAUV) is responsible for setting the task reward and assigning hunting tasks, while bidder AUVs (BAUVs) set the working time as bidding information. Combining the mobile energy consumption and communication energy consumption of hunter AUVs, we establish the revenue optimization model of BAUVs and the TAUV. Based on the above model, we model the interaction process of hunting task allocation process between BAUVs and the TAUV as a Stackelberg game, and use the backward induction method to prove that there is a unique Stackelberg equilibrium (SE) in the game. In addition, this article proposes a strategy search algorithm based on the steepest descent method (SSA_SDM) to obtain the optimal strategy of BAUVs and the TAUV, which can achieve SE. Finally, experimental results show that SSA_SDM can reach the SE and outperform other algorithms.**

***Index Terms*—Game theoretic, hunting task allocation, multiple autonomous underwater vehicle (multi-AUV) formation, target hunting.**

I. Introduction

MULTIPLE autonomous underwater vehicles (AUVs) aided Internet of Underwater Things (IoUT) have been widely used in the fields of seabed resource exploration, hydrographic survey, and pipeline laying due to multiple AUVs' advantages, such as strong autonomy, flexibility, and low cost [1], [2], [3]. With the increasing demand for IoUT applications, multiple AUV (multi-AUV) system based on cooperative operation has attracted extensive attention from the industry and academia [4], [5]. The dynamic multi-AUVs network is constructed with underwater acoustic communication between AUVs. In order to improve its adaptability to tasks and environments effectively, the system realizes the collaborative operation of multi-AUV through information interaction in the IoUT region. Presently, the typical application framework of multi-AUV in IoUT is shown as Fig. 1. The multiple AUVs system assists IoUT in completing data transmission and underwater target hunting through collaborative operations. Among them, sensors are deployed on the seabed and establish communication links through underwater acoustic communication; buoys are deployed on the sea surface and establish communication links through underwater acoustic and wireless communication; the multi-AUV system forms a formation in the sea and establishes communication links through underwater acoustic communication and wireless communication.

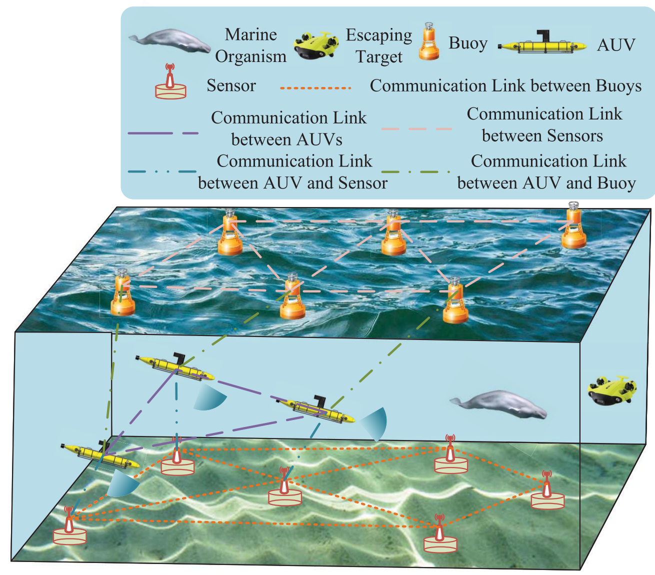

Fig. 1. Multi-AUV-aided IoUT.

Underwater target hunting is a typical application of the AUVs aided IoUT system [6], [7], [8]. Specifically, the multi-AUV formation system hunts the escaping targets that

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invade the important area to maintain security in the territorial sea. In addition, the multi-AUV system hunts the escaping targets, such as marine organisms, to complete marine biological observation. The hunting task allocation is a key issue in determining the effective application of multi-AUV system. If the hunting task allocation is unreasonable, the energy consumption of hunter AUVs will increase. Therefore, assigning hunting tasks reasonably and effectively is a challenging problem.

Presently, some scholars propose task allocation algorithms to allocate hunting tasks. Zhang et al. [9] proposed a task assignment method based on remaining energy, which assigns hunting tasks according to the remaining energy of hunter AUVs. Liu et al. [10] proposed a novel multi-AUV task assignment algorithm based on biologically inspired neural network, which compares the activity of hunter AUVs in the map to achieve multi-AUV task allocation. Cao and Xu [11] proposed a negotiated method to assign round-up tasks to each AUV, which regards the hunting time as the optimization goal to complete the task allocation. However, most current studies on hunting task allocation do not consider the selfishness of hunter AUVs. In addition, the reward expenditure also has an impact on the revenue of hunter AUVs. Therefore, designing a suitable hunting task assignment algorithm for hunting task allocation deserves specific study.

Based on the above analysis, this article proposes a hunting task assignment framework based on contract network (CN) to assign hunting tasks. Specifically, in this framework, the tenderee AUV (TAUV) is responsible for hunting task allocation, and bidder AUVs (BAUVs) are responsible for task bidding. Therefore, the TAUV attracts the BAUVs to participate in the hunting task allocation by setting task rewards. The TAUV chooses an appropriate reward strategy to ensure its own revenue, while the BAUVs set their working hours. Afterward, this article formulates the game model between BAUVs and the TAUV as a Stackelberg game. In this game, the TAUV is the leader, while the BAUVs are the followers. Furthermore, a strategy search algorithm based on the steepest descent method (SSA_SDM) is proposed to reach the Stackelberg equilibrium (SE). Briefly, the contributions of this article are as follows.

1) A hunting task assignment framework based on CN is proposed to assign hunting tasks. Specifically, the TAUV is responsible for hunting task allocation. The BAUVs set the working time as bidding information reasonably.
2) We formulate the game model between BAUVs and the TAUV as a Stackelberg game. The TAUV is regarded as a leader, while the BAUVs are regarded as followers in the game. The proposed game has two optimization models to maximize the revenue of participants.
3) We use the backward induction method to prove that the proposed game has a unique SE. The SSA_SDM is proposed to obtain the optimal strategies of BAUVs and TAUV. Simulation results show that SSA_SDM can reach the SE.

The remainder of this article is arranged as follows: Section II discusses the related works. Section III analyzes the system model. Section IV discusses the proposed game and proposes SSA_SDM to reach the SE. The performance of SSA_SDM is analyzed in Section V. Finally, the conclusion is summarized in Section VI.

II. Related Works

This section discusses the related works, including hunting task allocation and game theory for multi-AUV.

