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Secrecy capacity maximization in autonomous underwater vehicle-enabled underwater acoustic sensor networks

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Abstract

Data collection plays an essential role in underwater acoustic sensor networks (UASNs). To address the problem of underwater information collection, autonomous underwater vehicles (AUVs), which are dynamic and easy to reprogram, are expected to provide a feasible data-gathering solution. In this study, we examined covert data collection in AUV-assisted UASNs. Specifically, an AUV gathers covert information from all underwater sensor nodes (USNs) at the planned time, while an eavesdropper attempts to eavesdrop on this secret information. To improve the performance of UASNs, we formulate a complex optimization problem to maximize secrecy capacity under the constraints of the trajectory of the AUV, USN scheduling, connection outage probability, and secrecy outage probability. To solve the nonconvex problem, an efficient iterative optimization algorithm is proposed to optimize USN scheduling and AUV trajectories. Numerical results demonstrate the effectiveness of the proposed algorithm.

KEYWORDS

autonomous underwater vehicle (AUV), data collection, trajectory optimization, underwater acoustic sensor network (UASN)

1 | INTRODUCTION

With the rapid development of social technology, land resources have gradually become unable to meet human needs. Therefore, underwater acoustic sensor networks (UASNs) are considered to be a promising technology and indispensable component of smart oceans [1]. UASNs have been gradually applied in multiple fields such as military activities, resource surveying, and disaster warning [2,3]. Compared with traditional terrestrial microwave radio communication methods, sound waves, which have a longer transmission distance and less propagation attenuation, are considered to be the most reliable transmission method for long-distance underwater transmission [4]. However, the long-distance transmission and energy consumption of underwater sensors have resulted in several problems for UASNs. Autonomous underwater vehicles (AUVs) with flexible deployment and user-friendly operations are emerging as viable options for mobile data collectors in UASNs [5]. Therefore, research on AUV-enabled secure UASNs is critical.

Although AUVs are convenient for underwater acoustic (UWA) communications, transmitted information is prone to eavesdropping by malicious eavesdroppers (Eves) or unauthorized nodes as a result of the broadcast qualities of UWA channels [6]. For example, in underwater surveillance missions or oceanographic research, critical data can be exposed to adversaries, potentially compromising mission objectives. This vulnerability highlights the importance of designing secure communication mechanisms for UWA networks.

Traditionally, researchers have used upper-layer encryption methods for private communications. Although these methods are effective when the Eve's computational power is limited, they fail to adapt to the dynamic nature of UWA channels [7]. Furthermore, cryptographic methods with high computational complexity are impractical in UASNs, considering the limited energy of sensors and constrained bandwidth of UWA channels. Fortunately, physical-layer security (PLS) has emerged as a promising and secure communication technology that leverages the characteristics of a communication channel itself [8]. However, most current PLS studies assume that the channel state information (CSI) of an Eve is entirely available, which is often unrealistic in real-world underwater scenarios. In practice, the dynamic nature of the underwater environment and mobility of nodes make it almost impossible to obtain the accurate or complete CSI of an Eve. This gap in the literature motivated us to explore secure communication strategies under the practical constraints of unknown CSI.

In addition to security challenges, the introduction of AUVs creates new opportunities and unique challenges in UWA networks [9]. Considering the limited energy consumption of sensors and AUVs, the effective reduction of energy consumption through approaches such as wake-up mechanisms [10] can effectively improve the service life of wireless networks. Additionally, AUVs operate in a three-dimensional underwater environment, offering unparalleled flexibility in trajectory design. However, this flexibility results in increased energy consumption, necessitating careful trajectory planning to balance network performance and energy efficiency. By jointly optimizing the trajectories of AUVs and scheduling of underwater sensor nodes (USNs), it is possible to enhance both the secrecy capacity (SC) and energy efficiency of networks [11].

Motivated by the aforementioned challenges, we aimed to develop an energy-efficient method for gathering data from AUV-assisted UASNs. Specifically, we propose an algorithm that maximizes SC by jointly optimizing AUV trajectories and USN scheduling, while addressing the practical challenge of an unknown Eve's CSI. The main contributions of this study can be summarized as follows.

- We investigate AUV-assisted UASNs and address the problem of unknown CSI in eavesdropping links. By accounting for the unique characteristics of UWA channels, including path loss and complex noise sources, we derive a secrecy rate expression that integrates these factors into the underwater secure communication design.
- We discuss a tractable SC optimization problem by deriving the SC in closed-form expressions. Then, an SC maximization problem is formulated to optimize USN scheduling and AUV trajectories jointly under the constraints of the connection outage probability (COP), secrecy outage probability (SOP), communication requirements, and AUV trajectories.
- We propose an optimization algorithm for decomposing the nonconvex problem into two subproblems based on the block coordinate descent (BCD) method, namely, USN scheduling and AUV trajectory optimization. The relaxation approach is used to solve the subproblem of USN scheduling first, followed by sequential convex approximation of the AUV trajectory. Simulation results verify the resulting superiority of SC performance.

The remainder of this paper is organized as follows. Section 2 discusses relevant work. The proposed system model is discussed in Section 3. Section 4 formulates and transforms the SC optimization problem into a tractable problem. To address the transformed problem, Section 5 proposes an iterative optimization algorithm. Simulation results are presented in Section 6. Finally, we provide a summary in Section 7.

