

Self-Adaptive Differential Evolution-Based Inductance Optimization for Resonant Acoustic RIS in Underwater Communications

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ABSTRACT Underwater acoustic (UWA) communication systems suffer from limited bandwidth, severe multipath fading, and high propagation loss, which significantly constrain their achievable spectral efficiency and reliability. To improve UWA communication, reconfigurable intelligent surface (RIS) acts as a promising solution to enable controllable reflection of acoustic waves. However, optimizing the configuration of RIS in UWA systems is challenging due to hardware constraints, signal dispersion, and the dynamic environment. To address these challenges, this paper proposes an optimization framework for an RIS-assisted UWA system using self-adaptive mutation differential evolution (SaMDE) to maximize the achievable spectral efficiency. Specifically, the SaMDE algorithm is employed to search for the optimal RIS configuration for each element by integrating multiple mutation strategies and adaptive parameter control. Simulation results under an UWA environment generated using the Bellhop ray-tracing model demonstrate that the framework significantly improves spectral efficiency compared to several baseline approaches.

INDEX TERMS Differential evolution, reconfigurable intelligent surface, underwater acoustic communication.

I. Introduction

Underwater acoustic (UWA) communication is fundamental for the exploration and monitoring of the ocean world [1]. This is because underwater radio frequency (RF) communications that depend on electromagnetic (EM) waves suffer from severe absorption attenuation in aquatic settings, which strictly limits their transmission range compared to acoustic waves that travel farther with minimal energy loss [2].

While other underwater technologies such as optical [3] or magnetic induction [4] are emerging, UWA communication remains the principal approach for reliable underwater transmission because acoustic signals provide relatively low attenuation and robust propagation in marine environ-

ments [2], [5]. The authors in [5] identify several emerging applications that depend on the UWA systems, including underwater exploration, marine environment monitoring, underwater navigation and positioning, disaster prediction, emergency operations, and marine aquaculture, specifically for monitoring fish counts and marine carbon sequestration scenarios that collect active and passive submarine acoustic information. In addition, the UWA channel is important for marine animals, as they rely on acoustic signals for hunting, navigation, and survival [6]. Therefore, next-generation underwater communication systems should be designed to be environmentally friendly by operating at lower sound levels

and using accurate beam steering to reduce disturbance to the auditory systems of marine wildlife.

Although UWA communication systems have been developed for decades, several critical issues in existing systems still limit their effectiveness for contemporary oceanic applications [6], [2], [7]. Firstly, existing UWA systems achieve very low data rate that are not enough for high-bandwidth needs like real-time video streaming. This is mainly due to the very low bandwidth available in the acoustic channel. Furthermore, sound absorption increases significantly with frequency, thus restricting mid-to-long-range applications to a bandwidth of just tens of kilohertz [8]. Secondly, these systems exhibit poor reliability because of multipath fading, particularly in shallow waters, as well as spatially selective fading arising from variations in sound speed. The variations in sound speed and the resulting curved propagation of sound rays create shadow zones where no line-of-sight (LoS) path exists, thus making a reliable connection nearly impossible for traditional systems [2]. Besides, dynamic environments, such as waves and turbulence, also cause continuous motion, rotation, and swinging of communication nodes [1]. Consequently, current systems cannot provide the high quality of service (QoS) required for real-time underwater video streaming or high-rate multimedia data transfer. The lack of reliable and high-speed communication means that some applications, such as underwater earthquake and tsunami monitoring, cannot be effectively realized [1].

The integration of reconfigurable intelligent surface (RIS) into UWA communications offers several advantages. Firstly, the RIS enhances link reliability and performance by mitigating fading. Specifically, RIS can efficiently reflect the acoustic beams, thus reducing multipath fading as well as frequency-selective fading [2]. It acts as an enabler to address coverage challenges caused by sound speed variations, which typically create shadow zones in UWA communication systems [7]. The authors in [1] show that RIS can boost UWA data rate, extend communication ranges, and allow UWA links to achieve high-order modulations, which used to be impractical for low-cost devices. Moreover, its ability to focus transmission toward a desired target while operating at lower acoustic levels also minimizes the risk to marine wildlife [6]. Compared with amplify-and-forward (AF)/decode-and-forward (DF) relays, which receive and then amplify or decode and retransmit the acoustic signal, an acoustic RIS directly controls and reflects the incident wave without digital signal decoding or retransmission [1], [9]. Therefore, it reduces the transceiver and signal processing requirements at the assisting node while providing a controllable reflected propagation path. However, designing an acoustic RIS for underwater environments faces several challenges that distinguish it from terrestrial RIS.

- **Fundamental physical and hardware differences:**

(1) Unlike terrestrial RIS, which controls EM waves, underwater RIS manipulates mechanical (acoustic) waves [10]. This requires a different hardware mechanism,

which makes the metallic patch reflectors used in RF RIS ineffective because they cannot alter mechanical properties [6], [1]. Instead, designs use piezoelectric materials such as lead zirconate titanate (PZT) to enable electromechanical interactions that control signal reflection [11]. (2) Because acoustic waves have much longer wavelengths than radio waves, acoustic RIS requires larger reflecting elements and is generally heavier, which restricts the number of reflecting elements that can be integrated on a surface compared to the thousands of units on a terrestrial RIS [6]. (3) Terrestrial RIS typically uses varactor diodes to shift phases by adjusting transmission line lengths. However, at the low frequencies used for long-range underwater communication [10], the required capacitance variation for a phase shift exceeds the capabilities of most commercial varactors.

- **Dynamic environmental conditions:** Unlike terrestrial RIS, underwater surfaces are often affected by waves, currents, and turbulence, which can cause them to move and rotate continuously, leading to signal misalignment, channel variation, and time-varying Doppler shifts [1]. Therefore, the dynamic characteristics of the underwater environment motivate the implementation of underwater IoT devices and an effective RIS optimization to overcome propagation delays and channel coherence times [10], [11].
- **Varying material impedance:** The impedance of the PZT material used in acoustic reflectors is not static; it changes in response to water temperature, salinity, deployment depth, and the incident angle of the wave. This necessitates electronically reconfigurable matching circuits to adapt to environmental changes [10], [12].

A. Related Works

1) RIS in UWA Communications

Existing studies have demonstrated that the RIS can significantly enhance UWA communications [1], [2], [6], [7], [10], [11], [13]. Wang *et al.* [1] developed a detailed Tonpilz-based acoustic RIS model and formulated practical ultra-wideband (UWB) beamforming as the maximization of the frequency-dependent reflected power toward the desired direction. After reformulating the beamforming objective, the impedance of each reflecting element was determined independently to approximate the desired frequency-dependent phase response. This beamforming design enables the acoustic RIS to mitigate beam squint and improve underwater communication performance through efficient signal reflection. However, the optimization in [1] primarily addresses reflected beam formation and beam squint mitigation, rather than optimizing the complete impedance matrix according to the end-to-end spectral efficiency determined by the direct and RIS-assisted UWA channels. Shi *et al.* [2] proposed an acoustic RIS architecture using Tonpilz hardware and an equivalent circuit that incorporates an additional operational amplifier circuit. By

utilizing a negative resistor network, the system extends the controllable reflective phase range to the full phase interval. Specifically, the work in [2] optimizes the transmit precoder and the RIS reflection factors using fractional programming and a majorization–minimization procedure, while resistance and inductance settings are used to implement and quantize the optimized reflection states. Lou *et al.* [6] developed a 24-element 1-bit UWA RIS prototype and validated its beam steering and communication enhancement capabilities through water tank and lake experiments. Their experimental results demonstrate the practical feasibility of acoustic RIS hardware and confirm that beam steering can effectively enhance underwater acoustic communication performance. In [10], Sun *et al.* introduced a UWA RIS architecture for long-range UWA communication. Their beamforming design selects the RIS’s circuit parameters to compensate for the frequency-dependent dispersion of the individual elements and the array. However, a spectral efficiency maximization problem over the physical RIS configuration of the RIS was not formulated.

It is worth mentioning that there are UWA RIS studies that focus on optimizing other performance metrics like secrecy rate, coverage area, and transmit power to improve the performance of UWA RIS systems. For secure communications between buoyed nodes and autonomous underwater vehicles (AUVs), the authors formulate a max-min channel secrecy rate problem in [11] to maximize the minimum channel secrecy rate at the RIS and the receiver (Rx) while ensuring communication reliability stays above a specified threshold by using an exhaustive search to solve this problem. Then, the authors recognize that exhaustive search is computationally expensive and time-consuming to ensure the optimality of the beamwidths and RIS depth configuration. Although the signal model in [11] includes element reflection amplitudes and phases, the analysis assumes zero phase adjustment and an identical reflection coefficient for all RIS elements. Therefore, their optimization focuses on the beamwidth and deployment configuration rather than the element-wise configuration of the acoustic RIS. In addition, the authors in [7] focused on optimizing the coverage area of UWA RIS-assisted systems to address the underwater shadow zones. However, they focused on optimizing the RIS position rather than the element-wise configuration of the UWA RIS. The work in [13] investigated the performance of UWA RIS-assisted communications by formulating a transmission power minimization problem under incident angle, reflection angle and acoustic signal frequency constraints, but their optimization focuses on propagation parameters rather than the RIS element-wise hardware configuration.