A. Hunting Task Allocation for Multi-AUV

Hu et al. [12] proposed a cooperative hunting scheme based on the multitarget k-winner-take-all algorithm for hunting task allocation, which constructs the state equation to assign hunting tasks. Zhou et al. [13] proposed a hunting network algorithm based on improved bidder selection and evaluation mechanism to improve the allocation efficiency of hunting tasks. In order to complete the hunting task allocation, the proposed algorithm set the bidding information according to the hunting distance, hunting evenness, and hunting success rate. Wang et al. [7] proposed an energy-efficient distributed multiagent proximal policy optimization algorithm to assign hunting tasks. The proposed algorithm sets centralized training, decentralized execution, tracking rewards, hunting rewards, and search rewards for assigning hunting tasks. Fu et al. [14] proposed a strategy of hunting task allocation based on improved contract net protocol, which completes the hunting task allocation based on credibility and matching degree. Li and Zhang [15] proposed a multi-AUV task allocation strategy based on improved contract net algorithm. In order to reduce invalid bidding in the hunting process, this strategy requires the supervisor AUV to initiate hunting task bidding according to its own task load rate. Yang et al. [16] proposed a hunting task assignment algorithm based on improved gray wolf optimizer, which reduces the convergence factor by cosine law and introduces dynamic weights to improve the reliability of hunting task allocation. Li et al. [17] proposed a distributed robust auction algorithm to ensure the revenues of the TAUV. This algorithm adjusts the task rewards through the task reward feedback mechanism, which can reduce the cost of hunting task assignments. Zhu et al. [18] proposed a hunting task assignment algorithm based on biologically inspired neural network map. The algorithm constructs a 3-D underwater environment as a grid map and assigns hunting tasks to the hunter AUVs with the highest activity value. Although above algorithms can complete the hunting task allocation for multi-AUV, few of them consider the revenue optimization of the multi-AUV cooperation.

B. Game Theory for Multi-AUV

There are some researches to apply game theory into multi-AUV cooperative hunting. Wang et al. [19] proposed a multiround game-based source location privacy protection scheme to protect the source location privacy in underwater acoustic sensor networks. The scheme models the location privacy protection process between static sources and attackers as a zero-sum and nonzero-sum game. Liu et al. [20] proposed a multi-AUV dynamic maneuver countermeasure algorithm based on the interval information game theory, which models the multi-AUV confrontation process under uncertain environmental information as an interval information game and uses an improved fractional-order differential evolution algorithm for strategy optimization. Liu et al. [21] proposed a multi-AUV maneuvering decision-making algorithm. The algorithm uses interval-valued intuitionistic fuzzy rules to model the multi-AUV counter game and uses a fractional-order recurrent neural network to find the optimal adversarial strategy. Han et al. [22] modeled the hunting of multi-AUV as a pursuit-evasion game according to the kinematics model of AUVs. Then, this article proposes a hunting strategy and an evader strategy by using the geometry method. Wei et al. [23] analyzed the target hunting problem of multi-AUV according to differential game theory. This article constructs the Hamiltonian function to obtain a control strategy that satisfies the Nash equilibrium. Wang et al. [24] used an asymmetric game model to analyze the multi-AUV confrontation process, and propose a hierarchical decision-making algorithm to determine the confrontation strategy. Wei et al. [25] modeled the problem of multi-AUV cooperative confrontation as a dynamic game model. Then, this article uses the particle swarm algorithm to obtain the solution for the game model. Wei and Liu [26] used Bayesian Nash equilibrium theory to construct a multi-AUV game confrontation model for incomplete information. Then, this article uses a multiobjective discrete particle swarm algorithm to obtain a decision-making scheme that satisfies the Bayesian Nash equilibrium. Although existing research can achieve Nash equilibrium for multi-AUV, few of them consider the revenue optimization problem of hunting task allocation.

III. System Model

This section introduces the process of multiple AUV formations completing hunting task allocation, and establishes energy consumption models, BAUV models, and TAUV models, respectively.

In the section, we consider a formation composed of heterogeneous multi-AUV, where each hunter AUV differs in performance indicators, such as sailing speed v_j and remaining energy E_j^r. The multi-AUV formation is described as Fig. 2, where the TAUV and BAUVs complete the hunting task allocation through a CN. To describe the location of physical objects in the sea, the origin of world frame is set according to the seafloor and horizontal position of sensor. Then, the world frame is established according to the seafloor, in which the Z-direction is upward, and the X-direction is east. Hence, the hunter AUVs are divided into following types in the CN.

1) TAUV represents the hunter AUV located in the center of the formation and assigned hunting tasks.
2) BAUVs represent other AUVs in the formation and competing for hunting missions. Let $\mathbf{BAUV} = \{\text{BAUV}_1, \ldots, \text{BAUV}_j, \ldots, \text{BAUV}_n\}$ denote the set of BAUVs.
3) The successful BAUVs represent the BAUVs who obtain a hunting task.

Specifically, the hunting task allocation between TAUV and BAUVs has four stages [18], [27].

TABLE I
Summary of Key Notations

Notation	Description
$\mathbf{BAUV}$	The set of BAUVs
$\mathbf{Task}$	The hunting task information
$\mathbf{S}_j$	The status of BAUV j
E_j^1	The mobile energy consumption of BAUV j
R_j	The data transmission rate of BAUV j
R_z	The data reception rate of the TAUV
Y_j	The satisfaction of BAUV j with the hunting task
E_j^2	The communication energy consumption of BAUV j
U_j	The revenue of BAUV j
R_z	The hunting benefit of the TAUV
E_z	The communication energy consumption of the TAUV
$U_{z,j}$	The revenue of the TAUV

1) *Task Announcement Stage:* The TAUV sends hunting task information and rewards to all BAUVs through a broadcast communication mechanism. Let $\mathbf{Task} = \{P_e, v_e, E_e^r\}$ represent the hunting task information, where P_e is the location of the escaping target, v_e is the sailing speed of the escaping target, and E_e^r is the remaining energy of escaping target.
2) *Bidding Stage:* The BAUVs send the working time as bidding information to the TAUV according to the task requirements and their own status. Let $\mathbf{S}_j = \{l_j, v_j, E_j^r\}$ denote the status of BAUV j, where l_j is the distance between BAUV j and escaping target, v_j is the sailing speed of BAUV j, E_j^r is the remaining energy of BAUV j.
3) *Awarding Stage:* The TAUV selects some BAUVs as the successful BAUVs according to the bidding information. Then, the TAUV broadcasts its information through a multicast communication mode.
4) *Monitoring Stage:* The successful BAUVs establish a commitment monitor relationship with the TAUV for performing the hunting tasks. In the above process, there is a game model between the TAUV and BAUVs. Among them, the TAUV chooses an appropriate reward strategy to ensure its own revenue, while each BAUV chooses a bidding strategy, i.e., working time.