2 | RELATED WORK

2.1 | Foundations of UWA networks

UWA networks face fundamental challenges such as limited bandwidth, high-energy consumption, and environmental noise, which hinder their efficiency and scalability. To extend network lifetimes, Ryu and others [12] proposed a maximum or minimax Q-learning (M-Qubed)-based opportunistic routing method for underwater sensor networks that dynamically selects relay nodes and leverages reinforcement learning to optimize outcomes in a two-player game, reducing energy loss from jamming attacks and improving routing efficiency. In their research on underwater networks related to energy harvesting, Wang and others [13] suggested a learning strategy to maximize long-term communication throughput. The link-layer network flow was optimized by determining a feasible solution to the least-squares problem, considering the transmission delay of UWA channels [14], to extend the network's operational period. In underwater environments, it is impractical to employ a fixed channel gain over time [15]. To reduce the possibility of an outage in a single-decode-and-forward-relay UAN, Wang and others [16] proposed a multi-AUV communication scheme based on OFDMA downlink communication, incorporating a motion-sensing-based time control scheme and low-complexity subcarrier allocation algorithm to ensure reliable, real-time communication with reduced energy consumption, and improved bit error rate performance. In [17], Song and others proposed a method for optimizing the power of a base station and AUV scheduling to maximize the total throughput and energy efficiency in a downlink UAN. Although traditional UANs are limited by a fixed infrastructure and static nodes, the introduction of AUVs offers a dynamic and scalable solution for addressing these challenges.

2.2 | Enhancing UAN performance using AUVs

The introduction of AUVs significantly improves network flexibility and adaptability, enabling dynamic data collection and extended coverage. To enhance the performance of UAN systems further, Huang and others [18] proposed an energy-effective and reliable data collection scheme for UASNs using AUVs. They optimized AUV trajectories using a two-phase mechanism, selected secondary cluster heads to reduce the workload, and employed matrix completion for in-cluster data collection. Lin and others [18] focused on enhancing the controllability and scalability of AUV-assisted underwater wireless networks (UWNs) using software-defined networking (SDN). They divided UWNs into three layers, enabling data transmission, synchronization, and collection among AUVs. Gong and others [19] proposed a more economical and scalable approach to localization and time synchronization in underwater sensor networks by utilizing an AUV as a mobile anchor instead of a fixed buoy on the sea surface. Zeng and others [20] presented a novel simultaneous wireless power and data transfer system for AUV swarms. Their system achieves the advantages of a low core volume and high strength through the optimization of coil parameters using a multi-objective genetic algorithm. Chiche and others [21] proposed a sizing strategy for hybrid fuel cell/battery systems in AUVs to increase their range and endurance. By analyzing real AUV mission power profiles, their strategy identifies the optimum combination of battery size and fuel cell power.

Although AUVs significantly enhance UAN performance, their inherent mobility and broadcast nature introduce new security vulnerabilities, particularly in scenarios involving sensitive information transmission.

2.3 | Information security challenges in AUV-enabled UANs

AUV-assisted networks are particularly vulnerable to eavesdropping considering the broadcast nature of UWA channels, making secure communication a critical concern. Su and others [22] addressed the security risks in UASNs in hostile environments by proposing a secure transmission scheme using collaborative interference from auxiliary nodes to ensure data secrecy. A privacy protection scheme was proposed by Wang and others [23] to protect sensitive source positions in UASNs. This technique uses pseudo-random number generators for interference-free data delivery and phony source selection algorithms for passive attacks. To handle AUV path planning in dynamic and uncertain scenarios, Cao and others [24] developed a bioinspired neural network and potential field approach for AUV path planning to ensure safe and efficient obstacle avoidance. Lin and others [25] proposed an SDN-based architecture for multi-AUV collaboration that integrates beaconing, localization, cooperative control, and hybrid data scheduling. UASN location privacy protection against passive attacks was the primary focus of Han and others [26]. To protect node locations, the proposed privacy protection scheme, which is based on data importance, considers data relevance, AUV privacy breaches, and secure multi-hop transmission with false nodes. Simulation results demonstrate its success in terms of delay and safety time, with applications aimed at improving network security in smart ocean applications. These studies highlight the need for an integrated approach that combines trajectory design and scheduling optimization with SC enhancement to address the unique challenges posed by AUV-assisted UANs.

Existing research on UANs has primarily focused on optimizing their performance in terms of bandwidth, energy efficiency, and data throughput, with recent studies highlighting the benefits of using AUVs to improve flexibility and scalability. However, although AUVs enhance network performance, they also introduce new challenges, particularly in terms of energy optimization and trajectory planning. Additionally, security in AUV-enabled networks remains a critical concern, particularly with regard to vulnerability to eavesdropping. Most security approaches assume perfect knowledge of an Eve's CSI, which is often unrealistic. This paper addresses these gaps by proposing a method to optimize AUV trajectories and sensor scheduling jointly to maximize SC in a scenario where an Eve's CSI is unknown, thereby improving both performance and security in underwater networks.

3 | SYSTEM MODEL

AN AUV-enabled UASN consists of USNs for data collection, an AUV that gathers covert information from N sensor nodes, and an Eve that attempts to intercept transmissions, as shown in Figure 1. AUVs use in-band full-duplex communication technology that enables them to receive data and emit jamming signals simultaneously to disrupt an Eve's attempts [27]. This approach ensures secure and efficient communication by leveraging recent advances in UWA networks. This paper introduces a 3D Cartesian coordinate system to assist in further data processing and prevent a significant loss of generality. The set of USNs is denoted as $\mathcal{N} = \{1, ..., N\}$. The locations of the n-th USN, Eve, and AUV are denoted as $z_n = \{x_n, y_n, H_n\}$, $z_e = \{x_e[i], y_e[i], H_e\}$ and $z_a = \{x_a[i], y_a[i], H_a\}$, where x_n, x_e, x_a and y_n, y_e, y_a represent the horizontal coordinates of the USN, Eve, and AUV, respectively. H_n, H_e, H_a represent the heights of the USN, Eve, and AUV, respectively. i denotes the time gap after the total task time T is discretized into I parts, where $i = \{1, 2, ..., I\}$. Each time slot has a length of θ. Therefore, $T = \theta I$. The initial and final locations of the AUV execution tasks are assumed to be predetermined and expressed as $z_a^0 = \{x_0, y_0, H_a\}$ and $z_a^M = \{x_M, y_M, H_a\}$. Additionally, communication between the AUV and USNs utilizes the time-division multiple access method.