2) Metaheuristic Algorithms for RIS Configuration

Metaheuristic algorithms, particularly evolutionary algorithms (EAs), have emerged as powerful alternatives for solving non-convex optimization problems where gradient

information is unreliable [14], [15]. Classical metaheuristic algorithms, including genetic algorithm (GA), grey wolf optimization (GWO), and particle swarm optimization (PSO), have been widely adopted in different RIS-assisted communication scenarios. For example, Dong *et al.* [15] used GA to optimize RIS element allocation in a UWA system with energy holes, where an RIS-equipped AUV forwards accumulated data from a source node to multiple destination nodes. In this work, GA searches for the number of RIS elements assigned to each data stream according to data importance and security risk, but the objective is forwarding efficiency rather than spectral efficiency maximization. In underwater optical RIS systems, PSO has been applied to optimize the phase shifts, reflection coefficients, and resource allocation factors of multiple simultaneous transmission and reflection reconfigurable intelligent surface (STAR-RIS) elements for sum rate maximization [16], [17], while GWO has also been considered as a low-complexity benchmark for optical RIS phase shift optimization due to its simple control structure and fast convergence behavior [16], [18]. Compared with GA, PSO, and GWO, differential evolution (DE) is particularly suitable for RIS optimization because it directly operates on real-valued candidate vectors and updates the population through mutation, crossover, and selection. DE has been used to optimize RIS phase shift matrices in terrestrial unmanned aerial vehicle (UAV)-assisted RIS systems for spectral efficiency improvement [19], and has also been adopted as a benchmark in optical STAR-RIS phase optimization [16]. However, classical DE still suffers from fixed control parameters, limited mutation diversity, and possible premature convergence in large-scale non-convex search spaces [20], [21]. Therefore, improved DE variants have been developed for RIS optimization, showing better convergence and throughput performance than conventional DE and GA in cell-free and multiple-input multiple-output (MIMO) RIS-aided systems [20], [21]. Hence, in this work, we utilize an improved DE variant called self-adaptive mutation differential evolution (SaMDE) to solve the hardware-constrained optimization problem for the RIS-assisted UWA system. Unlike the methods that deal with phase-shift optimization or deployment optimization, this method self-adaptively selects mutation strategies to improve the achievable spectral efficiency under the considered acoustic RIS model.

B. Main Contributions

This paper proposes an optimization framework for RIS-assisted UWA communication, where the RIS configuration is optimized to maximize the achievable spectral efficiency. A SaMDE-based solution is utilized to solve the considered optimization problem. By integrating multiple mutation strategies with adaptive parameter control, SaMDE improves the exploration–exploitation trade-off, thereby enabling an effective search for the optimal RIS configuration in this

system. This paper's major contributions are listed as follows:

- We propose an UWA RIS-assisted communication framework, where the RIS is used to create a controllable reflected acoustic path and improve the achievable spectral efficiency.
- We construct a feasible inductance set based on the resonance condition of the acoustic reflecting elements and formulate a hardware-constrained spectral efficiency maximization problem, then develop a SaMDE-based optimization framework to solve the considered optimization problem.
- We assess the proposed system's performance under the UWA channel simulated by the Bellhop ray-tracing model, and compare it with other metaheuristic methods, including GA, DE, PSO, GWO, random search, and the baseline system without RIS. The results indicate that the considered SaMDE method provides the highest achievable spectral efficiency among the compared methods.
- Simulation results demonstrate that placing the acoustic RIS near the transmitter (Tx) is more effective for improving the spectral efficiency. They also indicate that the proposed method's advantage becomes more evident as the RIS size and transmit power increase. Overall, these findings support the impact of the proposed SaMDE-based optimization on UWA RIS systems.

C. Paper Organization

The structure of this paper is organized as follows: Section I-A reviews the existing literature on UWA RIS, conventional RIS optimization approaches, and metaheuristic algorithms for RIS configuration. Section II presents the UWA RIS hardware model, the proposed system model, and the achievable spectral efficiency problem formulation. Section III describes the methodology, including the construction of the feasible inductance set and the proposed SaMDE-based solution. Section IV extends the proposed system model to the respective multiple-input single-output (MISO) RIS-assisted UWA communication system. Section V discusses the simulation results and analyzes the proposed framework's performance. Finally, Section VI presents the conclusion and future work of this paper.

II. System Model and Problem Formulation

A. UWA RIS Hardware Model

Acoustic waves are mechanical and therefore cannot be controlled using metallic-patch reflectors with tunable circuits, as commonly used in terrestrial RIS-assisted systems. As a result, acoustic reflecting elements must be mechanically reconfigurable, which is difficult to achieve in underwater environments. Hence, a transducer, which is a commonly used piezoelectric device in UWA communications and has previously been utilized as an RIS reflecting element in [1],

is adopted in this work. The piezoelectric reflector considered in this paper follows a similar configuration to the Tonpilz transducer [22]. Each Tonpilz transducer is linked to a controller that adjusts its impedance, denoted by Z_{var} . We implement the tunable impedance Z_{var} of each RIS element as an RL series circuit with a fixed resistance R and a variable inductance L_{var} . These reflecting elements are arranged in an $M \times N$ array to form an acoustic RIS. Through the piezoelectric effect, the piston-surface vibration can be adjusted by tuning the transducer's electrical branch. As a result, the reflecting element becomes reconfigurable, allowing the phase of the reflected acoustic waves to be controlled. Let $\Gamma(L_{\text{var}}, f)$ denote the complex reflection coefficient of each reflecting element, which characterizes its effect on the reflected signal's phase and amplitude. With the amplification factor assumed by $\alpha \in \mathbb{R}_+$ [1], the reflection coefficient is written as follows:

$$\Gamma(L_{\text{var}}, f) = \frac{j}{2} \frac{\alpha \rho c \beta a_n^2 D_e A_n}{\xi(L_{\text{var}}, f) + j\omega(M_{\text{head}} + M_r) + R_r}, \quad (1)$$

where

$$\xi(L_{\text{var}}, f) = \frac{j\omega M_{\text{tail}} \left[\frac{N_{\text{em}}^2 L_{\text{var}}}{j\omega C_0 (R + j\omega L_{\text{var}} + \frac{1}{j\omega C_0})} + \frac{1}{j\omega C_E^n} \right]}{\frac{N_{\text{em}}^2 L_{\text{var}}}{j\omega C_0 (R + j\omega L_{\text{var}} + \frac{1}{j\omega C_0})} + \frac{1}{j\omega C_E^n} + j\omega M_{\text{tail}}}, \quad (2)$$

and $\omega = 2\pi f$ defines the acoustic signal's angular frequency. ρ represents the density of seawater, c is the sound speed in water, β denotes the acoustic wavenumber, a_n is the radius of the circular piston (the head of the reflecting element), D_e defines the diffraction constant, $A_n = \pi a_n^2$ is the piston surface area, $M_r = \frac{\rho c A_n H_1(2\beta a_n)}{\omega \beta a_n}$ denotes the radiation reactance, and $R_r = \rho c A_n \left(1 - \frac{J_1(2\beta a_n)}{\beta a_n} \right)$ represents the radiation resistance of the reflecting element, with $H_1(\cdot)$ and $J_1(\cdot)$ denoting the first-order Struve function and the first-order Bessel function, respectively. The head and tail masses are represented by M_{head} and M_{tail} , respectively. $N_{\text{em}} = \frac{\eta A_0}{st}$ represents the electromechanical transformer ratio that links the electrical and mechanical domains of the reflecting element, where η denotes the piezoelectric strain coefficient, A_0 defines the piezoelectric ceramic area, t denotes the piezoelectric section's thickness, and s represents the piezoelectric elastic constant. $C_0 = C_f (1 - \kappa^2)$ denotes the equivalent capacitor within the electrical branch of the acoustic RIS unit's equivalent circuit model, where κ denotes the piezoelectric coupling coefficient. $C_f = \frac{n_p \varepsilon A_0}{t}$, where n_p indicates the number of piezoelectric sections and ε models the free piezoelectric dielectric constant. $C_n^E = \frac{sL}{A_0}$ represents the mechanical compliance of the piezoelectric element within the acoustic RIS hardware, where L denotes the piezoelectric ceramic's length.

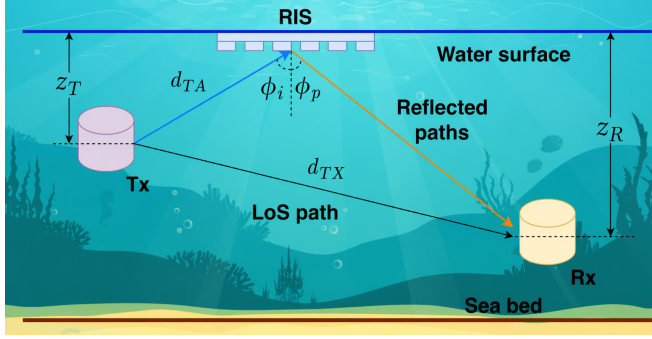


FIGURE 1: System model.