In addition, the BAUVs can participate in the hunting task assignment of the TAUV at most. To ensure the reliability of the communication process, the hunter AUVs do not move their positions when receiving the hunting tasks. For convenience, the necessary notations in this article are summarized in Table I.

A. Energy Computation Model

This section introduces the energy consumption model of BAUVs, including the motion model and communication model.

1) Motion Model: As we know, the BAUVs need to overcome seawater resistance during the movement. Therefore,

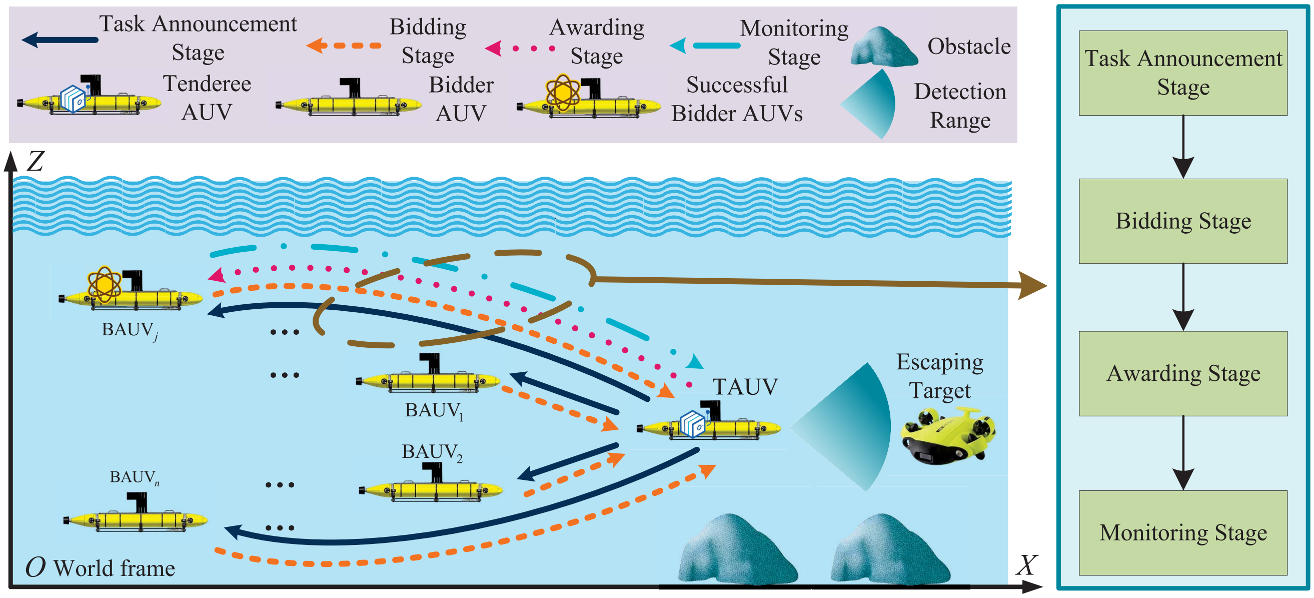

Fig. 2. Multi-AUV formation completing the hunting task allocation.

based on the hydrodynamic formula, the seawater resistance of BAUV j is

$$F_j = 0.5C\rho v_j^2 S_j \tag{1}$$

where C is the hydrodynamic coefficient and its value is usually 0.7 [9], [28], [29], ρ is the seawater density, and S_j is the cross-sectional area of BAUVs.

In this article, the thruster of BAUVs is a direct current (DC) brushless motor [30], [31]. Since the mechanical characteristic of DC brushless motor is affected by the sailing speed of BAUV j, a cubic function fitting is used to obtain the relationship between the working efficiency of the thruster η_j and the sailing speed v_j of BAUV j as follows:

$$\eta_j = -0.073v_j^3 + 0.189v_j^2 + 0.021v_j + 0.540. \tag{2}$$

It is assumed that the motion energy of BAUVs is fully converted into the energy of BAUVs' thrusters, and the BAUVs always maintain a constant sailing speed. When BAUV j is sailing at a constant speed, the propulsion force of BAUV j is equal to the seawater resistance. Therefore, the moving energy consumption of BAUV j is

$$E_j^1 = P_j^{\text{thr}} t_j/\eta_j = F_j v_j t_j/\eta_j = C\rho v_j^3 S_j t_j/2\eta_j \tag{3}$$

where t_j and P_j^{thr} denote the working time and thruster power of BAUV j, respectively.

2) Communication Model: In the system model, the BAUVs use underwater acoustic communication to report task with the TAUV. The acoustic signal attenuation of BAUV j for underwater acoustic communication can be defined as

$$\phi(o_j, f) = o_j^{\tau}\xi(f_j)^{o_j} \tag{4}$$

where o_j is the maximum communication distance of BAUV j, τ is the path loss factor, and f_j is the carrier frequency of BAUV j. The absorption factor $\xi(f_j)$ [32] is defined as

$$10\log\xi(f_j) = \frac{0.11(f_j)^2}{1+(f_j)^2} + \frac{44(f_j)^2}{4100+(f_j)^2} + 2.75\times10^{-4}\times(f_j)^2 + 0.003. \tag{5}$$

Therefore, the signal-to-noise ratio (SNR) of BAUVs for underwater acoustic communication is [33], [34]

$$\sigma_j = \frac{P_j^{\text{tran}}}{\phi(o_j, f_j)\varpi(f_j)b_j} \tag{6}$$

where P_j^{tran} is the transmit power of BAUV j and b_j is the channel bandwidth of BAUV j.

Since the communication noise $\varpi_1(f_j)$ consists of turbulent noise $\varpi_2(f_j)$, thermal noise $\varpi_3(f_j)$, shipping noise $\varpi_4(f_j)$, and wave noise $\varpi_5(f_j)$ [35], [36], the power spectral densities of them are defined as

$$\begin{cases} 10\log\varpi_2(f_j) = 40 + 20(\varepsilon_1 - 0.5) + 26\log f_j \\ -60\log(f_j + 0.03) \\ 10\log\varpi_3(f_j) = 50 + 7.5\sqrt{\varepsilon_2} + 20\log f_j \\ -40\log(f_j + 0.4) \\ 10\log\varpi_4(f_j) = -15 + 20\log f_j \\ 10\log\varpi_5(f_j) = 17 - 30\log f_j \end{cases} \tag{7}$$

where ε_1 is the shipping activity factor and ε_2 is the wind velocity.

