Evolutionary Optimization for Quantized RIS Phase Shift Design in MIMO Systems: Hyperparameter Analysis and SNR Performance

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***Abstract*—This paper investigates evolutionary optimization (EO)-based phase shift design for reconfigurable intelligent surface (RIS)-assisted MIMO systems under practical quantized phase constraints. The proposed EO framework optimizes 1-bit and 2-bit RIS phase configurations and systematically analyzes the impact of the crossover and mutation probabilities. Simulation results show that EO is highly sensitive to mutation probability, whereas crossover probability has a relatively smaller effect within the tested range. The best hyperparameter setting is identified through a parameter sweep, and the proposed EO-based design is shown to outperform the SDR-based benchmark for both 1-bit and 2-bit RIS configurations. The results demonstrate that EO is an effective and practical approach for quantized RIS phase optimization.**

***Index Terms*—Reconfigurable intelligent surface (RIS), evolutionary optimization, MIMO, quantized phase shift design, signal-to-noise ratio (SNR).**

I. Introduction

Reconfigurable intelligent surface (RIS) is widely regarded as a promising technology for enhancing coverage, reliability, and spectral efficiency in beyond-5G and 6G wireless systems. By intelligently tuning the phase shifts of a large number of nearly passive reflecting elements, an RIS can reconfigure the wireless propagation environment and improve the quality of the received signal. As a result, RIS phase shift design has emerged as a fundamental optimization problem in RIS-assisted communications.

A broad range of optimization methods has been investigated for RIS phase design. Metaheuristic methods such as Grey Wolf Optimization (GWO) [1] and Particle Swarm Optimization (PSO) [2] have been studied for beamforming and phase adaptation, owing to their ability to handle non-convex optimization problems with moderate implementation complexity. In [1], GWO-based phase optimization is shown to improve spectral efficiency relative to PSO-based optimization. In [2], PSO is applied to beamforming design in cell-free networks to reduce power consumption with relatively low implementation complexity.

Deep reinforcement learning methods have also been explored for RIS optimization. In [3], a Deep Q-Network (DQN)-based framework is proposed for RIS phase shift design and shown to provide faster optimization than conventional iterative methods such as successive convex approximation. Similarly, [4] employs a Model Predictive Control-Twin Delayed Deep Deterministic Policy Gradient (MPC-TD3) framework for joint beamforming and RIS phase optimization in integrated sensing and communication systems. Although such learning-based approaches can achieve strong performance, they generally involve significant training overhead and increased implementation complexity.

Several other RIS optimization methods have also been reported in the literature. In [5], RIS phase shifts and pilot power coefficients are optimized alternately using sequential convex approximation and fractional programming. In [6], RIS phase design is combined with user scheduling using a discrete Fourier transform codebook. Discrete-phase RIS optimization has also been studied in [7], where waveform design and RIS phase shifts are alternately optimized, and in [8], where the performance of a 3-bit RIS with imperfect channel state information is analyzed. An evolutionary multiobjective optimization approach is presented in [9], whereas [10] considers simulated annealing and Markov-chain-based RIS phase design. In addition, semidefinite relaxation (SDR)-based methods have been extensively used for RIS optimization [11], [12], although their computational burden can become high for large RIS dimensions.

Despite these advances, practical RIS phase optimization remains challenging, particularly under discrete phase constraints. Training-based schemes often incur substantial overhead, while SDR-based methods require convex relaxation and randomization steps that may lead to increased complexity and performance loss under quantized phase constraints. This motivates the need for a lower-complexity optimization framework that can directly operate on discrete RIS phase values while still achieving strong SNR performance.

Motivated by this, this paper investigates an evolutionary optimization (EO)-based framework for RIS phase shift design in an RIS-assisted MIMO system. The proposed method directly searches over quantized RIS phase configurations and is applied to both 1-bit and 2-bit phase resolution. In addition to evaluating its achievable SNR performance, this paper system-

atically studies the effect of the EO hyperparameters, namely the crossover probability P_c and the mutation probability P_m, on convergence behavior and final performance. The results show that mutation probability plays a much more critical role than crossover probability for the considered quantized RIS design problem.