B. System Model

Fig. 1 illustrates the simulated setup of the considered single-input single-output (SISO) UWA communication system^{1,2}, which consists of an RIS deployed on the water surface between a Tx located at a depth of z_T and a Rx located at a depth of z_R . d_{TA} and d_{TX} denote the distances from the Tx to the RIS and to the Rx, respectively. The noise variance at the Rx and the RIS is modelled as additive white Gaussian noise (AWGN). In this work, the considered system assumes that the channel remains approximately unchanged during one RIS configuration interval [1], [10]. The CSI knowledge can be acquired using suitable channel estimation techniques. For instance, as detailed in Section IV.C of [1], the acoustic RIS can acquire channel state information (CSI) autonomously by passively eavesdropping on standard transmitter-receiver handshake signals, thereby eliminating the need for dedicated pilot overhead. During the initial link setup, the RIS intercepts these signals to locally extract the baseline angle of arrival (AoA) and angle of departure (AoD). By handling all the channel estimation locally, the RIS maintains a fully decoupled architecture that requires zero centralized coordination with the communicating nodes.

The channel from the Tx to the (m, n) -th RIS element is given by

$$g_{m,n} = \frac{\cos(\phi_i)}{d_{TA}} e^{j\psi_{t,m,n}(\omega)}, \quad (3)$$

where ϕ_i denotes the acoustic signal's elevation angle of arrival from Tx to RIS. With θ_i denoting the azimuth angle of arrival of the wave from Tx to RIS, the spatial phase difference across the RIS array caused by the direction of the incoming acoustic wave with AoA (θ_i, ϕ_i) is given by $\psi_{t,m,n} = (md_{\text{col}} \cos(\theta_i) + nd_{\text{row}} \sin(\theta_i)) \sin(\phi_i) \frac{\omega}{c}$.

¹In Section IV, the respective MISO RIS-assisted UWA communication systems have been analyzed.

²The proposed framework can be extended to RIS-assisted UWA MIMO with specific requirements. In particular, the optimization problem should jointly consider the RIS configuration with transmit and receive beamforming [10].

The channel from the (m, n) -th RIS element to the Rx is given by

$$h_{m,n} = \frac{2J_1(\beta a_n \sin(\phi_p))}{\beta a_n \sin(\phi_p) d_{AR}} e^{j\psi_{p,m,n}(\omega)}, \quad (4)$$

where d_{AR} is the distance from RIS to Rx and ϕ_p denotes the elevation angle of departure that forms the reflected signal from RIS to Rx. The (m, n) -th reflecting element's phase shift is $\psi_{p,m,n} = (md_{\text{col}} \cos(\theta_p) + nd_{\text{row}} \sin(\theta_p)) \sin(\phi_p) \frac{\omega}{c}$, where θ_p represents the azimuth angle of departure formed by the reflected signal from RIS to Rx.

To account for imperfect channel knowledge on the direct and RIS-assisted links [23], the channels are modeled as

$$\hat{h}_d = h_d + \tilde{e}_d, \quad (5)$$

$$\hat{h}_{m,n} = h_{m,n} + \tilde{e}_{h,m,n}, \quad (6)$$

$$\hat{g}_{m,n} = g_{m,n} + \tilde{e}_{g,m,n}, \quad (7)$$

where h_d , $h_{m,n}$, and $g_{m,n}$ are the actual direct, Tx-RIS, and RIS-Rx channel matrices, respectively, while $\hat{h}_d$, $\hat{h}_{m,n}$, and $\hat{g}_{m,n}$ represent the corresponding estimated channels. The estimation errors $\tilde{e}_d$, $\tilde{e}_{h,m,n}$, and $\tilde{e}_{g,m,n}$ follow zero-mean complex Gaussian distributions with variances $\delta_d^2 |h_d|^2$, $\delta_h^2 |h_{m,n}|^2$, and $\delta_g^2 |g_{m,n}|^2$, respectively, where $\delta_d, \delta_h, \delta_g \in [0, 1]$ control the level of channel estimation error on each link. Setting $\delta_d = \delta_h = \delta_g = 0$ reduces this model to perfect CSI, which is the default case considered in the simulations.

Let h_d denote the direct channel from Tx to Rx generated by the Bellhop ray-tracing model. With transmit power P , the received signal-to-noise ratio (SNR) [1] is computed as

$$\text{SNR} = \frac{P \left| h_d + \sum_{m,n} h_{m,n} \Gamma(L_{\text{var}}^{m,n}, \omega) g_{m,n} \right|^2}{\sigma_{\text{RIS}}^2 \sum_{m,n} |h_{m,n} \Gamma(L_{\text{var}}^{m,n}, \omega)|^2 + \sigma_{\text{Rx}}^2}, \quad (8)$$

with $L_{\text{var}}^{m,n}$ representing the variable inductance of the (m, n) -th RIS element and $\sigma_{\text{RIS}}^2 = \sigma_{\text{Rx}}^2 = n_0 B$ denoting the noise variance at the RIS and Rx.

Hence, the achievable spectral efficiency is calculated as

$$C = \log_2(1 + \text{SNR}). \quad (9)$$

C. Problem Formulation

Let $Z_{\text{var}}^{m,n}$ be the (m, n) -th RIS element's impedance. Since $Z_{\text{var}}^{m,n}$ is determined by $L_{\text{var}}^{m,n}$, the matrix $\mathbf{L}_{\text{var}}$ thus controls all RIS elements' corresponding reflection coefficients and is considered as the optimization variable. Therefore, the objective is to determine the inductance matrix $\mathbf{L}_{\text{var}}$ that maximizes the achievable spectral efficiency. The optimization problem is established as

$$\max_{\mathbf{L}_{\text{var}}} C(\mathbf{L}_{\text{var}}) \quad \text{s.t.} \quad L_{\text{var}}^{m,n} \in \mathcal{F}_Z, \quad \forall m, n. \quad (10)$$

The above problem is non-convex because the reflection coefficients depend nonlinearly on the inductance values, and all RIS elements jointly affect the effective channel. To solve this problem, we employ a SaMDE algorithm to iteratively search for the most suitable inductance configuration $\mathbf{L}_{\text{var}}^*$ that maximizes the achievable spectral efficiency.

III. Methodology

Before presenting the proposed optimization method, the RIS configuration search space is first defined. Specifically, Section III-A constructs the discrete feasible inductance set $\mathcal{F}_Z$, which contains only the inductance values that satisfy the resonance constraint of the acoustic reflecting elements. This feasible set is designed to retain the inductance values that maximize the reflection coefficient, thereby improving the controllability of the reflecting elements. Based on this set, the RIS configuration is represented by the tunable inductance matrix $\mathbf{L}_{\text{var}}$, where each entry corresponds to the variable inductance assigned to one RIS element. Therefore, the optimization problem is transformed into an element-wise search over $\mathcal{F}_Z$, ensuring that each candidate RIS configuration satisfies the considered resonance constraint. Then, Section III-B introduces the proposed SaMDE-based optimization framework, which searches for the optimal inductance matrix by combining multiple mutation strategies with self-adaptive control of the mutation and crossover parameters.

A. Defining the Discrete Feasible Inductance Set $\mathcal{F}_Z$

As described in Section II-A, the equivalent circuit and control mechanism indicate that jointly controlling the impedance of all RIS elements allows the reflected acoustic waves to combine at the Rx, thereby enhancing the effective channel gain. In addition, when the equivalent circuit of the reflecting element is adjusted to its resonant frequency, the velocity phase shift in the acoustic branch becomes zero, while the reflected pressure reaches its maximum amplitude. At this resonant state, the maximized amplitude of the reflection coefficient $|\Gamma_{\text{max}}(L_{\text{var}}, f)|$ is mathematically approximated based on the properties of the water and the physical characteristics of the transducer [1]. This resonant state represents the most efficient point of reflection for the hardware, where the impedance $Z_{\text{var}}^{m,n}$ is adjusted by tuning the variable inductance $L_{\text{var}}^{m,n}$ so that the mechanical and acoustical branch impedances effectively balance, thus allowing for the highest possible vibration velocity for a given incident pressure.

Therefore, the feasible inductance set $\mathcal{F}_Z$ is constructed to include only those inductance values that ensure resonance within the operational frequency band. Specifically, for each candidate inductance value L_r , the corresponding reflection coefficient $\Gamma(L_r, f)$ is evaluated over a range of frequencies, and the resonant frequency is defined as

$$f_{\text{res}}^r = \arg \max_f |\Gamma(L_r, f)|. \quad (11)$$

An inductance value L_r is considered feasible if its resonant frequency lies within the system bandwidth $[f_c - B/2, f_c + B/2]$. Therefore, the discrete inductance library is defined as

$$\mathcal{F}_Z = \left\{ L_r \mid f_c - \frac{B}{2} \leq f_{\text{res}}^r \leq f_c + \frac{B}{2} \right\}, \quad (12)$$

with B representing the system bandwidth and f_c indicating the carrier frequency, respectively. By constructing $\mathcal{F}_Z$, the optimization is restricted to inductance values that are capable of operating efficiently within the desired frequency range. This ensures that the resulting impedance

$$Z_{\text{var}}^{m,n} = R + j2\pi f L_{\text{var}}^{m,n}, \quad \forall m, n, \quad (13)$$

achieves effective control of the reflection coefficient for RIS-assisted communication. The inductance values of all RIS elements can be represented by the following $M \times N$ matrix

$$\mathbf{L}_{\text{var}} = \begin{bmatrix} L_{\text{var}}^{1,1} & L_{\text{var}}^{1,2} & \dots & L_{\text{var}}^{1,N} \\ L_{\text{var}}^{2,1} & L_{\text{var}}^{2,2} & \dots & L_{\text{var}}^{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ L_{\text{var}}^{M,1} & L_{\text{var}}^{M,2} & \dots & L_{\text{var}}^{M,N} \end{bmatrix}, \quad (14)$$

where each element $L_{\text{var}}^{m,n} \in \mathcal{F}_Z$ corresponds to the inductance assigned to the (m, n) -th RIS element.