In summary, the data transmission rate R_j of BAUV j is

$$R_j = b_j\log_2\left(1 + \frac{P_j^{\text{tran}}}{\phi(o_j, f_j)\varpi_1(f_j)b_j}\right). \tag{8}$$

In the process of completing the hunting task, the communication energy consumption of BAUV j is

$$E_j^2 = \frac{\delta_j P_j^{\text{tran}}}{R_j}\frac{t_j}{\vartheta_j} \tag{9}$$

where δ_j is the communication data size of BAUV j and ϑ_j is the communication interval of BAUV j.

In addition, the communication energy consumption of the TAUV is

$$E_z = \frac{\delta_j P_z^{\text{rece}}}{R_j} \frac{t_j}{\vartheta_j} \tag{10}$$

where P_z^{rece} is the received power of the TAUV.

B. BAUV's Model

A logarithmic function is used to describe the suitability of BAUVs for the hunting task [20], [37]. If a BAUV becomes a successful BAUV, it can receive rewards from the TAUV. Therefore, the satisfaction of BAUV j with the hunting task is

$$Y_j = \beta_j \ln\left(1 + t_j\right) + t_j r_j \tag{11}$$

where r_j is the unit reward of working time. Due to the performance heterogeneity of multi-AUV formations, the task-matching coefficient of BAUV j can be calculated as

$$\beta_j = \lambda_1 \varphi_j^E + \lambda_2 \varphi_j^v + \lambda_3 \varphi_j^l \tag{12}$$

where φ_j^E is the ratio of remaining energy of BAUV j to the remaining energy of escaping target, φ_j^v is the ratio of the sailing speed of BAUV j to the sailing speed of the escaping target, φ_j^l is the reciprocal of the distance between BAUV j and the escaping target, and λ_1, λ_2, and λ_3 are the weight coefficient.

In summary, the revenue of BAUV j is the benefit minus energy consumption. The benefit refers to the satisfaction of BAUV j with the hunting task. The energy consumption refers to the energy consumption of BAUV j to complete complex hunting task. Therefore, the revenue of BAUV j can be defined as

$$\begin{aligned} U_j &= Y_j - E_j^1 - E_j^2 \\ &= \beta_j \ln\left(1 + t_j\right) + t_j r_j - \frac{C \rho v_j^3 S_j t_j}{2\eta} - \frac{\delta_j P_j^{\text{tran}}}{R_j} \frac{t_j}{\vartheta_j}. \end{aligned} \tag{13}$$

C. TAUV's Model

In order to quickly trace the escaping target, the TAUV assigns hunting tasks through the CN. Therefore, when an escaping target is successfully hunted, the TAUV can obtain a hunting benefit. The hunting benefit of the TAUV is

$$R_z = R_A + R_B \exp(-\lambda_4 \beta_z) \tag{14}$$

where R_A is the fixed hunting benefit of the TAUV, R_B is the variable hunting benefit of the TAUV, and λ_4 is the weight coefficient. The task-matching coefficient β_z of the TAUV is

$$\beta_z = \lambda_1 \varphi_z^E + \lambda_2 \varphi_z^v + \lambda_3 \varphi_z^l \tag{15}$$

where φ_z^E is the ratio of the remaining energy of the TAUV to the remaining energy of escaping target, φ_z^v is the ratio of the sailing speed of the TAUV to the sailing speed of the escaping target, and φ_z^l is the reciprocal of the distance between the TAUV and the escaping target.

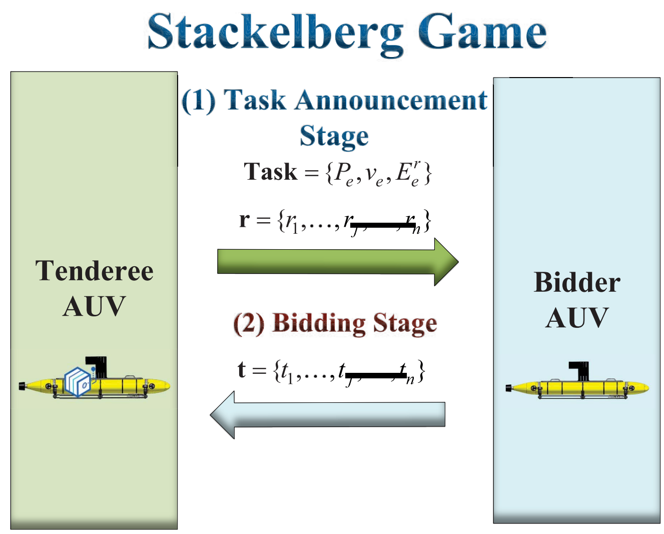

Fig. 3. Stackelberg game model.

So far, the revenue of the TAUV is the hunting benefit minus reward expenditure. The hunting benefit refers to the benefit of the TAUV successfully hunting an escaping target. The reward expenditure refers to the reward that motivates BAUVs to participate in the distribution of hunting tasks. Therefore, the revenue of the TAUV with respect to BAUV j can be defined as

$$\begin{aligned} U_{z,j} &= R_z - E_z - r_j t_j \\ &= R_A + R_B \exp(-\lambda_4 \beta_z) - \frac{\delta_j P_z^{\text{rece}}}{R_j} \frac{t_j}{\vartheta_j} - r_j t_j. \end{aligned} \tag{16}$$

IV. Game Formulation and Analysis

This section defines the game model of BAUVs and the TAUV as a Stackelberg game and uses the backward induction method to analyze the SE of the model. Finally, SSA_SDM is proposed to reach the SE.