The main contributions of this paper are summarized as follows:

- An EO-based framework is developed for RIS phase shift optimization in an RIS-assisted MIMO system under practical discrete phase constraints, with both 1-bit and 2-bit quantized RIS configurations considered.
- A systematic hyperparameter sensitivity study is carried out by sweeping the crossover probability P_c and mutation probability P_m. The study shows that the EO performance is highly sensitive to P_m while being relatively insensitive to P_c over the tested range, and it identifies an effective hyperparameter setting for the considered problem.
- The proposed EO-based design is shown to outperform the SDR-based benchmark by 1.91 dB and 2.88 dB for 1-bit and 2-bit RIS phase quantization, respectively, while also achieving lower outage probability as demonstrated through cumulative distribution function (CDF) analysis.
- A complexity discussion shows that the proposed EO method scales as $\mathcal{O}(GPN_tN_rN)$, offering an attractive complexity–performance trade-off compared to SDR-based optimization and training-based methods such as DQN and MPC-TD3.

The rest of the paper is organized as follows. Section II presents the system model and the proposed EO-based RIS phase optimization framework. Section III discusses the simulation results and compares the proposed approach with benchmark methods. Finally, Section IV concludes the paper.

II. System Model and EO-Based RIS Phase Shift Design

We consider an RIS-assisted multiple-input multiple-output (MIMO) wireless communication system, where the transmitter (Tx) and receiver (Rx) are equipped with N_t and N_r antennas, respectively. An RIS with N passive reflecting elements is deployed to assist the communication link between Tx and Rx. The direct Tx–Rx channel is denoted by $\mathbf{H}_d \in \mathbb{C}^{N_r \times N_t}$, the Tx–RIS channel by $\mathbf{G} \in \mathbb{C}^{N \times N_t}$, and the RIS–Rx channel by $\mathbf{H}_{RI} \in \mathbb{C}^{N_r \times N}$. The RIS phase shift matrix is given by

$$\mathbf{\Phi} = \mathrm{diag}\big(e^{j\theta_1}, e^{j\theta_2}, \ldots, e^{j\theta_N}\big) \in \mathbb{C}^{N \times N}, \tag{1}$$

where $\theta_i \in [0, 2\pi)$ denotes the phase shift introduced by the ith RIS element. For a transmitted signal vector $\mathbf{s} \in \mathbb{C}^{N_t \times 1}$, the received signal at the Rx can be written as

$$\mathbf{y} = (\mathbf{H}_d + \mathbf{H}_{RI}\mathbf{\Phi}\mathbf{G})\,\mathbf{s} + \mathbf{n}, \tag{2}$$

where the vector quantity $\mathbf{n} \in \mathbb{C}^{N_r \times 1}$ denotes the circularly symmetric complex additive white Gaussian receiver noise. The objective of RIS phase design is to select $\mathbf{\Phi}$ such that the received SNR is maximized. Assuming equal transmit power allocation and fixed noise variance, maximizing the received SNR is equivalent to maximizing the effective channel gain induced by the direct and RIS-assisted links. The RIS phase optimization problem is formulated using the following objective:

$$\max_{\boldsymbol{\theta}} \;\; C(\boldsymbol{\theta}) = \big\|\mathbf{H}_d + \mathbf{H}_{RI}\,\mathrm{diag}\big(e^{j\boldsymbol{\theta}}\big)\,\mathbf{G}\big\|_F^2, \tag{3}$$

where $\boldsymbol{\theta} = [\theta_1, \theta_2, \ldots, \theta_N]^T$ and $\|\cdot\|_F$ denotes the Frobenius norm. The objective in (3) measures the overall effective channel power and serves as a surrogate for SNR maximization.

A. EO for Continuous RIS Phase Shift Design

To solve (3), this work employs an evolutionary optimization (EO) algorithm. The initial population at generation $g = 0$ is denoted by

$$\mathcal{X}^{(0)} = \{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, \ldots, \boldsymbol{\theta}_P\}, \tag{4}$$

where P is the population size and each candidate solution represents an RIS phase shift vector of the form

$$\boldsymbol{\theta}_p = [\theta_{p,1}, \theta_{p,2}, \ldots, \theta_{p,N}]^T. \tag{5}$$

Each individual in the vector is initialized randomly over the continuous phase interval $[0, 2\pi)$.