B. Applying SaMDE to solve the spectral efficiency optimization problem

Our considered problem includes a nonlinear and non-convex objective function, where the decision variables are inter-dependent across the RIS elements, and the search space's size increases rapidly with the number of RIS elements. Motivated by the demonstrated benefits of improved DE variants, SaMDE [24] is utilized to avoid premature convergence and enhance search robustness, where each individual in the population represents one candidate inductance matrix $\mathbf{L}_{\text{var}}$. By self-adaptively selecting among multiple mutation strategies and updating its control parameters during evolution, SaMDE provides a better exploration-exploitation trade-off to find the optimal RIS inductance configurations in the optimization problem.

It is worth noting that the SaMDE algorithm can be implemented on typical underwater internet-of-things (IoT) devices that are compact-sized, low-power, and hardware-constrained, such as AUVs and sensors, as discussed in [6], [10].

1) Individual Representation

Each individual $\mathbf{x}_i$ in the population encodes both the variable inductance matrix and the self-adaptive strategy parameters:

$$\mathbf{x}_i = \{\mathbf{L}_{\text{var}}, \mathbf{V}_i, \mathbf{F}_i, \mathbf{CR}_i\}, \quad (15)$$

where $\mathbf{L}_{\text{var},i} \in \mathbb{R}^{M \times N}$ represents the inductance matrix of the i -th individual. The vectors $\mathbf{V}_i = [V_i^1, \dots, V_i^K]$, $\mathbf{F}_i = [F_i^1, \dots, F_i^K]$, and $\mathbf{CR}_i = [CR_i^1, \dots, CR_i^K]$ denote the strategy scores, mutation scaling factors, and crossover rates associated with the K mutation strategies, respectively. Specifically, $V_i^k \in [0, 1]$ represents the score used for strategy selection, while $F_i^k \in [0.1, 1]$ and $CR_i^k \in [0, 1]$ correspond to the mutation factor and crossover rate of the k -th strategy, respectively. These parameters are encoded

within each individual and are self-adaptively evolved during the optimization process.

2) Self-Adaptation Mechanism

At each iteration g , a random scaling factor $F' \sim U(0.7, 1)$ [24] is drawn to update the following strategy scores:

$$V_i^k \leftarrow V_{r_1}^k + F' (V_{r_2}^k - V_{r_3}^k), \quad (16)$$

where $U(a, b)$ denotes a random variable sampled from the uniform distribution over the interval (a, b) . r_1 , r_2 , and r_3 are randomly chosen indices. A mutation strategy w is then selected by roulette-wheel selection according to these probabilities. Once the strategy w is defined, its associated control parameters are updated via differential mutation:

$$F_i^w = F_{r_1}^w + F' (F_{r_2}^w - F_{r_3}^w), \quad (17)$$

$$CR_i^w = CR_{r_1}^w + F' (CR_{r_2}^w - CR_{r_3}^w). \quad (18)$$

3) Mutation Strategies

The mutation operators are applied to the inductance matrix $\mathbf{L}_{\text{var},i}$ of each individual to create the mutation matrix $\mathbf{L}_{\text{var},v}$. Four mutation strategies are considered as follows, each providing different exploration and exploitation characteristics in the search space.

- a) **rand/1**: This strategy generates a mutant matrix based on randomly selected individuals, thus promoting strong exploration of the search space:

$$\mathbf{L}_{\text{var},v} = \mathbf{L}_{\text{var},r_1} + F_i^w (\mathbf{L}_{\text{var},r_2} - \mathbf{L}_{\text{var},r_3}). \quad (19)$$

Since it does not rely on the current or best solution, it helps avoid premature convergence and maintains population diversity.

- b) **best/1**: This strategy chooses the base matrix as the current population's best individual, which strengthens the exploitation capability of the search:

$$\mathbf{L}_{\text{var},v} = \mathbf{L}_{\text{var},\text{best}} + F_i^w (\mathbf{L}_{\text{var},r_1} - \mathbf{L}_{\text{var},r_2}). \quad (20)$$

By guiding the search toward the current best solution, this strategy accelerates convergence.

- c) **rand/2**: This strategy extends **rand/1** by incorporating two difference matrices:

$$\mathbf{L}_{\text{var},v} = \mathbf{L}_{\text{var},r_1} + F_i^w (\mathbf{L}_{\text{var},r_2} - \mathbf{L}_{\text{var},r_3}) + F_i^w (\mathbf{L}_{\text{var},r_4} - \mathbf{L}_{\text{var},r_5}). \quad (21)$$

This increases perturbation strength and improves global exploration capability, making it suitable for escaping local optima.

- d) **current-to-rand/1**: This strategy combines information from the current individual and randomly selected individuals:

$$\mathbf{L}_{\text{var},v} = \mathbf{L}_{\text{var},i} + F_i^w (\mathbf{L}_{\text{var},r_1} - \mathbf{L}_{\text{var},i}) + F_i^w (\mathbf{L}_{\text{var},r_2} - \mathbf{L}_{\text{var},r_3}). \quad (22)$$

It balances exploration and exploitation by partially following the current solution while introducing stochastic perturbations.

After mutation, each element $L_{\text{var},v}^{m,n}$ of $\mathbf{L}_{\text{var},v}$ is projected onto the feasible inductance set $\mathcal{F}_Z$ by selecting the nearest valid inductance value. This ensures that all candidate solutions satisfy the resonance constraint.

4) Crossover and Selection

A binomial crossover is performed on each inductance element $L_{\text{var},i}^{m,n}$ of the target matrix $\mathbf{L}_{\text{var},i}$ and $L_{\text{var},v}^{m,n}$ of the mutant matrix $\mathbf{L}_{\text{var},v}$ to construct the trial inductance element $L_{\text{var},u}^{m,n}$ of the trial matrix $\mathbf{L}_{\text{var},u}$:

$$L_{\text{var},u}^{m,n} = \begin{cases} L_{\text{var},v}^{m,n}, & \text{if } U[0, 1] \leq CR_i^w, \\ L_{\text{var},i}^{m,n}, & \text{otherwise.} \end{cases} \quad (23)$$

The trial matrix $\mathbf{L}_{\text{var},u}$ is evaluated using the achievable spectral efficiency. A greedy selection mechanism is then applied. If the trial matrix is accepted, the revised self-adaptive parameters are carried over to the next iteration:

$$\mathbf{x}_i^{g+1} = \begin{cases} \{\mathbf{L}_{\text{var},u}, \mathbf{V}_i, \mathbf{F}_i, \mathbf{CR}_i\}, & \text{if } C(\mathbf{L}_{\text{var},u}) \geq C(\mathbf{L}_{\text{var},i}), \\ \mathbf{x}_i^g, & \text{otherwise.} \end{cases} \quad (24)$$

Only the parameters F_i^w and CR_i^w associated with the chosen strategy are updated in the current iteration, whereas the other components of $\mathbf{F}_i$ and $\mathbf{CR}_i$ are passed without modification. The SaMDE framework allows adaptive selection among multiple mutation strategies while simultaneously tuning their associated parameters, thereby improving the exploration–exploitation balance in the search space of the considered spectral efficiency optimization. Furthermore, by incorporating the feasible inductance set $\mathcal{F}_Z$, the algorithm ensures that all candidate solutions operate efficiently within the system bandwidth. The stopping criterion is defined based on the improvement of the best achievable spectral efficiency between two consecutive iterations. Let

$$C_{\text{best}}^g = \max_i C(\mathbf{L}_{\text{var},i}^g) \quad (25)$$

denotes the best achievable spectral efficiency obtained by the population at iteration g . The optimization process is terminated when $C_{\text{best}}^g - C_{\text{best}}^{g-1} \leq \delta$, where δ is a sufficiently small positive constant. This criterion indicates that the optimization process has converged because the improvement in the best achievable spectral efficiency becomes insignificant. The overall SaMDE optimization procedure for RIS inductance selection is summarized in Algorithm 1.