A. Game Model for the TAUV-BAUV

As shown in Fig. 3, the game problem between the TAUV and BAUVs is modeled as a Stackelberg game. As the leader of the game model, the TAUV determines its reward strategy $\mathbf{r} = \{r_1, \ldots, r_j, \ldots, r_n\}$ to ensure its own benefits. As a follower of the game model, each BAUV determines its bidding strategy, i.e., working time t_j, to maximize its own benefits. Therefore, the game problem between the TAUV and BAUVs can be formally defined as the following:

$$\begin{aligned} \Theta = \Big\{ &(\text{TAUV} \cup \textbf{BAUV}); t_1, \ldots, t_j, \ldots, t_n; U_1, \ldots, U_j, \ldots \\ &U_n; r_1, \ldots, r_j, \ldots, r_n; U_{z,1}, \ldots, U_{z,j}, \ldots, U_{z,n} \Big\} \end{aligned} \tag{17}$$

where:

1) In the **BAUV** set, the BAUVs choose the bidding strategy $\mathbf{t} = \{t_1, \ldots, t_j, \ldots, t_n\}$ to deal with the reward strategy of the TAUV;
2) $\{U_1, \ldots, U_j, \ldots, U_n\}$ is the revenue of each BAUV in the **BAUV** set, i.e., (13);

3) $\{r_1, \ldots, r_j, \ldots, r_n\}$ is the reward strategy of the TAUV;
4) $\{U_{z,1}, \ldots, U_{z,j}, \ldots, U_{z,n}\}$ is the revenue of the TAUV with respect to the BAUVs, i.e., (16).

For each BAUV, it maximizes its own revenue by adjusting its bidding strategy. Therefore, the optimization model for each BAUV is

$$\begin{aligned} \text{Problem} \underset{t_j}{:} \ \max \ & U_j \quad \forall j \in \mathbf{BAUV} \\ \text{s.t.} \ & t_{\min} \le t_j \le t_{\max} \\ & E_j^1 + E_j^2 \le E_j^r \end{aligned} \tag{18}$$

where $t_{\min}$ and $t_{\max}$ are the value range of BAUV j working time, and $E_j^1 + E_j^2 \le E_j^r$ refers to the energy consumption of BAUV j during the execution of the hunting task cannot be greater than its remaining energy.

Meanwhile, the TAUV ensures its own revenue by adjusting the reward strategy for each BAUV. Therefore, the optimization model for the TAUV is

$$\begin{aligned} \text{Problem} \underset{r_j}{:} \ \max \ & U_{z,j} \quad \forall j \in \mathbf{BAUV} \\ \text{s.t.} \ & 0 \le r_j \le r_{\max} \end{aligned} \tag{19}$$

where $r_{\max}$ is the upper limit value of the TAUV's reward.

B. Analysis of Game Problem

For the Stackelberg game composed of above two optimization problems, we use the backward induction method to solve the SE of the model.

In the first stage, we analyze the optimal bidding strategy for BAUVs.

Definition 1: Let $\mathbf{r}^*$ denote the optimal reward strategy of the TAUV, i.e., $\mathbf{r}^* = \{r_1{}^*, \ldots, r_j{}^*, \ldots, r_n{}^*\}$. When the game reaches the SE, any BAUV cannot increase its revenue by changing its own bidding strategy [38], [39]. The specific formula is

$$U_j\left(t_j^*, \mathbf{t}_{-j}^*, \mathbf{r}^*\right) \ge U_j\left(t_j, \mathbf{t}_{-j}^*, \mathbf{r}^*\right) \quad \forall j \in \mathbf{BAUV} \tag{20}$$

where t_j^* is the optimal bidding strategy for BAUV j and $\mathbf{t}_{-j}^*$ is the optimal bidding strategy for other BAUVs.

Theorem 1: In the first stage, a unique SE exists [40], [41] if the following conditions are satisfied.

1) The strategy set of each BAUV is nonempty, convex, and compact.
2) Each BAUV has a unique bidding strategy in response to the reward strategy of the TAUV.

Proof: It can be seen from (18) that the strategy of each BAUV is nonempty, convex, and compact.

Then, the first-order reciprocal of (18) with respect to t_j can be expressed as

$$\frac{\partial U_j}{\partial t_j} = \frac{\beta_j}{1+t_j} + r_j - \frac{C\rho v_j^3 S_j}{2\eta} - \frac{\delta_j P_j^{\text{tran}}}{R_j \vartheta_j}. \tag{21}$$

Setting (21) equal to 0, we can obtain t_j^{BAUV}

$$t_j^{\text{BAUV}} = \frac{\beta_j}{\frac{C\rho v_j^3 S_j}{2\eta} + \frac{\delta_j P_j^{\text{tran}}}{R_j \vartheta_j} - r_j} - 1. \tag{22}$$

The second-order reciprocal of (18) with respect to t_j can be expressed as

$$\frac{\partial^2 U_j}{\partial t_j^2} = \frac{-\beta_j}{\left(1+t_j\right)^2}. \tag{23}$$

Equation (23) is less than 0 since $\beta_j > 0$ and $t_j > 0$. It can be seen that the revenue function of BAUVs is a convex function, and each BAUV has the best response strategy to deal with the reward strategy of the TAUV.

Therefore, the proof of Theorem 1 is completed. ■

In the second stage, the optimal reward strategy for TAUV is analyzed.

Definition 2: Let $\mathbf{t}^*$ denote the optimal bidding strategy of BAUVs, i.e., $\mathbf{t}^* = \{t_1{}^*, \ldots, t_j{}^*, \ldots, t_n{}^*\}$. When the game reaches the SE, the TAUV cannot increase its revenue by changing its own reward strategy [38], [39]. The specific formula is

$$U_{z,j}\left(r_j^*, \mathbf{t}^*\right) \ge U_{z,j}\left(r_j, \mathbf{t}^*\right) \quad \forall j \in \mathbf{BAUV}. \tag{24}$$

Theorem 2: If there is a unique SE in the second stage [40], [41], it needs to meet the following conditions.

1) The strategy set of the TAUV is nonempty, convex, and compact.
2) The TAUV has a unique reward strategy in response to the optimal bidding strategy of the TAUV.

Proof: According to (19), the strategy of the TAUV is nonempty, convex, and compact.

Substituting the best response strategy of BAUV t_j^{BAUV} into (16), the revenue of the TAUV is rewritten as

$$\begin{aligned} U_{z,j} = {} & R_A + R_B \exp(-\lambda_4 \beta_z) - K_1\left(\frac{\beta_j}{K_2 + K_3 - r_j} - 1\right) \\ & - r_j\left(\frac{\beta_j}{K_2 + K_3 - r_j} - 1\right) \end{aligned} \tag{25}$$

where $K_1 = (\delta_j P_z^{\text{rece}}/R_j)(1/\vartheta_j)$, $K_2 = (C\rho v_j^3 S_j/2\eta)$, and $K_3 = (\delta_j P_j^{\text{tran}}/R_j \vartheta_j)$.