At each generation g, the objective value of every candidate solution is evaluated using (3). Based on these objective values, a breeding pool $\mathcal{B}^{(g)} \subseteq \mathcal{X}^{(g)}$ is selected, where individuals with higher objective values are assigned a higher chance of being selected. The selected parents then undergo crossover and mutation to generate an offspring population $\mathcal{S}^{(g)}$, which can be expressed as

$$\mathcal{S}^{(g)} = \mathcal{U}\Big(\mathcal{R}\Big(\mathcal{B}^{(g)}\Big)\Big), \tag{6}$$

where $\mathcal{R}(\cdot)$ and $\mathcal{U}(\cdot)$ denote the crossover and mutation operators, respectively.

The crossover operator combines portions of two parent phase vectors to produce new candidate solutions, thereby exploiting promising regions of the search space. The mutation operator randomly perturbs selected RIS phase values to maintain population diversity and prevent premature convergence. The crossover and mutation operations are controlled by the probabilities P_c and P_m, respectively. In addition, an elitism mechanism is used to preserve the best-performing individuals across generations. Let

$$\mathcal{Y}^{(g)} = \mathcal{X}^{(g)} \cup \mathcal{S}^{(g)} \tag{7}$$

denote the union of the parent and offspring populations, and let $K = |\mathcal{X}^{(g)}| = P$. The next generation population is formed by retaining the best K individuals from $\mathcal{Y}^{(g)}$, i.e.,

$$\mathcal{X}^{(g+1)} = \big\{\boldsymbol{\theta}_{(1)}, \boldsymbol{\theta}_{(2)}, \ldots, \boldsymbol{\theta}_{(K)}\big\}, \tag{8}$$

where

$$C\big(\boldsymbol{\theta}_{(1)}\big) \geq C\big(\boldsymbol{\theta}_{(2)}\big) \geq \cdots \geq C\big(\boldsymbol{\theta}_{(K)}\big), \qquad \boldsymbol{\theta}_{(k)} \in \mathcal{Y}^{(g)}. \tag{9}$$

After $G_{\max}$ generations, the best individual in the final population is selected as the optimized continuous RIS phase vector:

$$\boldsymbol{\theta}_{\mathrm{opt}} = \arg \max_{\boldsymbol{\theta} \in \mathcal{X}^{(G_{\max})}} C(\boldsymbol{\theta}), \tag{10}$$

and the corresponding RIS phase shift matrix is obtained as

$$\mathbf{\Phi}_{\text{opt}} = \text{diag}\big(e^{j\boldsymbol{\theta}_{\text{opt}}}\big)\,. \tag{11}$$

B. EO for Quantized RIS Phase Shift Design

In practical RIS implementations, the phase shifts are quantized due to hardware constraints. Therefore, in addition to the continuous-phase design, this work also considers EO-based optimization for quantized RIS phase shifts. For an n-bit RIS, the admissible phase set is given by

$$\mathcal{Q}_n = \left\{ \frac{2\pi k}{2^n} \,\middle|\, k = 0, 1, \ldots, 2^n - 1 \right\}. \tag{12}$$

Accordingly, each RIS element is constrained to take its phase value from $\mathcal{Q}_n$. In this work, both 1-bit and 2-bit RIS phase quantization are considered. For the 1-bit case, the feasible phase set is

$$\mathcal{Q}_1 = \{0, \pi\}\,, \tag{13}$$

whereas for the 2-bit case, the feasible phase set is

$$\mathcal{Q}_2 = \left\{0, \frac{\pi}{2}, \pi, \frac{3\pi}{2}\right\}. \tag{14}$$

Under quantized phase constraints, the EO procedure remains the same as in the continuous case, except that the initialization, crossover, and mutation operations are all restricted to the discrete set $\mathcal{Q}_n$. Hence, each candidate vector satisfies

$$\theta_{p,i} \in \mathcal{Q}_n, \qquad i = 1, 2, \ldots, N. \tag{15}$$

The corresponding optimization problem is written as

$$\boldsymbol{\theta}_{\text{opt}}^{(n\text{-bit})} = \arg \max_{\substack{\boldsymbol{\theta} \in \mathcal{X}^{(G_{\max})} \\ \theta_{p,i} \in \mathcal{Q}_n,\ \forall i}} C(\boldsymbol{\theta}). \tag{16}$$

Since the discrete search space is significantly smaller than the continuous one, the EO algorithm can converge faster while remaining compatible with practical RIS hardware constraints.