Seawater absorbs the propagation of UWA signals, which differs from ground wireless communication channels. Consequently, the pass loss over distance d is expressed as follows:

$$\mathrm{F}(d, f) = d^k \beta(f)^d, \tag{1}$$

where $k = 1.5$ denotes the propagation geometry and f denotes the signal frequency. The absorption coefficient $\beta(f)$ is expressed as [28]

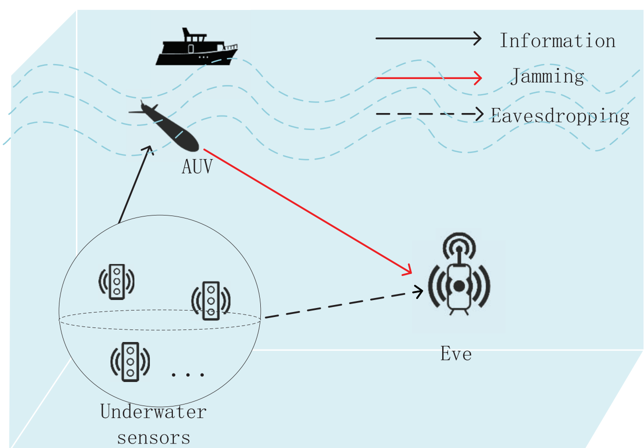

FIGURE 1 System model.

$$10\log\beta(f) = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f^2} + 0.000275f^2 + 0.003. \tag{2}$$

Therefore, the channel gains from USN n to AUV $g_{n,\mathrm{auv}}[i]$, USN n to Eve $g_{n,e}[i]$, and AUV to Eve $g_{\mathrm{auv},e}[i]$ can be expressed as follows:

$$\begin{aligned} g_{n,\mathrm{auv}}[i] &= \frac{1}{\mathrm{F}(d_{n,\mathrm{auv}}[i], f)} = \frac{1}{\mathrm{F}_0 d_{n,a}^k[i]\beta(f)^{d_{n,\mathrm{auv}}[i]}}, \\ g_{n,e}[i] &= \frac{1}{\mathrm{F}(d_{n,e}[i], f)} = \frac{1}{\mathrm{F}_0 d_{n,e}^k[i]\beta(f)^{d_{n,e}[i]}}, \\ g_{\mathrm{auv},e}[i] &= \frac{1}{\mathrm{F}(d_{\mathrm{auv},e}[i], f)} = \frac{1}{\mathrm{F}_0 d_{\mathrm{auv},e}^k[i]\beta(f)^{d_{\mathrm{auv},e}[i]}}, \end{aligned} \tag{3}$$

where $d_{n,\mathrm{auv}}[i] = \|z_n - z_a\|$ and $d_{n,e}[i] = \|z_n - z_e\|$ are the distances between USN n and the AUV/Eve. $d_{\mathrm{auv},e}[i] = \|z_a - z_e\|$ denotes the distance between the AUV and Eve. F_0 is a unit-normalizing constant.

We assume quasi-static fading channels in which the instantaneous channel coefficients between the AUV and USNs/Eve remain constant during a single transmission period but may vary across different transmission intervals. Consequently, the instantaneous channel gains between the USN and AUV/Eve and the AUV and Eve can be represented as [29]

$$\begin{aligned} \gamma_{n,\mathrm{auv}}[i] &= \sqrt{g_{n,\mathrm{auv}}[i]}\lambda, \\ \gamma_{n,e}[i] &= \sqrt{g_{n,e}[i]}\lambda, \\ \gamma_{\mathrm{auv},e}[i] &= \sqrt{g_{\mathrm{auv},e}[i]}\lambda, \end{aligned} \tag{4}$$

where λ follows $E[|\lambda|^2] = 1$, which represents the fading component of the AUV signal to the USN channel.

The noise components of underwater communication include four sources, namely, turbulence, distant shipping, wind-driven waves, and thermal noise, which are more complex than the noise in ground communication environments. The power spectral density was calculated as follows:

$$\begin{aligned} &10\log A_{\mathrm{th}}(f) = -15 + 20\log f, \\ &10\log A_{\mathrm{w}}(f) = 50 + 7.5\sqrt{w} + 20\log f - 40\log(f + 0.4), \\ &10\log A_{\mathrm{s}}(f) = 40 + 20(s - 0.5) + 26\log f - 60\log(f + 0.03), \\ &10\log A_{\mathrm{t}}(f) = 17 - 30\log f. \end{aligned} \tag{5}$$

Therefore, the ambient noise $A(f)$ can be computed as

$$A(f) = A_t(f) + A_s(f) + A_w(f) + A_{th}(f). \tag{6}$$

Considering the limited power of USNs, we assumed the use of wake-up and data transmission policies. Specifically, the AUV communicates with one sensor through trajectory design control, while keeping the other sensors turned off. We define the binary scheduling variables $\tau_n[i] \in \{0, 1\}$ as the wake-up schedule variables in time-slot m. If USN n delivers data to the AUV, then $tau_n[i] = 1$; otherwise, $\tau_n[i] = 0$. The scheduling constraints of USNs are given by

$$\tau_n[i] \in \{0, 1\}, \sum_{n=1}^{N} \tau_n[i] \leq 1, \forall m. \tag{7}$$

The transmission powers of the AUV and USNs are denoted as P_{auv} and P_n, respectively. In time slot m, when the USNs are awakened and the AUV communicates with them, meaning $\tau_n[i] = 1$, the AUV-USN channel capacity can be expressed as

$$C_{n,\text{auv}}[i] = \log_2\left(1 + \frac{P_n |\gamma_{n,\text{auv}}[i]|^2}{A(f)}\right). \tag{8}$$

Simultaneously, the channel capacity between USN n and the Eve is given by

$$C_{n,e}[i] = \log_2\left(1 + \frac{P_n |\gamma_{n,e}[i]|^2}{P_{\text{auv}} |\gamma_{\text{auv},e}[i]|^2 + A(f)}\right). \tag{9}$$