Computational Complexity: Let $D = M \times N$ denote the number of RIS elements, and let G denote the number of iterations required for the algorithm to satisfy the convergence criterion. The computational complexity of GA is given by $C_{\text{GA}} = \mathcal{O}(N_P G D)$, and the complexity of PSO is $C_{\text{PSO}} = \mathcal{O}(N_P G D)$, while the complexity of GWO can be expressed as $C_{\text{GWO}} = \mathcal{O}(N_P G \log(D))$. The computational complexity of DE is $C_{\text{DE}} = \mathcal{O}(N_P G D)$. However, in

Algorithm 1 SaMDE for the considered spectral efficiency optimization problem

Require: Population size N_P , convergence threshold δ , feasible inductance set $\mathcal{F}_Z$, number of strategies K

Ensure: Optimal inductance matrix $\mathbf{L}_{\text{var}}^*$

```

1: Initialize the population;
2: Evaluate  $C(\mathbf{L}_{\text{var},i})$  for all individuals;
3: Obtain the initial best spectral efficiency:
    $C_{\text{best}}^0 \leftarrow \max_i C(\mathbf{L}_{\text{var},i})$ ;
4: Set  $g \leftarrow 1$ ;
5: while  $\Delta C > \delta$  do
6:   for  $i = 1$  to  $N_P$  do
7:     Sample  $F' \sim U(0.7, 1)$ ;
8:     for  $k = 1$  to  $K$  do
9:       Update strategy scores by (16);
10:    end for
11:    Select strategy  $w$  by roulette wheel with  $\mathbf{V}_i$ ;
12:    Update the selected control parameters by (17)
    and (18);
13:    Generate  $\mathbf{L}_{\text{var},v}$  using strategy  $w$ ;
14:    Project each entry of  $\mathbf{L}_{\text{var},v}$  onto  $\mathcal{F}_Z$ ;
15:    Generate  $\mathbf{L}_{\text{var},u}$  by performing the crossover;
16:    Evaluate  $C(\mathbf{L}_{\text{var},u})$ ;
17:    if  $C(\mathbf{L}_{\text{var},u}) \geq C(\mathbf{L}_{\text{var},i})$  then
18:       $\mathbf{L}_{\text{var},i} \leftarrow \mathbf{L}_{\text{var},u}$ ;
19:      Propagate updated  $\mathbf{V}_i$ ,  $\mathbf{F}_i$ , and  $\mathbf{CR}_i$ ;
20:    end if
21:  end for
22:  Obtain the best spectral efficiency at iteration  $g$ :
     $C_{\text{best}}^g \leftarrow \max_i C(\mathbf{L}_{\text{var},i}^g)$ ;
23:  Compute the improvement:
     $\Delta C \leftarrow C_{\text{best}}^g - C_{\text{best}}^{g-1}$ ;
24:   $g \leftarrow g + 1$ ;
25: end while
26: Obtain the optimal inductance matrix:
     $\mathbf{L}_{\text{var}}^* \leftarrow \arg \max_i C(\mathbf{L}_{\text{var},i})$ ;
27: return  $\mathbf{L}_{\text{var}}^*$ 

```

the DE algorithm, the target vector is updated by mutation and crossover, which is more complicated than the implementation of PSO to obtain the optimal solution [16]. For the SaMDE, each individual produces a trial RIS configuration through mutation and crossover, then SaMDE selects one mutation strategy from K candidate strategies and updates the associated adaptive control parameters. Therefore, its complexity is $C_{\text{SaMDE}} = \mathcal{O}(N_P G D K)$, which is higher than the other methods; however, by adjusting the mutation factor and crossover rate during the evolutionary process, SaMDE obtains a more effective balance between global exploration and local exploitation, thereby allowing the algorithm to explore the search space of RIS inductance values, avoid premature convergence, and reach a higher achievable spectral efficiency.

IV. Extension To MISO RIS-Assisted UWA Communication Systems

In this section, we are extending the proposed system model in subsection II-B by considering multiple transducers at the Tx.

The channel from the Tx to the (m, n) -th RIS element is given by

$$\mathbf{g}_{m,n} = [g_{m,n}^1, g_{m,n}^2, \dots, g_{m,n}^{N_t}] \in \mathbb{C}^{1 \times N_t}, \quad (26)$$

where N_t denotes the number of transducers at the Tx. The channel from the q -th transmit transducer to the (m, n) -th RIS element is expressed as

$$g_{m,n}^q = \frac{\cos(\phi_i^q)}{d_{TA}^q} \exp(j\psi_{t,m,n}^q(\omega)), \quad q = 1, \dots, N_t, \quad (27)$$

where $\psi_{t,m,n}^q(\omega) = (md_{\text{col}} \cos \theta_i^q + nd_{\text{row}} \sin \theta_i^q) \sin \phi_i^q \frac{\omega}{c}$. Here, $d_{TA,q}$ represents the distance from the q -th Tx transducer to the RIS, while (θ_i^q, ϕ_i^q) are the corresponding azimuth and elevation AoA. It is worth to mention the channel from the (m, n) -th RIS element to the Rx follows (4). Next, the direct channel from Tx to Rx is given by

$$\mathbf{h}_d = [h_d^1, h_d^2, \dots, h_d^{N_t}] \in \mathbb{C}^{1 \times N_t}. \quad (28)$$

Let us denote $\mathbf{h}_{\text{eff}} = \mathbf{h}_d + \sum_{m,n} h_{m,n} \Gamma(L_{\text{var}}^{m,n}, \omega) \mathbf{g}_{m,n}$. Then, the received SNR can be expressed as

$$\text{SNR}_{\text{MISO}} = \frac{P |\mathbf{h}_{\text{eff}} \mathbf{w}_{\text{MRT}}|^2}{\sigma_{\text{RIS}}^2 \sum_{m,n} |h_{m,n} \Gamma(L_{\text{var}}^{m,n}, \omega)|^2 + \sigma_{\text{Rx}}^2}, \quad (29)$$

where $\mathbf{w}_{\text{MRT}} = \mathbf{h}_{\text{eff}}^H / \|\mathbf{h}_{\text{eff}}\|_2$ represents the maximum ratio transmission (MRT) transmit beamforming vector for the proposed MISO RIS-assisted, with $\|\cdot\|_2$ and $(\cdot)^H$ being the 2-norm and Hermitian transpose, respectively. Therefore, the achievable spectral efficiency is given by

$$C_{\text{MISO}} = \log_2(1 + \text{SNR}_{\text{MISO}}), \quad (30)$$

and the respective optimization problem is provided as

$$\max_{\mathbf{L}_{\text{var}}} C_{\text{MISO}}(\mathbf{L}_{\text{var}}) \quad \text{s.t.} \quad L_{\text{var}}^{m,n} \in \mathcal{F}_Z, \quad \forall m, n. \quad (31)$$

It is worth noting that the optimization problem (31) is solved by the proposed method in Section III.

V. Simulation Results

This section evaluates the proposed SaMDE-based RIS optimization framework's performance under a shallow water medium-range UWA channel environment. The considered RIS-assisted UWA communication system, shown in Fig. 1, is simulated using the Bellhop ray-tracing model. The simulation setup, including the parameters used to generate the results, the sea-bottom parameters used in Bellhop, and the parameters of the RIS reflecting elements, is summarized in Table. 1.

To account for the stochastic nature of the considered metaheuristic algorithms, each optimization algorithm is evaluated over 50 independent runs with different random initializations. Based on the constructed feasible inductance

TABLE 1: Simulation Parameters [1], [2], [22], [26]

Parameter	Value
Depth from water surface to seabed (D)	200 m
Depth of Tx (z_T)	40 m
Depth of Rx (z_R)	60 m
Sea-bottom density (ρ_B)	1800 kg/m ³
Sea-bottom sound speed (c_B)	1600 m/s
Sea-bottom absorption loss (λ_B)	0.8 dB
Center frequency (f_c)	50 kHz
Transmitted power (P)	30 dBm
Bandwidth (B)	20 kHz
Power spectral density (n_0)	57 dB re $\mu\text{Pa}^2/\text{Hz}$
Speed of acoustic waves (c)	1480 m/s
RIS element spacing ($d_{\text{row}} = d_{\text{col}}$)	1.1 cm
Density of seawater (ρ)	1023.6 kg/m ³
Radius of the circular piston (a_n)	0.5 cm
Diffraction constant (D_e)	1
Length of the piezo-ring (L)	8 mm
Thickness of the piezo-ring (t)	2 mm
Number of piezoelectric layers (n_p)	4
Piezoelectric ceramic area (A_0)	0.6283 cm ²
Piezoelectric elastic constant (s)	1.55×10^{-11} Pa ⁻¹
Piezoelectric strain constant (η)	2.89×10^{-10} C/N
Free dielectric constant (ϵ)	1.151×10^{-8} F/m
Piezoelectric coupling coefficient (κ)	0.7
Head mass (M_{head})	4.3 g
Tail mass (M_{tail})	7.9 g

set $\mathcal{F}_Z$, the following simulations first examine the phase response of inductance values and the deployment position of the acoustic RIS. Then, the effectiveness of the proposed SaMDE method is assessed regarding convergence behavior, RIS size, and transmit power, with comparisons against PSO [14], GWO [18], DE [19], GA [25], random search, and the baseline system without RIS.