C. Hyperparameter Sweep for EO-Based RIS Optimization

The performance of EO depends on the choice of the crossover probability P_c and mutation probability P_m. Therefore, the proposed method performs a systematic sweep over the sets $P_c \in \{0.6, 0.7, 0.8, 0.9\}$, and $P_m \in \{0.01, 0.03, 0.05, 0.1\}$ for both 1-bit and 2-bit RIS phase quantization.

For each Monte Carlo channel realization and each quantization level, the EO algorithm is executed for all (P_c, P_m) pairs. The corresponding performance is recorded at every generation in terms of

$$\text{SNR}_{\text{EO}}(g) = 10 \log_{10}\Big(C\Big(\boldsymbol{\theta}_{\text{best}}^{(g)}\Big)\Big)\,, \tag{17}$$

where $\boldsymbol{\theta}_{\text{best}}^{(g)}$ denotes the best solution at generation g. After averaging over all Monte Carlo runs, the pair (P_c, P_m) that yields the highest final average SNR is selected as the best hyperparameter setting. The resulting EO performance is then compared with a no-RIS baseline and an SDR-based RIS optimization method.

Algorithm 1 EO-Based RIS Phase Shift Optimization with Hyperparameter Sweep

Require: Channel dimensions N_t, N_r, and N; maximum generations $G_{\max}$; population size P; elitism count $\mathcal{E}$; crossover probabilities $P_c \in \{0.6, 0.7, 0.8, 0.9\}$; mutation probabilities $P_m \in \{0.01, 0.03, 0.05, 0.1\}$; Monte Carlo runs M; quantization levels $n \in \{1, 2\}$

Ensure: Best hyperparameter pair $(P_c^\star, P_m^\star)$, optimized phase vector $\boldsymbol{\theta}_{\text{opt}}$, and RIS matrix $\mathbf{\Phi}_{\text{opt}}$

Initialize performance storage tensor $\mathbf{S}$
for $m = 1$ to M **do**
  Generate channel realizations $\mathbf{H}_d$, $\mathbf{H}_{RI}$, and $\mathbf{G}$
  for each quantization level $n \in \{1, 2\}$ **do**
    Define quantized phase set $\mathcal{Q}_n = \left\{ \frac{2\pi k}{2^n} \,\middle|\, k = 0, 1, \ldots, 2^n - 1 \right\}$
    for each $P_c \in \{0.6, 0.7, 0.8, 0.9\}$ **do**
      for each $P_m \in \{0.01, 0.03, 0.05, 0.1\}$ **do**
        Randomly initialize population $\mathcal{X}^{(0)} = \{\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_P\}$ with $\theta_{p,i} \in \mathcal{Q}_n$
        for $g = 0$ to $G_{\max} - 1$ **do**
          Evaluate $C(\boldsymbol{\theta}) = \left\|\mathbf{H}_d + \mathbf{H}_{RI}\,\text{diag}(e^{j\boldsymbol{\theta}})\mathbf{G}\right\|_F^2$ for all $\boldsymbol{\theta} \in \mathcal{X}^{(g)}$
          Select parent pool $\mathcal{B}^{(g)}$ according to objective values
          Generate offspring $\mathcal{S}^{(g)}$ using crossover with probability P_c and mutation with probability P_m
          Preserve the top $\mathcal{E}$ elite individuals
          Form $\mathcal{X}^{(g+1)}$ by survivor selection from the union of elites and offspring
          Let $\boldsymbol{\theta}_{\text{best}}^{(g+1)} = \arg\max_{\boldsymbol{\theta} \in \mathcal{X}^{(g+1)}} C(\boldsymbol{\theta})$
          Store performance:

$$\mathbf{S}(g{+}1, P_c, P_m, n, m) = 10 \log_{10}\Big(C(\boldsymbol{\theta}_{\text{best}}^{(g+1)})\Big)$$

        end for
      end for
    end for
  end for
end for
Compute the average performance tensor over all Monte Carlo runs