4 | PROBLEM FORMULATION AND TRANSFORMATION

Based on the presence of the inference channel, the channel capacity $C_{n,\text{auv}}[i]$ may be less than the codeword rate $R_{n,\text{auv}}[i]$ between the AUV and USN, and the connection links may be disrupted. The COP, which is denoted as $p_n^{\text{cout}}[i]$, describes the current state and can be expressed as follows:

$$\begin{aligned} p_n^{\text{cout}}[i] &= \Pr(C_{n,\text{auv}}[i] < R_{n,\text{auv}}[i]) \\ &= \Pr\left(\log_2\left(1 + \frac{P_n |\gamma_{n,\text{auv}}[i]|^2}{A(f)}\right) < R_{n,\text{auv}}[i]\right) \\ &= \Pr\left(|\lambda|^2 < \frac{(2^{R_{n,\text{auv}}[i]} - 1)A(f)}{P_n g_{n,\text{auv}}[i]}\right) \\ &= F\left(\frac{(2^{R_{n,\text{auv}}[i]} - 1)A(f)}{P_n g_{n,\text{auv}}[i]}\right). \end{aligned} \tag{10}$$

Additionally, because the AUV is typically unable to know Eve's CSI, a secrecy outage may occur. The likelihood of this circumstance occurring, which is denoted as p_d^s, can be calculated as

$$\begin{aligned} p_d^s[i] &= \Pr(C_{n,e}[i] > R_{n,e}[i]) \\ &= \Pr\left(\log_2\left(\frac{P_n |\gamma_{n,e}[i]|^2}{P_{\text{auv}} |\gamma_{\text{auv},e}[i]|^2 + A(f)} + 1\right) > R_{n,e}[i]\right) \\ &= \Pr\left(|\lambda|^2 > \frac{(2^{R_{n,e}[i]} - 1)A(f)}{P_n g_{n,e}[i] - (2^{R_{n,e}[i]} - 1)P_{\text{auv}} g_{\text{auv},e}[i]}\right) \\ &= 1 - F\left(\frac{(2^{R_{n,e}[i]} - 1)A(f)}{P_n g_{n,e}[i] - (2^{R_{n,e}[i]} - 1)P_{\text{auv}} g_{\text{auv},e}[i]}\right). \end{aligned} \tag{11}$$

We assume that the maximum SOP and COP that the system can accept are Θ_s and Θ_c. Therefore, $p_d^c = \Theta_c$ and $p_d^s = \Theta_s$. By using (10) and (11), the throughputs of the USN-Eve and USN-AUV channels can be expressed as

$$\begin{aligned} R_{n,\text{auv}}[i] &= \log_2\left(1 + \frac{-\omega F^{-1}(\Theta_c) P_n g_{n,\text{auv}}[i]}{A(f)}\right), \\ R_{n,e}[i] &= \log_2\left(1 + \frac{-\omega F^{-1}(1 - \Theta_s) P_n g_{n,e}[i]}{A(f) - \omega ln(\Theta_s) P_{\text{auv}} g_{\text{auv},e}[i]}\right). \end{aligned} \tag{12}$$

Let $\Gamma = \{\tau_n[i]\}, \forall n, m$ and $Q = \{z_a[i]\}, \forall m$. Our objective is to maximize the SC of an AUV. The SC maximization problem can be mathematically formulated as follows:

$$\max_{\{\Gamma, Z\}} \sum_{n=1}^{N} \sum_{m=1}^{M} R_{\sec}[i] \tag{13a}$$

$$\text{s.t.} \sum_{m=1}^{M} \tau_n[i](R_{n,\text{auv}}[i] - R_{n,e}[i]) \geq \xi, \forall n, \tag{13b}$$

$$\tau_n[i] \in \{0, 1\}, \sum_{n=1}^{N} \tau_n[i] \leq 1, \forall m, \tag{13c}$$

$$\|z_a[i] - z_a[m-1]\| \leq V_{\max}\theta, \forall m \geq 2, \tag{13d}$$

$$z_a[1] = z_a^0, z_a[M] = z_a^M, \tag{13e}$$

where ξ denotes the minimum SC that must be obtained. Equation (13c) defines the scheduling constraint for the USNs. Only one USN communicates with the AUV in a single time slot. Equations (13d) and (13e) represent the AUV's mobile constraints. This is a nonconvex optimization problem. In the next section, we solve this problem by using the BCD method.

5 | SOLUTION TO THE OPTIMIZATION PROBLEM

5.1 | USN scheduling optimization

First, we solve the USN scheduling optimization problem using the supplied AUV trajectory. By loosening the binary restrictions in the optimization problem, the conventional linear program can be rewritten as follows:

Therefore, the USN scheduling problem can be rewritten as follows by relaxing the binary constraints in (13c):

$$\begin{aligned}&\max_{\{\Gamma\}}\sum_{n=1}^{N}\sum_{m=1}^{M}R_{\text{sec}}[i]\\ \text{s.t. }&\sum_{n=1}^{N}\tau_m[i](R_{n,\text{auv}}[i]-R_{n,e}[i])\geq\xi,\ \forall n,\\ &\sum_{n=1}^{N}\tau_n[i]\leq 1,\ \forall m,\ 0\leq\tau_n[i]\leq 1,\end{aligned}\tag{14}$$

where $R_{n,\text{auv}}[i]$ and $R_{n,e}[i]$ can be obtained from (12) because (14) is an integer programming problem that can be solved using convex optimization.