Motivated by the resonance constraint described in Section III-A, we construct a feasible inductance set $\mathcal{F}_Z$ that only contains inductance values whose resonant frequencies lie inside the operating frequency band. This feasible inductance set is constructed to enhance the RIS reflection coefficient and provide more effective control over the RIS response. Specifically, candidate inductance values are uniformly sampled over the interval $[L_{\min}, L_{\max}]$ with resolution ΔL . Since the UWA-RIS operates with inductances in the millihenry (mH) range [6], the inductance interval $[L_{\min}, L_{\max}]$ is therefore chosen as $[0.1, 10]$ mH with a step size $\Delta L = 0.1$ mH. The sampling resolution ΔL determines the spacing between the candidate inductance values. A smaller ΔL generates more candidate values within the considered inductance range and provides a larger

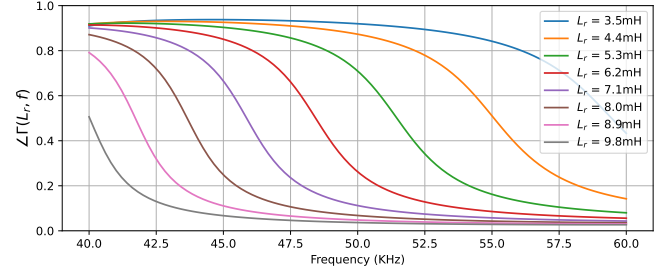


FIGURE 2: Phase response of inductance $\angle\Gamma(L_r, f)$ values that ensure resonance lies within the operational frequency band.

feasible set after applying the resonance-band constraint. Therefore, constructing $\mathcal{F}_Z$ removes the inductance values that do not satisfy the resonance requirement while preserving the valid values used by the optimization. After the mutation and crossover operations, each element $L_{\text{var},v}^{m,n}$ of $\mathbf{L}_{\text{var},v}$ is mapped to its nearest value in $\mathcal{F}_Z$. This step ensures that every candidate inductance matrix satisfies the resonance constraint. The spacing between the values in $\mathcal{F}_Z$ determines how closely the mapped inductance can follow the value produced by the optimizer. Hence, a smaller ΔL provides more feasible choices and supports finer element-wise inductance adjustment during the SaMDE search. For each candidate inductance, the resonance frequency was obtained from the peak of $|\Gamma(L_r, f)|$. After applying the band-selection criterion, the satisfied L_r inductance values were retained, whose resonant frequencies span within the considered frequency band from 40 kHz to 60 kHz.

Fig. 2 illustrates the phase response $\angle\Gamma(L_r, f)$ of selected inductance values retained in the feasible inductance set $\mathcal{F}_Z$. This figure shows how the retained inductance values affect the reflection coefficient over the operating band from 40 kHz to 60 kHz, which corresponds to the bandwidth constraint used in constructing $\mathcal{F}_Z$. Since each $L_r \in \mathcal{F}_Z$ has a resonant frequency inside this band, the selected inductance values provide different phase responses that can be used to configure the RIS elements. As a result, Fig. 2 confirms that the optimization does not search over arbitrary inductance values, but only over the inductance values that satisfy the resonance constraint defined in Section III-A. This reduces the RIS configuration search space and ensures that the SaMDE algorithm optimizes the inductance matrix using candidate values that are compatible with the considered acoustic RIS model and operating frequency band. For example, when the system operates at the carrier frequency $f_c = 50$ kHz with bandwidth $B = 20$ kHz, only the inductance values whose resonant frequencies lie between 40 kHz and 60 kHz are included in $\mathcal{F}_Z$ and used in the following simulations.

Fig. 3 investigates the effect of the inductance sampling resolution ΔL on the convergence of SaMDE, which has similar simulation settings as Fig. 5. When ΔL is increased

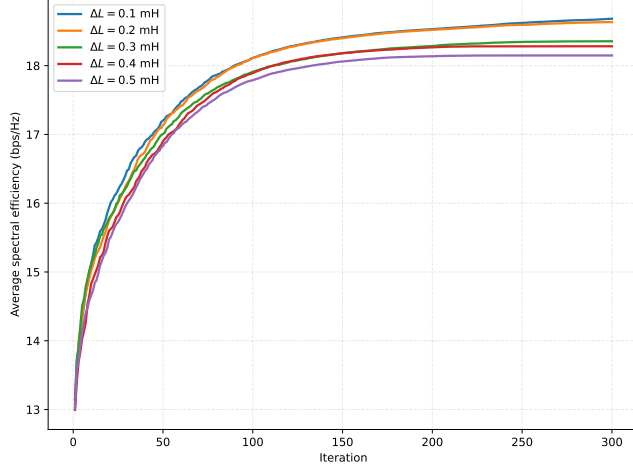


FIGURE 3: Average spectral efficiency of SaMDE for different inductance sampling resolutions ΔL .

from 0.1 to 0.5 mH, the number of candidate inductance values decreases, leading to the reduction of the number of values satisfying the resonance constraint. Thus, for example, when $\Delta L = 0.1$ mH, constructing $\mathcal{F}_Z$ reduces the number of possible inductance matrices. This reduction becomes increasingly significant as the number of RIS elements increases. As ΔL increases, fewer feasible values are available. Consequently, $\Delta L = 0.1$ mH achieves the highest final average spectral efficiency among the tested resolutions. This setting provides the largest feasible inductance set and gives the nearest value mapping more choices when updating each RIS element. Therefore, the results support the use of $\Delta L = 0.1$ mH in the remaining simulations because it satisfies the resonance constraint and provides the best spectral efficiency performance among the considered sampling resolutions.

Before SaMDE is applied to the UWA RIS-aided system, the acoustic RIS's proper location needs to be examined to optimize the spectral efficiency. The distance d_{TX} is fixed at 400 m, and d_{TA} is varied between 10 m and 390 m, as shown in Fig. 4. The Rx position is fixed while the RIS is moved along the line between the Tx and the Rx. Three RIS sizes are considered, corresponding to 10×10 , 15×15 , and 25×25 , and the results are compared with the baseline case without RIS. As shown in Fig. 4, the position of the acoustic RIS significantly affects the achievable spectral efficiency when the RIS is placed close to the Tx. In particular, when $d_{TA} = 10$ m, the RIS-assisted system obtains the greatest spectral efficiency, reaching approximately 18 bps/Hz for the largest RIS configuration. In this region, the RIS effectively reflects the acoustic waves toward the Rx, resulting in a strong combination of the direct and reflected signals. As the distance d_{TA} increases, the spectral efficiency gradually decreases for all RIS configurations due to the increased propagation loss in the Tx–RIS channel. Nevertheless, larger

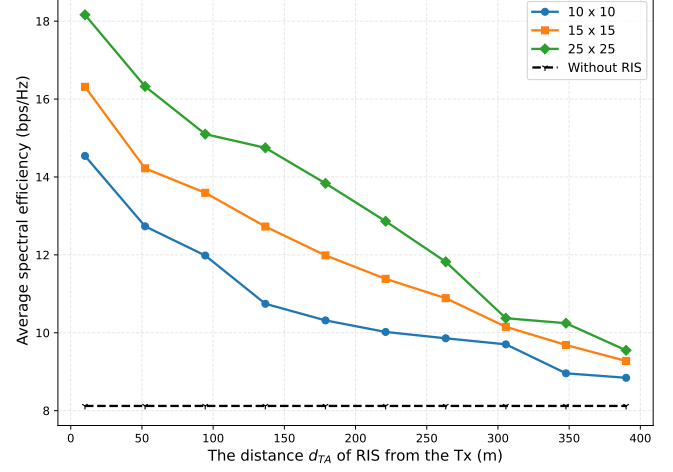


FIGURE 4: Average spectral efficiency with different distances d_{TA} of RIS from the Tx.

RIS arrays consistently achieve higher achievable spectral efficiency across all deployment distances, since more reflecting elements contribute to enhancing the received signal strength. However, when the RIS is placed farther away, the performance gain diminishes significantly. At distances around $d_{TA} = 350$ – 390 m, the reflected path becomes too weak to provide a meaningful gain. This behavior highlights the importance of proper RIS deployment in UWA communications. We vary the horizontal distance between the Tx and the RIS while keeping the Tx–Rx distance fixed. As shown in Fig. 4, placing the RIS near the Tx provides the highest spectral efficiency under the considered geometry because the RIS receives a stronger incident signal. This result is also supported by experimental studies showing that deploying an acoustic RIS near the Tx can improve the communication range and spectral efficiency [1], [6]. However, the preferred RIS position depends on the communication objective and the underwater environment. In practice, placement must therefore balance the received signal strength at the RIS, the required coverage area, and the availability of a stable mounting position under waves and currents [6], [7]. Accordingly, $d_{TA} = 10$ m is selected as a favourable point for the subsequent simulations under the adopted geometry, rather than as a general placement rule.