Then, the first-order reciprocal of (25) with respect to r_j can be expressed as

$$\begin{aligned} \frac{\partial U_{z,j}}{\partial r_j} = {} & -\frac{K_1 \beta_j}{\left(K_2 + K_3 - r_j\right)^2} \\ & - \frac{\beta_j}{K_2 + K_3 - r_j} - \frac{r_j \beta_j}{\left(K_2 + K_3 - r_j\right)^2} + 2. \end{aligned} \tag{26}$$

The second-order reciprocal of (25) with respect to r_j can be expressed as

$$\begin{aligned} \frac{\partial^2 U_{z,j}}{\partial r_j^2} = {} & -\frac{2K_1 \beta_j}{\left(K_2 + K_3 - r_j\right)^3} - \frac{2\beta_j}{\left(K_2 + K_3 - r_j\right)^2} \\ & - \frac{2 r_j \beta_j}{\left(K_2 + K_3 - r_j\right)^3} < 0. \end{aligned} \tag{27}$$

Equation (27) is less than 0 since $K_1 > 0$, $K_2 > 0$, $K_3 > 0$ and $\beta_j > 0$. Hence, the revenue function of the TAUV is a convex function, and the TAUV has the best response strategy to deal with the bidding strategy of BAUVs.

Therefore, the proof of Theorem 2 is completed. ■

Algorithm 1 SSA_SDM

Require: The number of BAUV n, The seawater density ρ, The path loss factor τ, and other parameters;
Ensure: The optimal revenue of BAUV j U_j^* and the optimal revenue of the TAUV $U_{z,j}^*$;
Initialization $\psi = 0$, the maximum number of iterations $\alpha = 80$, the step size $\varsigma = 1$, and other parameters;
$\mathbf{r}, \mathbf{t} \Leftarrow$ Randomly generate;
while $\psi < \alpha$ **do**
    $\varsigma \Leftarrow$ The TAUV updates a step size according to the steepest descent method;
    $\mathbf{r}(\psi) \Leftarrow$ The TAUV performs the update operation of steepest descent method for the formula (19);
    $U_{z,j}(\psi) \Leftarrow$ The formula (19);
    $\mathbf{t}(\psi) \Leftarrow$ Each BAUV use the MOSEK solver for the formula (18) ;
    $U_j(\psi) \Leftarrow$ The formula (18);
    $\psi = \psi + 1$;
end while
$\mathbf{r}^* = \mathbf{r}(\psi), \mathbf{t}^* = \mathbf{t}(\psi)$;
$U_{z,j}^*(\psi) \Leftarrow$ The formula (19), $U_j^* \Leftarrow$ The formula (18);
return $U_{z,j}^*$, U_j^*,

C. Algorithm to Reach the SE

This section proposes the SSA_SDM to obtain the optimal strategies of BAUVs and the TAUV. Since the steepest descent method speeds up the convergence speed by optimizing the step size, it is widely used in many fields [42], [43].

The pseudocode of SSA_SDM is illustrated in Algorithm 1. First, the proposed algorithm initializes the current iteration number ψ, the maximum number of iterations α, the step size ς, and other parameters. Then, the TAUV optimizes the step size according to the steepest descent method. At the same time, the TAUV performs an update operation of the steepest descent method for (19). The TAUV calculates its own revenue $U_{z,j}(\psi)$ according to (19). For each BAUV, it updates its own bidding strategy according to the MOSEK solver. Then, each BAUV calculates its own revenue $U_j(\psi)$ according to (18). If the current iteration number ψ is greater than the maximum number of iterations α, the proposed algorithm can obtain the optimal revenue of the TAUV $U_{z,j}^*$ and the optimal revenue of BAUVs U_j^*.

The time complexity of SSA_SDM is analyzed on the basis of pseudocode. SSA_SDM mainly includes four parts, such as the update operation of the steepest descent method, the update operation of MOSEK solver, revenue calculation of BAUVs, and the TAUV. The first part is that SSA_SDM uses the update operation of the steepest descent method to obtain the updated reward strategy $r(\psi)$. The time complexity of part is $\Theta(\alpha n)$, where n represents the number of BAUVs. The second part is that BAUVs use the update operation of MOSEK to obtain the updated bidding strategy $t(\psi)$. The time complexity of part is $\Theta(\kappa\alpha n)$, where κ represents the time complexity of MOSEK. The third part is that SSA_SDM calculates the revenue of BAUVs and the TAUV according to (18) and (19), respectively. The time complexity of part is $\Theta(\alpha n)$. In summary, the time complexity of SSA_SDM is $\Theta(\kappa\alpha n)$.

TABLE II
PERFORMANCE PARAMETERS OF HUNTER AUVS

Number	The sailing speed v_j (m/s)	The remaining energy E_j^r (J)	The type
1	2.5	2.0×10^5	BAUV
2	2.5	2.0×10^5	BAUV
3	2.0	2.5×10^5	BAUV
4	2.0	2.5×10^5	BAUV
5	1.5	1.8×10^5	BAUV
6	1.5	1.8×10^5	BAUV
7	2.0	2.0×10^5	TAUV

TABLE III
SIMULATION AND PARAMETERS

Parameters	Value	Parameters	Value
S_j	0.035 m^2	ρ	1.03 g/cm^3
τ	1.5	o_j	300 m
f_j	25 Khz	P_j^{tran}	0.1 W
b_j	1 Khz	ε_1	1
ε_2	0	ϑ_j	120 s
P_z^{rece}	8×10^{-4} W	n	6
R_A	40	R_B	30
α	80	ψ	0
λ_1	45	λ_2	45
λ_3	45	λ_4	0.01

V. SIMULATION RESULTS

A. Simulation Setup

This section analyzes the performance of SSA_SDM from convergence, parameter influence, and performance comparison. We set up a multi-AUV formation composed of seven hunter AUVs. Among them, the performance parameters of hunter AUVs are shown in Table II.

The sailing speed v_e and remaining energy E_e^r of the escaping target are 2.0 m/s and 2.0×10^5 J, respectively. In terms of the motion model and communication model, we set the corresponding parameters of hunter AUVs according to [44], [45], and [46]. Table III presents a summary of key parameters used in our simulation. In this section, we choose the average revenue of the TAUV and BAUVs as evaluation indicators.