5.2 | AUV trajectory optimization

Subsequently, we optimize the AUV's trajectory using the given USN schedule. The trajectory planning for an AUV can be expressed as follows:

$$\max_{\{Z\}}\sum_{n=1}^{N}\sum_{m=1}^{M}R_{\text{sec}}[i]\tag{15a}$$

$$\text{s.t.}\sum_{n=1}^{N}\tau_m[i](R_{m,a}[i]-R_{m,e}[i])\geq\xi,\ \forall d,\tag{15b}$$

$$\|z_u[i]-z_u[n-1]\|\leq V_{\max}\theta,\forall n\geq 2,\tag{15c}$$

$$z_u[1]=z_u^0,\ z_u[N]=z_u^N.\tag{15d}$$

Let $R_{n,\text{auv}}[i]=\log_2(1+Z_a/D_a)$, $R_{n,e}[i]=\log_2\ (1+Z_eD_e/(N(f)D_e+G))$, where $D_a=d_{n,a}^k[i]\beta(f)^{d_{n,\text{auv}}[i]}$, $D_e=d_{a,e}^k[i]\beta(f)^{d_{\text{auv},e}[i]}$, $Z_a=(-\omega F^{-1}(\Theta_c)P_n)/(A_0N(f))$, $Z_e=-\omega F^{-1}(1-\Theta_s)P_ng_{n,e}[i]$, and $G=-\omega ln\ (\Theta_s)P_{\text{auv}0}$. Then, we have the following lemma for handling nonconvex constraints.

Lemma 1. *The lower bound of $R_{m,a}$ and upper bound of $R_{m,e}$ can be given by the following expression:*

$$\begin{aligned}R_{m,\text{auv}}^{lb}[i]&=f_1[i]+g_1[i](D_a[i]-D_a^n[i]),\\ R_{m,e}^{ub}[i]&=f_2[i]+g_2[i](D_e[i]-D_e^n[i]),\end{aligned}\tag{16}$$

where

$$\begin{aligned}f_1[i]&=\log_2\left(1+Z_a[i]/D_a^n[i]\right),\\ g_1[i]&=-\frac{Z_a[i]}{\ln 2(D_a^m[i]+Z_a[i]D_a^n[i])},\\ f_2[i]&=\log_2\left(1+\frac{Z_eD_e^n[i]}{A(f)D_e^n[i]+G}\right),\\ g_2[i]&=\frac{-\log_2^eZ_e[i]G(D_e[i]-D_e^n[i])}{(A(f)D_e^n[i]+G)((Z_e[i]+A(f))D_e^n[i]+G)}.\end{aligned}\tag{17}$$

Proof. Clearly, $R_{n,\text{auv}}[i]$ is not a convex function relative to $d_{n,\text{auv}}^k[i]$ but $R_{n,\text{auv}}[i]$ is a convex function centered on D_a. Similarly, $R_{n,e}[i]$ is a concave function of D_e. Assuming that $D^l[i]=\{D_a^n[i],D_e^n[i],\forall m\}$ reflects the trajectory planning outcomes of the AUV in the l-th iteration, and we can determine the lower limit of $R_{n,\text{auv}}[i]$ and upper bound of $R_{n,e}$ at the feasible point $z_a^l[i]$ as follows:

$$\begin{aligned}R_{n,\text{auv}}[i]&\geq R_{n,\text{auv}}^{lb}[i]=f_1[i]+g_1[i](D_a[i]-D_a^n[i]),\\ R_{n,e}[i]&\leq R_{n,e}^{ub}[i]=f_2[i]+g_2[i](D_e[i]-D_e^n[i]).\end{aligned}\tag{18}$$

■

Based on the above conclusions, the optimization problem can be approximated as follows:

$$\begin{aligned}&\max_{\{Z,D_e,D_a\}}\sum_{n=1}^{N}\sum_{m=1}^{M}\tau_n[i](R_{n,\text{auv}}^{lb}[i]-R_{n,e}^{ub}[i])\\ \text{s.t. }&\sum_{m=1}^{M}\tau_n[i]\left(R_{n,\text{auv}}^{lb}[i]-R_{n,e}^{ub}[i]\right)\geq\xi,\forall n,\\ &\|z_u[i]-z_u[n-1]\|\leq V_{\max}\theta,\ \forall n\geq 2,\\ &q_u[1]=q_u^0,\ q_u[N]=q_u^N,\\ &D_a[i]\geq d_{m,\text{auv}}^k[i]\beta(f)^{d_{m,\text{auv}}[i]},\ \forall n,m,\\ &D_e[i]\geq d_{\text{auv},e}^k[i]\beta(f)^{d_{\text{auv},e}[i]}\forall n.\end{aligned}\tag{19}$$

Equation (19) is a convex problem that can be solved efficiently using convex optimization. Algorithm 1 presents the intricacies of AUV trajectory optimization.

Algorithm 1 Trajectory planning algorithm for (19)

Initialize $Q^0[i]$ and iterations $l = 0$;
for each time solt $m \in \{1, 2..., M\}$ **do**
solving (19) with fixed $Q^l[i]$, $\tau_n[i]$, and get the optimal results $\{x_a[i], y_a[i]\}^*$
update $Z^{m+1}[i]=\{x_a[i], y_a[i]\}^*$
Until convergence.
end for

Algorithm 2 Alternating iterative algorithm for solving problem (13)

Initialize $\tau_n^0[i]$, $l = 0$ and $Z^0[i]$;
for each time slot $m \in \{1, 2..., M\}$ **do**
Solving (14) with fixed $Z^l[i]$, and get the results $\tau_n^l[i]$.
update $Z^{m+1}[i]=\{x_a[i], y_a[i]\}^*$
Solving (19) with fixed $Z^l[i]$, $\tau_n^l[i]$, and get optimal results $Z^{m+1}[i]$. ; Let $m = m + 1$
Until convergence.
end for

5.3 | Joint optimization of USN scheduling and AUV trajectories

In this paper, we propose an iterative optimization algorithm to maximize the AUV's SC by alternately optimizing the sensor scheduling and AUV trajectories. The original nonconvex problem is decomposed into two subproblems using the BCD method: (i) USN scheduling: The binary scheduling variables are relaxed to continuous values and the final schedule is obtained using a rounding technique. (ii) AUV trajectory optimization: The rate expressions for the AUV-Eve and AUV-sensor channels are approximated using Taylor expansions at feasible points, transforming the nonconvex optimization problem into a convex problem, which is then solved using convex optimization methods. This iterative approach ensures efficient optimization and convergence to a near-optimal solution. Algorithm 2 summarizes the iterative approach to solving (13).