The SaMDE method is implemented in comparison to other optimization techniques, including DE, GWO, PSO, GA, and a random search strategy. For the random search baseline, a new feasible RIS inductance configuration is randomly sampled at each iteration, and the best configuration found up to the current iteration is retained. The baseline system without RIS is also included for comparison. Fig. 5 shows the convergence behavior of the SaMDE-based RIS impedance design scheme with the RIS size set to 25×25 . In this simulation, $\delta = 10^{-4}$ is used to monitor the improvement of the best spectral efficiency

between consecutive iterations. To account for the stochastic nature of the metaheuristic algorithms, the statistical results are summarized in Table 2. The statistical performance is summarized using the minimum, maximum, mean, and standard deviation of the spectral efficiency achieved by each algorithm. According to Table 2, SaMDE achieves the highest mean spectral efficiency of 18.5816 bps/Hz and the lowest standard deviation of 0.0694 bps/Hz, indicating consistent performance across the independent runs. Among the benchmark methods, DE ranks second with a mean of 17.1356 bps/Hz and a standard deviation of 0.2809 bps/Hz, followed by PSO, GWO, GA, and random search with mean values of 16.2988, 15.8043, 14.9245, and 12.6098 bps/Hz, respectively, while GWO exhibits the largest variation with a standard deviation of 0.5330 bps/Hz. All optimization-based approaches significantly outperform the baseline system without RIS, which maintains a constant spectral efficiency of approximately 8.1 bps/Hz. Within the first 50 iterations, GWO, PSO, DE, and SaMDE rapidly improve the spectral efficiency from initial values around 12–13 bps/Hz to above 14.5 bps/Hz, indicating that even small optimization of the RIS impedance parameters can enhance performance gains. Among the compared algorithms, the SaMDE achieves the highest spectral efficiency. Specifically, SaMDE increases the spectral efficiency from approximately 13 bps/Hz at the initial iteration to almost 18 bps/Hz within the first 100 iterations, and gradually converges to around 18.5 bps/Hz after 300 iterations. In Fig. 5, the improvement between the last two recorded iterations for the SaMDE algorithm is approximately 4.0×10^{-6} bps/Hz, which is below the threshold $\delta = 10^{-4}$. As shown in Table 2, SaMDE achieves the highest mean spectral efficiency of 18.5816 bps/Hz with a standard deviation of 0.0694 bps/Hz, which confirms its robust performance over multiple independent runs. In comparison, DE achieves a mean spectral efficiency of 17.1 bps/Hz, which shows the benefit of DE-based search but remains lower than SaMDE. This indicates that the self-adaptive mutation strategy selection in SaMDE improves the exploration–exploitation balance compared with vanilla DE. Moreover, PSO converges more quickly in the early stage but saturates at a lower spectral efficiency of approximately 16.3 bps/Hz. This indicates that although PSO offers fast initial convergence, it suffers from several limitations: particles tend to cluster around the current global best prematurely, thus leading to loss of diversity and stagnation in local optima [14]. Additionally, while GWO provides a significant advantage due to its much lower computational complexity [18], it achieves a lower mean spectral efficiency than SaMDE, DE, and PSO. Meanwhile, GA shows slower convergence and reaches a mean spectral efficiency of 14.9 bps/Hz, because GA usually requires many fitness evaluations, which becomes computationally costly when each evaluation depends on acoustic propagation simulation [15]. In contrast, the random search baseline improves only when a newly sampled RIS configuration provides

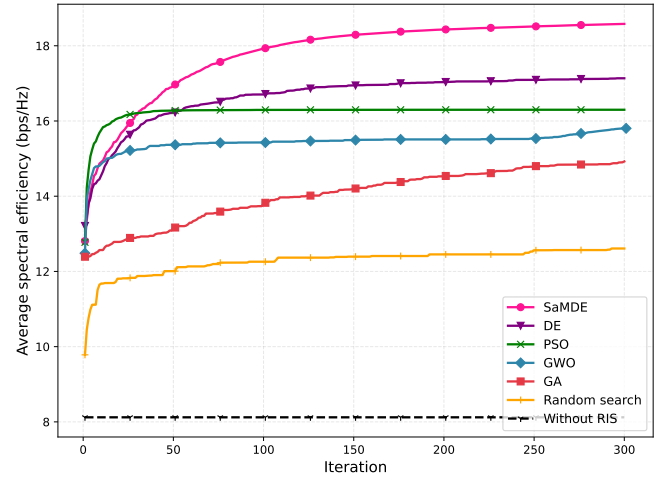


FIGURE 5: The convergence curves of the SaMDE algorithm in comparison against DE [19], GWO [18], PSO [14], GA [25], random search, and the baseline system without RIS.

TABLE 2: Statistical comparison of the SaMDE, DE, GWO, PSO, GA, and random search

Algorithm	Min	Max	Mean	Std
SaMDE	18.458339	18.683828	18.581558	0.069436
DE	16.732985	17.675338	17.135583	0.280923
PSO	15.948900	16.562306	16.298768	0.214124
GWO	15.252420	16.840643	15.804313	0.532969
GA	14.746305	15.152152	14.924476	0.132975
Random search	12.344474	12.999525	12.609800	0.220749

a higher spectral efficiency than the previously retained best solution. Although random search can occasionally identify improved configurations, its progress increases from around 9.8 bps/Hz to approximately 12.6 bps/Hz, which is much slower than the metaheuristic algorithms because it does not exploit information from previous candidate solutions. Therefore, this result highlights the need for guided optimization to effectively configure RIS parameters. Furthermore, the convergence curves and statistical results indicate that the performance gap between SaMDE and the other algorithms progressively increases as the number of iterations grows. This observation suggests that SaMDE exhibits stronger robustness for the considered optimization problem, which is particularly important for RIS-assisted UWA systems where numerous reflecting elements must be optimized simultaneously. Overall, the results confirm that the SaMDE-based framework achieves effective convergence and the highest mean spectral efficiency among the compared metaheuristic algorithms under the adopted simulation setup.

To put the performance of the proposed SaMDE algorithm into perspective, an exhaustive-search comparison is conducted for a small 2×2 RIS, where all feasible inductance

TABLE 3: Statistical comparison between SaMDE and the exhaustive-search upper bound for a 2×2 RIS

Algorithm	Min	Max	Mean	Std
SaMDE	8.458733	8.625094	8.624369	0.009774
Exhaustive search	8.625094	8.625094	8.625094	0.0

configurations can be evaluated, as shown in Table 3. Since the feasible inductance set contains $|\mathcal{F}_Z|$ values and the RIS has $D = M \times N$ elements, the total number of possible configurations is $|\mathcal{F}_Z|^D$. Therefore, exhaustive search is only feasible for very small RIS sizes. As shown in Table 3, SaMDE approaches the exhaustive-search upper bound of 8.6 bps/Hz for the 2×2 case, indicating that the proposed method can achieve near-optimal performance where exhaustive search is feasible, while remaining applicable to larger RIS arrays where exhaustive search becomes computationally prohibitive.

Fig. 6 shows the average spectral efficiency achieved by SaMDE and other algorithms across different RIS sizes, ranging from 5×5 to 25×25 . One can see that the baseline system without RIS maintains a constant spectral efficiency of approximately 8.1 bps/Hz, while all optimized RIS configurations achieve higher values, demonstrating the effectiveness of RIS-assisted UWA communication under the considered simulation setup. As shown in Fig. 6, the random search baseline also benefits from larger RIS sizes because a larger surface provides more configurable reflecting elements. However, it remains lower than the guided optimization algorithms, reaching around 12.4 bps/Hz at 25×25 , because random sampling becomes increasingly inefficient as the inductance search space's dimension grows. For example, when the RIS size is 5×5 , the SaMDE algorithm achieves an average spectral efficiency of approximately 11.6 bps/Hz, which increases to about 16.5 bps/Hz at 15×15 and further reaches around 18.5 bps/Hz at the RIS size 25×25 . Among all algorithms, the SaMDE approach consistently achieves the largest spectral efficiency across all RIS sizes. For instance, at the RIS size 25×25 , SaMDE achieves approximately 18.5 bps/Hz, while DE, PSO, GWO, and GA obtain around 16.9 bps/Hz, 16.1 bps/Hz, 15.2 bps/Hz, and 14.7 bps/Hz, respectively. It is also observed that the difference in performance between the optimization algorithms grows with increasing RIS size. With a larger number of RIS elements, the optimization problem becomes increasingly complex, making it more challenging to efficiently search the solution space. SaMDE demonstrates stronger robustness and scalability, maintaining effective performance compared to the other algorithms under the adopted simulation assumptions.