To validate performance advantages, this section selects the following existing algorithms for performance comparison with the proposed SSA_SDM.

1) *Random Reward Algorithm (RRA) [39]:* In the game model, the TAUV randomly determines its reward strategy, while the BAUVs use an optimization algorithm to determine their bidding strategy.
2) *Fixed Reward Algorithm (FRA) [47]:* The TAUV does not change its own reward strategy, while the

TABLE IV
IMPACT OF λ_1 ON THE AVERAGE REVENUE OF THE TAUV

The sailing speed of escaping target v_e	The average revenue of the TAUV					
	$\lambda_1 = 20$	$\lambda_1 = 25$	$\lambda_1 = 30$	$\lambda_1 = 35$	$\lambda_1 = 40$	$\lambda_1 = 45$
1.7 (m/s)	47.40	46.68	46.09	45.61	45.24	44.98
2.0 (m/s)	48.75	47.84	47.07	46.43	45.91	45.51
2.3 (m/s)	49.92	48.87	47.96	47.19	46.55	46.03

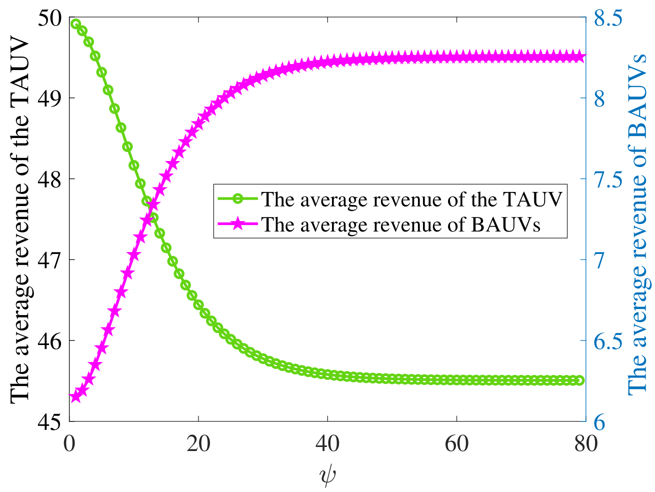

Fig. 4. Convergence behavior.

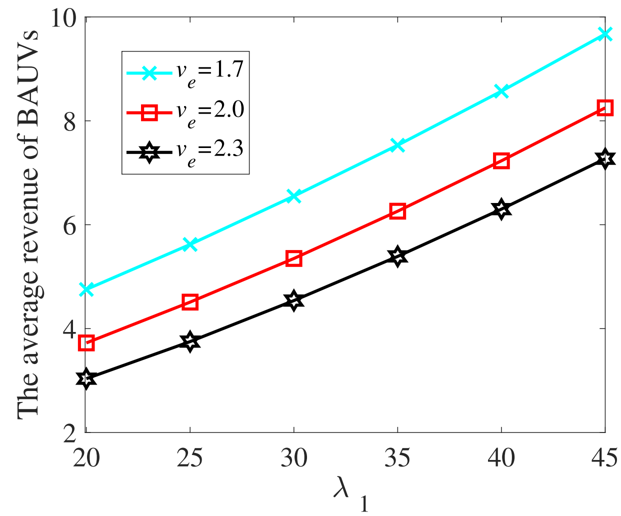

Fig. 5. Impact of λ_1 on the average revenue of BAUVs.

BAUVs determine the bidding strategy according to the maximization principle.

3) *Differential Reward Algorithm (DRA) [48]:* The TAUV determines the reward strategy according to its task-matching coefficient, while the BAUVs also determine the bidding strategy according to their task-matching coefficient.

B. Convergence Performance

Fig. 4 presents the convergence behavior of the average revenue of BAUVs and the TAUV. Among them, the average revenue of the TAUV refers to the TAUV obtains the average revenue by assigning hunting tasks, the average revenue of BAUVs refers to BAUVs obtain the average revenue by accepting hunting tasks, and range of iteration number ψ is 1 to 80. It is clear that the average revenue of the TAUV and BAUVs reach a convergence state when the number of iterations ψ is 40. According to Fig. 4, we can find that as the number of iterations ψ increases, the average revenue of BAUVs gradually increases, and a convergence value (8.25) is obtained when the number of iterations ψ is 40. In addition, we can see that as the number of iterations ψ increases, the decline in the average revenue of the TAUV decreases gradually, and a convergence value (45.51) is obtained when the number of iterations ψ is 40. In summary, these results show that SSA_SDM can guarantee the average revenue of BAUVs and the TAUV, i.e., achieve the SE.

C. Impact of Parameters

The purpose of this section is to analyze the impact of λ_1 and λ_2 on the average revenue of BAUVs and the TAUV. Fig. 5 shows the impact of λ_1 on the average revenue of BAUVs. Among them, the range of sailing speed of escaping target v_e is 1.7 to 2.3, range of weight coefficient λ_1 is 20 to 45, average revenue of BAUVs have the same meaning as in Section V-B. It is obvious that as the λ_1 increases, the average revenue of BAUVs gradually increases. The specific reason is that the increase of λ_1 can improve the benefit of BAUVs. In addition, it is not difficult to find that the average revenue of BAUVs gradually decreases as the sailing speed of the escaping target v_e increases. This is because an increment in the sailing speed of escaping target v_e will lead to an increase in the energy consumption of BAUVs.

Table IV summarizes the impact of λ_1 on the average revenue of the TAUV. Among them, the range of sailing speed of escaping target v_e is 1.7 to 2.3, range of weight coefficient λ_1 is 20 to 45, average revenue of the TAUV have the same meaning as in Section V-B. We can observe that as the λ_1 increases, the average revenue of the TAUV decreases gradually. The reason for this phenomenon is that the increase of λ_1 ensures the enthusiasm of BAUVs to participate in hunting, which leads to the TAUV spending more on reward expenditures. In addition, we can find that the average revenue of TAUV gradually increases as the sailing speed of the escaping target increases.