Next, we prove the convergence of the optimization problem. Let $R_{sec}(\Gamma^{(m)}, Z^{(m)})$ represent the l-th iteration value for the optimization problem and define $R^a_{\sec}(\Gamma^{(m)}, Z^{(m)})$ and $R^b_{\sec}(\Gamma^{(m)}, Z^{(m)})$ as the objective values of optimization problems (14) and (19) in steps 3 and 4 of Algorithm 2, respectively. We obtain $W^{(m+1)}$ using Algorithm 2. Then, we have

$$\begin{aligned} R_{\sec}(\Gamma^{(m)}, Z^{(m)}) & \leq R^a_{\sec}(\Gamma^{(m+1)}, Z^{(m)}) \\ & = R_{\sec}(\Gamma^{(m+1)}, Z^{(m)}). \end{aligned} \tag{20}$$

For a given $(Z^{(m)}, \Gamma^{(m+1)})$, by using step 4 in Algorithm 2 to optimize the trajectory of the AUV, we obtain

$$\begin{aligned} R_{\sec}(\Gamma^{(m+1)}, Z^{(m)}) & \leq R^b_{\sec}(\Gamma^{(m+1)}, Z^{(m+1)}) \\ & = R_{\sec}(\Gamma^{(m+1)}, Z^{(m+1)}). \end{aligned} \tag{21}$$

By combining (20) and (21), we obtain the following conclusions:

$$R_{\sec}(\Gamma^{(m)}, Z^{(m)}) \leq R_{\sec}(\Gamma^{(m+1)}, Z^{(m+1)}), \tag{22}$$

which implies that the value of each iteration of Algorithm 2 does not decrease. Furthermore, the objective function of the optimization problem is bounded. Therefore, the convergence of the algorithm is proven.

The computational complexity of Algorithm 2 stems from the optimization of USN scheduling and AUV trajectories. The computational complexity of the proposed algorithm is $\mathcal{O}(IM^{(3.5)})$, where M and I are the number of time slots and iterations, respectively.

6 | SIMULATIONS RESULTS

This section presents simulation results to demonstrate the effectiveness of the proposed algorithm. We assume that there are $N = 13$ USNs randomly distributed underwater, and the start/end locations of the AUV are preset as $(-800, 0, 0)$ and $(800, 0, 0)$. In this study, we assumed that the Eve utilizes an underwater beacon for eavesdropping. These beacons can be anchored to fixed underwater positions, employ global positioning system localization, and automatically transmit or receive data. This technology minimizes the influence of ocean currents on the Eve's position [30]. The fading coefficient λ is modeled as $|\lambda|^2 \backsim \text{Rayleigh}(\sigma^2)$, $\sigma^2 = 0.64$. The other parameter settings are as follows: $H_n = H_e = 100$ m, $H_a = 10$ m, $V_{\max} = 50$ m/s, $\theta = 0.5$ s, $\xi = 100$ Kbit, $P_n = P_{\text{auv}} = 10$ dBm, $\Theta_s = \Theta_c = 0.05$.

Figure 2 presents the optimal AUV trajectory are various times T as calculated by the proposed algorithm. One can observe that the AUV is always as close to each USN as possible to maintain a favorable channel state. Additionally, when the AUV approaches USNs, it will attempt to get as close as possible to the Eve to cause more interference and gain additional SC. The scheduling

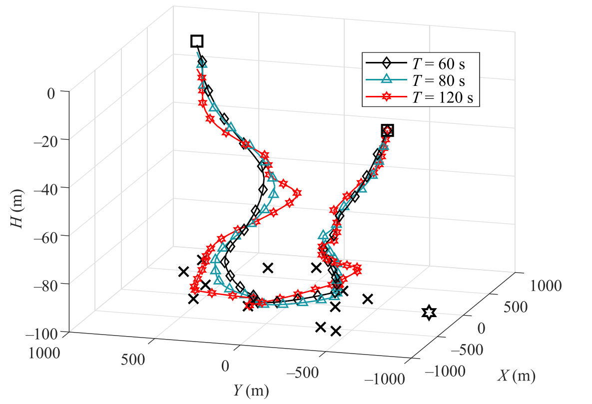

FIGURE 2 AUV trajectory optimization for various T values. AUV, autonomous underwater vehicle.

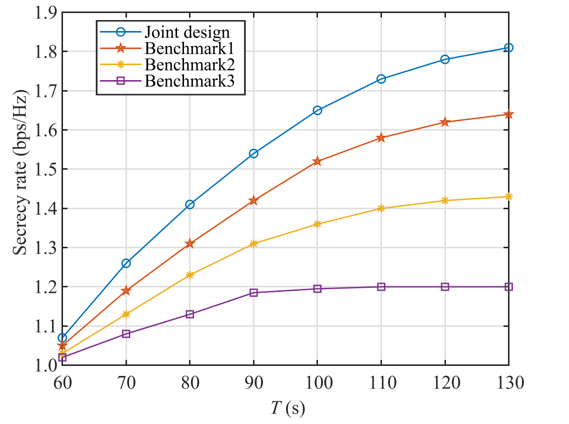

FIGURE 4 Comparison of secrecy rates for various methods and T values.

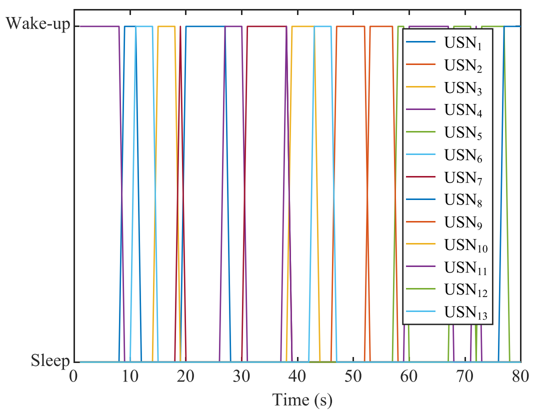

FIGURE 3 Optimized USN scheduling. USN, underwater sensor node.