$$\bar{\mathbf{S}} = \frac{1}{M} \sum_{m=1}^{M} \mathbf{S}(:, :, :, :, m)$$

For the chosen quantization level n, extract the final-generation performance matrix

$$\mathbf{S}_b = \bar{\mathbf{S}}(G_{\max}, :, :, n)$$

Determine the best hyperparameter pair

$$(P_c^\star, P_m^\star) = \arg \max_{P_c, P_m} \mathbf{S}_b(P_c, P_m)$$

Obtain the final optimized phase vector corresponding to $(P_c^\star, P_m^\star)$:

$$\boldsymbol{\theta}_{\text{opt}} = \arg \max_{\substack{\boldsymbol{\theta} \in \mathcal{X}^{(G_{\max})} \\ \theta_{p,i} \in \mathcal{Q}_n,\ \forall i}} C(\boldsymbol{\theta})$$

Compute $\mathbf{\Phi}_{\text{opt}} = \text{diag}\big(e^{j\boldsymbol{\theta}_{\text{opt}}}\big)$
return $(P_c^\star, P_m^\star)$, $\boldsymbol{\theta}_{\text{opt}}$, $\mathbf{\Phi}_{\text{opt}}$

III. Results and Discussion

This section evaluates the performance of the proposed EO-based RIS phase optimization scheme. We consider an RIS-assisted MIMO system in which the transmitter and receiver are equipped with $N_t = 3$ and $N_r = 4$ antennas, respectively, while the RIS consists of $N = 100$ reflecting elements. All propagation links are modeled as independent Rayleigh fading channels, and the reported performance is averaged over 100 independent Monte Carlo channel realizations and $\mathcal{E} = 1, G_{\max} = 100$. The EO algorithm employs a population of 30 candidate solutions and evolves them over 100 generations using crossover, mutation, and elitism. The RIS phase shifts are constrained to discrete quantized values with either 1-bit (2 phase levels) or 2-bit (4 phase levels) resolution. To identify the best hyperparameter setting, the crossover probability and mutation probability are swept over the sets $P_c \in \{0.6, 0.7, 0.8, 0.9\}$ and $P_m \in \{0.01, 0.03, 0.05, 0.1\}$, respectively. The proposed EO-based design is benchmarked against a no-RIS baseline and an SDR-based beamforming method.

Fig. 1 illustrates the convergence behavior of the EO algorithm for different mutation probabilities P_m while fixing the crossover probability at $P_c = 0.9$, for both 1-bit and 2-bit RIS phase quantization. It can be observed that lower mutation rates, particularly $P_m = 0.01$, consistently achieve higher average SNR throughout the optimization process. In contrast, a larger mutation probability such as $P_m = 0.1$ leads to slower convergence and a lower final SNR because excessive mutation disrupts high-quality candidate solutions accumulated over successive generations. These results indicate that, for discrete RIS phase optimization, maintaining good solutions through a low mutation rate is more beneficial than introducing excessive randomness into the search process.

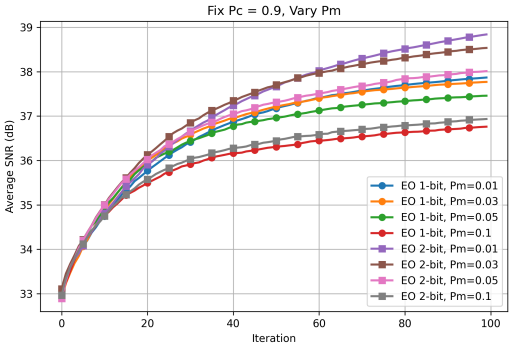

Fig. 1: Average SNR convergence of the EO algorithm for 1-bit and 2-bit RIS phase quantization with fixed P_c and varying P_m.

In contrast, Fig. 2 presents the convergence behavior of the EO algorithm for different crossover probabilities P_c while fixing the mutation probability at $P_m = 0.01$. The closely overlapping curves for all tested P_c values suggest that the EO algorithm is relatively insensitive to the crossover probability within the considered range. It is also evident that the 2-bit RIS configuration consistently outperforms the 1-bit configuration by approximately 1 dB throughout the optimization process. Based on the results of these hyperparameter sweeps, $P_c = 0.9$ and $P_m = 0.01$ are selected as the optimal settings for the subsequent performance evaluation.