TABLE V
IMPACT OF λ_2 ON THE AVERAGE REVENUE OF THE TAUV

The sailing speed of escaping target v_e	The average revenue of the TAUV					
	$\lambda_2 = 20$	$\lambda_2 = 25$	$\lambda_2 = 30$	$\lambda_2 = 35$	$\lambda_2 = 40$	$\lambda_2 = 45$
1.7 (m/s)	47.99	47.14	46.43	45.83	45.35	44.98
2.0 (m/s)	48.57	47.77	47.07	46.43	45.91	45.51
2.3 (m/s)	49.03	48.28	47.61	47.01	46.48	45.98

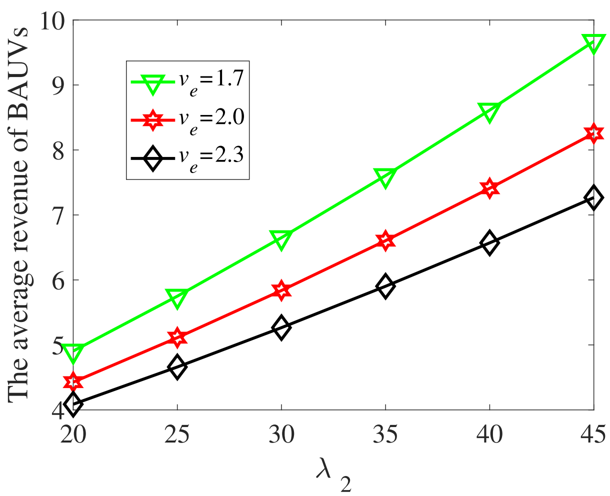

Fig. 6. Impact of λ_2 on the average revenue of BAUVs.

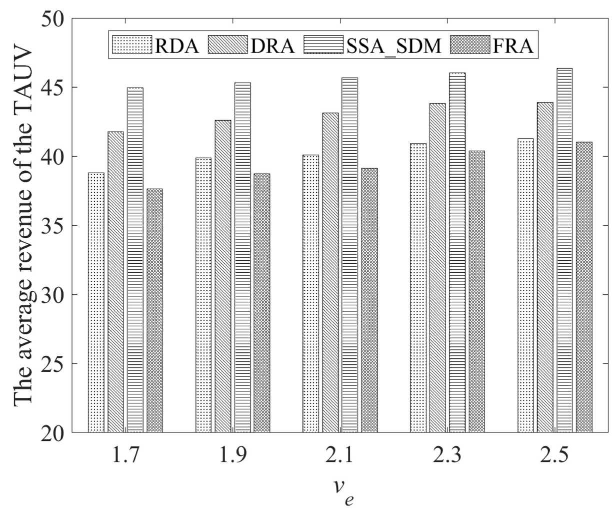

Fig. 7. Impact of different algorithms on the average revenue of the TAUV.

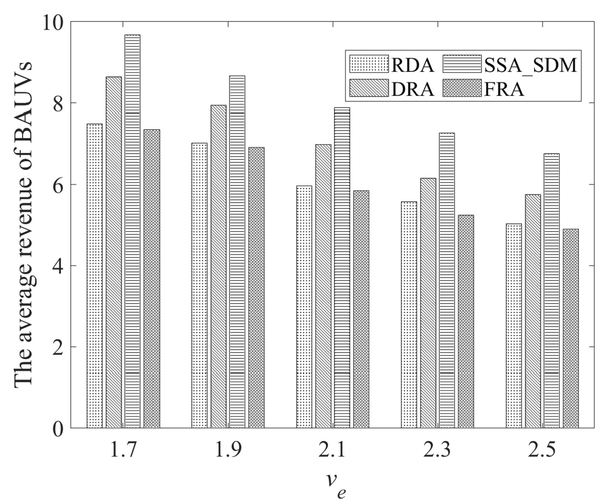

Fig. 8. Impact of different algorithms on the average revenue of BAUVs.

Fig. 6 illustrates the impact of λ_2 on the average revenue of BAUVs. Among them, the range of sailing speed of escaping target v_e is 1.7 to 2.3, range of weight coefficient λ_2 is 20 to 45, average revenue of BAUVs have the same meaning as in Section V-B. It is apparent from Fig. 6 that as the λ_2 increases, the average revenue of BAUVs increases gradually. In addition, Table V summarizes the impact of λ_2 on the average revenue of the TAUV. Among them, the range of sailing speed of escaping target v_e is 1.7 to 2.3, range of weight coefficient λ_2 is 20 to 45, average revenue of the TAUV have the same meaning as in Section V-B. What stands out in Table V is that there is an obvious trend that the average revenue of the TAUV gradually decreases as the λ_2 increases. The reasons for these phenomena are similar to the impact of the λ_1 on the average revenue of BAUVs and the TAUV.

D. Performance Comparison

Figs. 7 and 8 compare the impact of different algorithms on the average revenue of BAUVs and the TAUV. Among them, the range of sailing speed of escaping target v_e is 1.7 to 2.5, RDA, DRA, and FRA are different algorithms, average revenue of the TAUV and average revenue of BAUVs have the same meaning as in Section V-B. It is apparent from Figs. 7 and 8 that SSA_SDM outperforms the existing algorithms in terms of the average revenue of BAUVs and the TAUV. The explanation for this phenomenon is that the proposed algorithm obtains the optimal revenue of BAUVs and the TAUV through two-layer optimization. The performance of DRA is better than that of RDA and FDA in terms of average revenue of BAUVs and the TAUV. This is because DRA adjusts the reward strategy of TAUV according to the task-matching coefficient. The performance of RDA is close to that of FDA in terms of the average revenue of BAUVs and the TAUV. The result is related to their failure to consider the game strategy when adjusting the reward strategy of TAUV.

VI. Conclusion

This article aims to ensure the revenue of BAUVs and the TAUV when the multi-AUV formation performs hunting task assignments. First, a hunting task assignment framework based on CN is proposed, which is used to complete the hunting task allocation under a distributed architecture. In this framework, the TAUV attracts BAUVs to participate in hunting tasks by setting task rewards, while BAUVs compete for hunting tasks by setting their own working hours. According to the mobile energy consumption and communication energy consumption of hunter AUVs, we establish the revenue optimization model of BAUVs and the TAUV. In addition, the interaction process of hunting task allocation between BAUV and TAUV is modeled as a Stackelberg game, and the existence of SE in this game is analyzed by the backward induction method. Finally, we propose SSA_SDM to obtain the optimal strategy of BAUVs and the TAUV, which can maximize the revenue of BAUVs and the TAUV. Extensive simulation results show that SSA_SDM can maximize the revenue of BAUVs and the TAUV, and is better than the comparison algorithms. In terms of future research directions, further work can focus on the optimization of the proposed method. In particular, we will further consider the impact of the following factors on task allocation.

1) The information of escaping targets cannot be fully obtained.
2) The hunter AUVs have the possibility of malfunction.

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