Fig. 7 illustrates the average spectral efficiency with respect to the Tx transmit power P for the considered optimization algorithms. In this simulation, the RIS size is set to 15×15 . The achievable spectral efficiency grows with

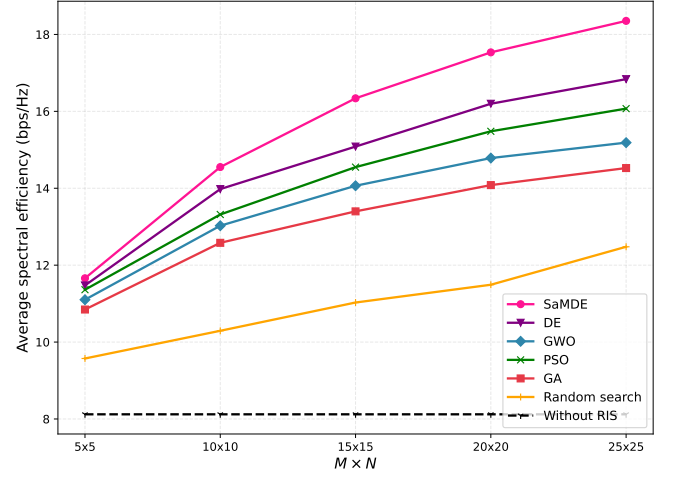


FIGURE 6: Average spectral efficiency with different RIS sizes.

increasing transmit power across all schemes, since a higher transmit power improves the received signal strength. For example, when the transmit power increases from -25 dBm to 20 dBm, the spectral efficiency achieved by the SaMDE configuration increases from approximately 0.3 bps/Hz to about 12.8 bps/Hz. When the transmit power increases to 40 dBm, the spectral efficiency reaches approximately 19.3 bps/Hz. In comparison, the baseline system without RIS achieves only about 11.4 bps/Hz at 40 dBm, demonstrating the performance improvement provided by RIS-assisted transmission under the considered simulation setup. Among the metaheuristic algorithms, SaMDE maintains the highest achievable spectral efficiency throughout the considered transmit-power range. For instance, at $P = 40$ dBm, SaMDE achieves around 19.3 bps/Hz, while DE, PSO, GWO, and GA achieve approximately 18.3 bps/Hz, 18.0 bps/Hz, 17.3 bps/Hz, and 15.3 bps/Hz, respectively. However, SaMDE further improves upon conventional DE by allowing the mutation factor and crossover rate to be adjusted during the evolutionary process, and thereby enables broader exploration of the inductance search space during early iterations and more precise exploitation near promising solutions in later stages. As shown in Fig. 7, the random search baseline remains lower than the metaheuristic algorithms across the considered power range. Although increasing transmit power improves the spectral efficiency of all schemes, random search does not effectively exploit the structure of the RIS inductance optimization problem and reaches only about 14.3 bps/Hz at 40 dBm. Therefore, it provides limited improvement compared with the proposed SaMDE method. These results confirm that the SaMDE-based optimization framework is an effective approach for configuring acoustic RIS systems under the adopted UWA simulation assumptions.

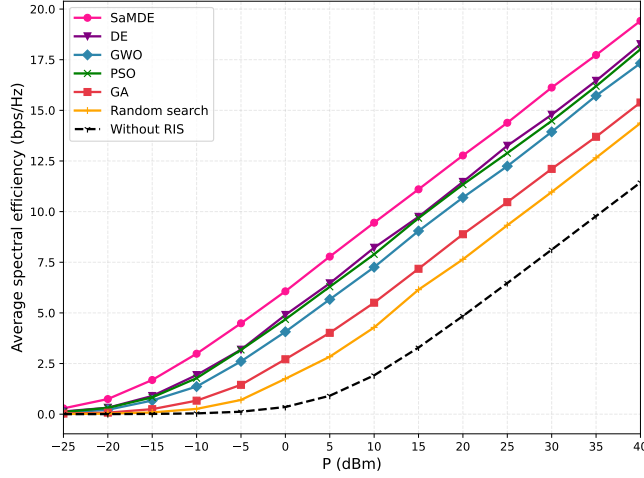


FIGURE 7: Average spectral efficiency with different Tx transmit power values.

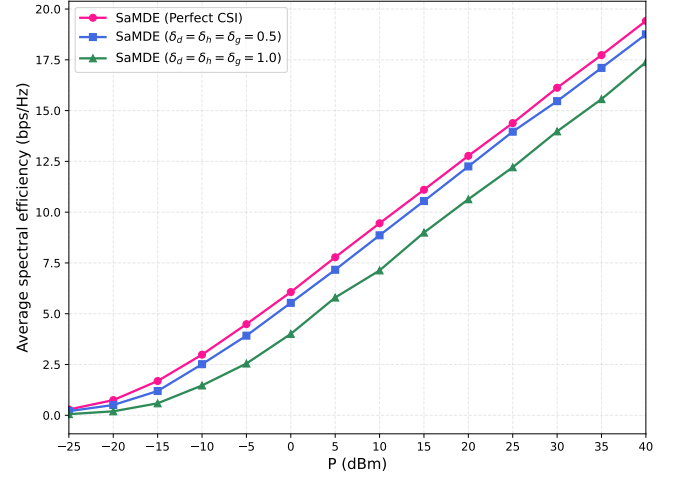


FIGURE 8: Average spectral efficiency achieved by SaMDE under perfect and imperfect CSI for different Tx transmit power values.

To evaluate the system performance under imperfect CSI, Fig. 8 shows the average spectral efficiency achieved by SaMDE versus transmit power P for the perfect-CSI case, $\delta_d = \delta_h = \delta_g = 0$, and two imperfect-CSI cases of $\delta_d = \delta_h = \delta_g = 0.5$ and 1.0 , following the channel estimation error model in Section II. The achievable spectral efficiency decreases as the estimation error increases. At $P = 40$ dBm, SaMDE achieves approximately 19.3 bps/Hz under perfect CSI, which decreases to about 18.7 bps/Hz with 50% estimation error and reduces to around 17.3 bps/Hz with 100% estimation error, corresponding to spectral efficiency losses of approximately 3.1% and 10.4%, respectively. This gap widens with increasing transmit power but stays small at low power. At higher power, performance is more sensitive to how accurately the optimized RIS configuration matches the actual channel condition, so larger $\delta_d, \delta_h, \delta_g$ increasingly mismatch the resulting inductance matrix from the actual channel, reducing the effective gain of the reflected signal at the Rx. Overall, although SaMDE is designed assuming perfect CSI, it degrades moderately with about 10% loss under 100% estimation error, rather than significantly decreasing, indicating reasonable robustness to channel estimation error in the considered RIS-assisted UWA system.

Fig. 9 shows the average spectral efficiency for the MISO RIS-assisted UWA communication system with respect to the number of transmit transducers N_t . For a fixed RIS size, the achievable spectral efficiency performance consistently improves as N_t increases from 1 to 32. This improvement is attributed to the additional transmit beamforming gain provided by MRT when more acoustic transmit transducers are available. However, the incremental gain becomes smaller as N_t grows. Besides, for a fixed N_t , increasing the RIS size results in a clear improvement in average spectral efficiency.

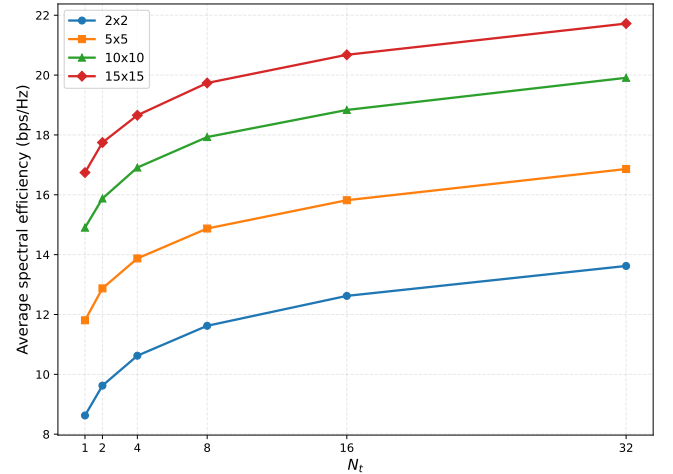


FIGURE 9: Average spectral efficiency achieved by SaMDE for the MISO RIS-assisted UWA communication system.

VI. Conclusions and Future Work

In this paper, we investigate an RIS-assisted UWA communication system to address the challenges in UWA channels. We consider the acoustic RIS hardware constraints by restricting each RIS element to a feasible inductance set determined by the resonance constraint of the reflecting elements. Based on this formulation, a SaMDE-based optimization framework is utilized to search for the optimal RIS configuration that maximizes the achievable spectral efficiency in a non-convex search space. The proposed framework integrates multiple mutation strategies and adaptive parameter control to improve the exploration–exploitation trade-off during the optimization process. By constructing a feasible search space, the optimized RIS configurations remain consistent with the considered hardware constraints while

still providing enough flexibility for channel improvement. Simulation results based on Bellhop-generated UWA channels demonstrate that the proposed SaMDE method achieves a higher spectral efficiency than the benchmark schemes, including DE, GWO, PSO, GA, random search, and the baseline system without RIS. The results further show that the placement of the acoustic RIS plays an important role in system performance, where deploying the RIS closer to the Tx provides more effective spectral efficiency improvement. In addition, the proposed method's performance becomes more significant as the RIS size and transmit power increase. These findings confirm the effectiveness of the proposed SaMDE-based RIS optimization framework and demonstrate its potential for improving the UWA communication systems.

Future work should extend the proposed framework to MIMO and multi-user UWA systems, where the RIS inductance configuration must be jointly optimized with beamforming and user scheduling [1], [2]. Furthermore, the joint design must handle the frequency, depth, and temperature-dependent impedance shifts of the piezoelectric elements [6]. Another possible extension is the use of multiple RISs. Multiple RISs could improve coverage, provide additional controllable propagation paths, and help mitigate shadow zones in complex UWA environments. However, this extension would also introduce new challenges such as considering multivariate optimization designs with coupled optimization variables [13]. Additionally, future work should also consider robust acoustic RIS optimization under imperfect CSI, including the effects of Doppler shifts, mobility, and time-varying environmental conditions in practical UWA channels. Moreover, the considered system model is used as a 2D deployment model to reduce the number of placement variables and allows the proposed hardware-constrained RIS optimization framework to be evaluated more clearly. Therefore, extending the model to full three-dimensional deployment would require joint optimization over horizontal position, depth, and orientation, which is left for future work.

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