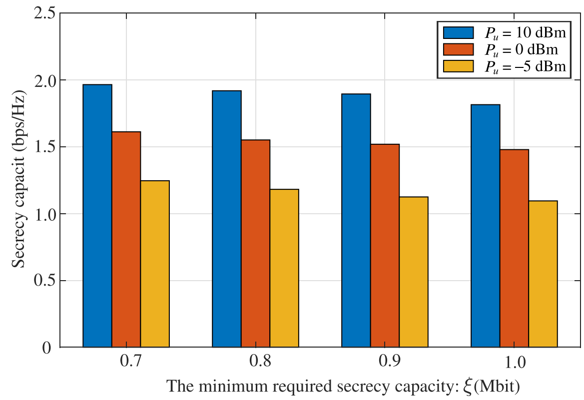

FIGURE 5 SC comparison for different values of P_u. SC, secrecy capacity.

optimization results of USNs when $T = s$ are presented in Figure 3. One can see that when the USN does not communicate with the AUV, it is always in a closed state and can only be in a communication state when the AUV is entirely closed. This behavior can not only transmit more confidential information but also effectively reduce the energy consumption of USNs.

Figure 4 compares the secrecy rate achieved by our collaborative design strategy with that of three benchmark methods over time T. The selected benchmarks include (i) elliptic trajectory planning with transmission power optimization [31], (ii) elliptic trajectory planning with a fixed transmission power [32], and (iii) a circular trajectory with a radius of 800 centered at the origin [33]. The secrecy rate of the AUV increases over time, primarily because the AUV spends more time near the USNs, allowing for greater data collection. Additionally, the results demonstrate that methods incorporating trajectory planning outperform those without trajectory planning, highlighting the significant benefit of trajectory optimization for enhancing the secrecy rate. These findings confirm that our proposed approach leads to superior performance compared with the benchmark schemes.

Figure 5 compares the SC achieved by our proposed algorithm with the minimum secure data quantity ξ. One can see that the SC rapidly diminishes as the amount of secure data collected increases. These results can be explained in two ways. First, a larger secrecy rate is required to meet greater secure data collection criteria, resulting in increased USN transmission power. Therefore, the SC decreases as ξ increases as a result of restricted communication resources. Additionally, to satisfy the secrecy rate requirements, USNs must be awoken many times to transmit data. As a result, while approaching the two USNs, the AUV must remain above them for an extended period, consuming more propulsion energy and resulting in a lower SEE. Figure 5 further shows that as the AUV's maximum transmission power grows, so does its SC. Increasing the maximum AUV transmission power improves the SC and optimizes the AUV trajectory to save energy.

7 | CONCLUSIONS

We investigated the SC of an AUV-assisted secure UASN. Given that the CSI of an Eve is often difficult to determine, we proposed an SC maximization problem under SOP and COP restrictions. Considering the difficulty in directly solving the established nonconvex problem, we first transformed it into two more tractable subproblems and then proposed an iterative algorithm using the BCD method. These two subproblems are solved iteratively to accomplish optimization. Simulation results demonstrated the importance of trajectory planning and the efficacy of the proposed algorithm.

CONFLICT OF INTEREST STATEMENT

The authors declare no potential conflicts of interest.

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REFERENCES

1. L. Liu, Z. Xi, and J. Wu, *Strengthening the achilles' heel: an AUV-aided message ferry approach against dissemination vulnerability in UASNs*, IEEE Internet Things J. **8** (2021), no. 19, 14948–14958.
2. Y. Wang, S. Song, J. Liu, X. Guo, and J. Cui, *Efficient AUV-aided localization for large-scale underwater acoustic sensor networks*, IEEE Internet Things J. **11** (2024), no. 19, 31776–31790.
3. F. Ye, H. Xu, Y. Li, T. Jiang, and Z. Zhou, *QoS-optimized deployment of mobile relay AUVs in underwater acoustic sensor networks*, (IEEE 99th Vehicular Technology Conference (VTC2024-Spring), Singapore), 2024, pp. 1–6.
4. M. Huang, K. Zhang, Z. Zeng, T. Wang, and Y. Liu, *An AUV-assisted data gathering scheme based on clustering and matrix completion for smart ocean*, IEEE Internet Things J. **7** (2020), no. 10, 9904–9918.
5. C. Zeng, J.-B. Wang, C. Ding, H. Zhang, M. Lin, and J. Cheng, *Joint optimization of trajectory and communication resource allocation for unmanned surface vehicle enabled maritime wireless networks*, IEEE Trans. Commun. **69** (2021), no. 12, 8100–8115.
6. M. Noohi, A. Pourmand, H. B. Ghavifekr, and A. Mirvakili, *Design and simulation of a rectangular planar printed circuit board coil for nuclear magnetic resonance, radio frequency energy harvesting, and wireless power transfer devices*, ETRI J. **46** (2024), no. 4, 581–594. DOI 10.4218/etrij.2023-0163
7. G. Han, Y. Chen, H. Wang, Y. He, and J. Peng, *AUV-aided data importance based scheme for protecting location privacy in smart ocean*, IEEE Trans. Veh. Technol. **71** (2022), no. 9, 9925–9936.
8. J. Yan, D. Guo, X. Luo, and X. Guan, *AUV-aided localization for underwater acoustic sensor networks with current field estimation*, IEEE Trans. Veh. Technol. **69** (2020), no. 8, 8855–8870.
9. S. Song, J. Liu, J. Guo, C. Zhang, T. Yang, and J. Cui, *Efficient velocity estimation and location prediction in underwater acoustic sensor networks*, IEEE Internet Things J. **9** (2022), no. 4, 2984–2998.
10. G. Han, Z. Tang, Y. He, J. Jiang, and J. A. Ansere, *District partition-based data collection algorithm with event dynamic competition in underwater acoustic sensor networks*, IEEE Trans. Ind. Informat. **15** (2019), no. 10, 5755–5764.
11. G. Han, Y. Chen, H. Wang, Y. He, and J. Peng, *AUV-aided data importance based scheme for protecting location privacy in smart ocean*, IEEE Tran. Veh. Technol. **71** (2022), no. 9, 9925–9936.
12. J. Ryu and S. Kim, *Mitigating jamming attacks in underwater sensor networks using M-Qubed-based opportunistic routing protocol*, ETRI J. (2024). DOI 10.4218/etrij.2023-0526
13. R. Wang, A. Yadav, E. A. Makled, O. A. Dobre, R. Zhao, and P. K. Varshney, *Optimal power allocation for full-duplex underwater relay networks with energy harvesting: a reinforcement learning approach*, IEEE Wirel. Commun. Lett. **9** (2020), no. 2, 223–227.
14. Y. Zhou, H. Yang, Y.-H. Hu, and S.-Y. Kung, *Cross-layer network lifetime maximization in underwater wireless sensor networks*, IEEE Syst. J. **14** (2020), no. 1, 220–231.
15. K. Song, B. Ji, and C. Li, *Resource allocation for relay-aided underwater acoustic sensor networks with energy harvesting*, Phys. Commun. **33** (2019), no. C, 241–248. DOI 10.1016/j.phycom.2019.01.006
16. X. Wang, Y. Su, S. Yang, and R. Fan, *An OFDMA downlink acoustic communication scheme for AUV-based mobile underwater sensor network*, IEEE Sens. J. **24** (2024), no. 7, 11527–11536.
17. Y. Zhang, Y. Huang, L. Wan, S. Zhou, X. Shen, and H. Wang, *Adaptive OFDMA with partial CSI for downlink underwater acoustic communications*, J. Commun. Netw. **18** (2016), no. 3, 387–396.
18. C. Lin, G. Han, J. Du, Y. Bi, L. Shu, and K. Fan, *A path planning scheme for AUV flock-based internet-of-underwater-things systems to enable transparent and smart ocean*, IEEE Internet Things J. **7** (2020), no. 10, 9760–9772.
19. Z. Gong, C. Li, and F. Jiang, *AUV-aided joint localization and time synchronization for underwater acoustic sensor networks*, IEEE Signal Process. Lett. **25** (2018), no. 4, 477–481.
20. Y. Zeng, C. Lu, R. Liu, X. He, C. Rong, and M. Liu, *Wireless power and data transfer system using multidirectional magnetic coupler for swarm AUVs*, IEEE Trans. Power Electron. **38** (2023), no. 2, 1440–1444.
21. A. Chiche, G. Lindbergh, I. Stenius, and C. Lagergren, *A strategy for sizing and optimizing the energy system on long-range auvs*, IEEE J. Ocean. Eng. **46** (2021), no. 4, 1132–1143.
22. Y. Su, L. Li, R. Fan, Y. Liu, and Z. Jin, *A secure transmission scheme with energy-efficient cooperative jamming for underwater acoustic sensor networks*, IEEE Sens. J. **22** (2022), no. 21, 21287–21298.
23. H. Wang, G. Han, Y. Liu, A. Li, and J. Jiang, *AUV-assisted stratified source location privacy protection scheme based on network coding in UASNs*, IEEE Internet Things J. **10** (2023), no. 12, 10636–10648.
24. X. Cao, L. Chen, L. Guo, and W. Han, *AUV global security path planning based on a potential field bio-inspired neural network*

in underwater environment, Intell. Autom. Soft Comput. **27** (2021), no. 2. DOI 10.32604/iasc.2021.01002
25. C. Lin, G. Han, M. Guizani, Y. Bi, J. Du, and L. Shu, *An SDN architecture for AUV-based underwater wireless networks to enable cooperative underwater search*, IEEE Wirel. Commun. **27** (2020), no. 3, 132–139.
26. G. Han, Y. Chen, H. Wang, Y. He, and J. Peng, *AUV-aided data importance based scheme for protecting location privacy in smart ocean*, IEEE Trans. Veh. Technol. **71** (2022), no. 9, 9925–9936.
27. Y. Wang, T. Li, M. Zeng, J. Mai, P. Gu, and D. Xu, *An underwater simultaneous wireless power and data transfer system for AUV with high-rate full-duplex communication*, IEEE Trans. Power Electron. **38** (2023), no. 1, 619–633.
28. L. M. Brekhovskikh, Y. P. Lysanov, and R. T. Beyer, *Fundamentals of ocean acoustics*, 1982. https://api.semanticscholar.org/CorpusID:221271538
29. C. Zhang, Y. Wang, L. Liu, and L. Yan, *AUV-enabled data collection for underwater acoustic sensor networks*, (OCEANS 2022, Hampton Roads, Hampton Roads, VA, USA), 2022, pp. 1–6.
30. J. Zhang, Y. Han, C. Zheng, and D. Sun, *Underwater target localization using long baseline positioning system*, Appl. Acoust. **111** (2016), 129–134. DOI 10.1016/j.apacoust.2016.04.009
31. J. Chen, J. Wang, Z. Wei, Y. Ren, C. Masouros, and Z. Han, *Joint autonomous underwater vehicle trajectory and energy optimization for underwater covert communications*, IEEE Trans. Commun. **72** (2024), no. 11, 7327–7341.
32. M. Cheng, Q. Guan, F. Ji, J. Cheng, and Y. Chen, *Dynamic-detection-based trajectory planning for autonomous underwater vehicle to collect data from underwater sensors*, IEEE Internet Things J. **9** (2022), no. 15, 13168–13178.
33. X. Zhuo, M. Liu, Y. Wei, G. Yu, F. Qu, and R. Sun, *AUV-aided energy-efficient data collection in underwater acoustic sensor networks*, IEEE Internet Things J. **7** (2020), no. 10, 10010–10022.

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