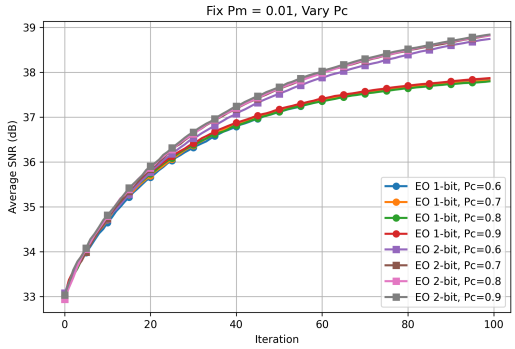

Fig. 2: Average SNR convergence of the EO algorithm for 1-bit and 2-bit RIS phase quantization with fixed P_m and varying P_c.

Fig. 3 shows the empirical cumulative distribution function (CDF) of the final SNR over all Monte Carlo channel realizations. The EO-based curves are consistently shifted to the right of the SDR curve, indicating that the proposed method achieves higher SNR over a broad range of channel conditions and also provides a lower outage probability. The inferior performance of the SDR-based scheme can be attributed to the relaxation of the original discrete optimization problem and the performance loss introduced by the subsequent Gaussian randomization step. In addition, the relatively tight spread of the EO-based CDF curves highlights the robustness and reliability of the proposed evolutionary approach under random fading environments.

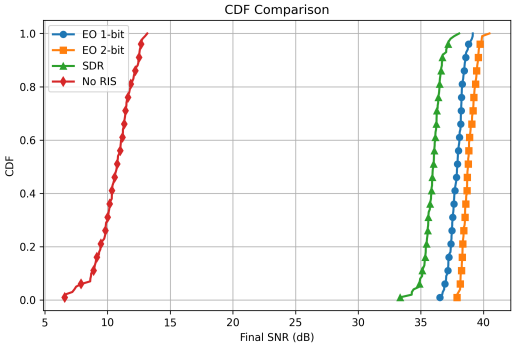

Fig. 3: Empirical CDF of the final SNR for the proposed EO-based scheme (1-bit and 2-bit), SDR, and the no-RIS baseline.

Fig. 4 presents the average SNR achieved by the four considered schemes. The no-RIS baseline attains only 10.62 dB, which highlights the severe performance degradation in the absence of RIS-assisted passive beamforming. By incorporating the RIS, the SDR-based beamforming scheme improves the average SNR to 35.96 dB. However, its performance

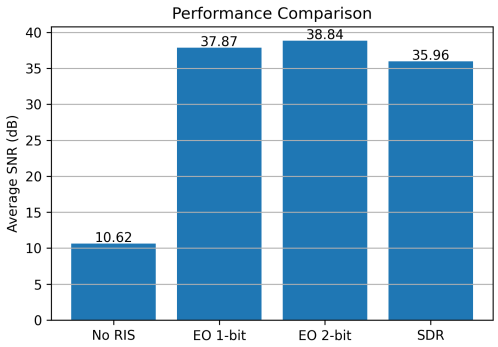

Fig. 4: Average SNR comparison of the proposed EO-based RIS beamforming scheme with 1-bit and 2-bit phase quantization against SDR and the no-RIS baseline.

remains limited because the discrete unit-modulus phase constraint is first relaxed into a continuous convex domain and the resulting solution is then mapped back to the feasible discrete set through Gaussian randomization, which introduces performance loss. In contrast, the proposed EO-based method directly searches the discrete phase space and therefore achieves better performance. Specifically, the EO algorithm with 1-bit quantization attains an average SNR of 37.87 dB, corresponding to a gain of 1.91 dB over SDR. When the phase resolution is increased to 2 bits, the average SNR further improves to 38.84 dB, providing an additional gain of 0.97 dB over the 1-bit EO case and a total gain of 2.88 dB over SDR. These results confirm that the proposed EO approach is more effective for quantized RIS phase design, while also showing that the incremental benefit of increasing the phase resolution becomes smaller as the number of quantization bits increases.

Next, the computational complexity of the proposed EO method is compared with that of the baseline schemes. For a MIMO system with N_t transmit antennas, N_r receive antennas, and an RIS with N reflecting elements, the computational complexity of EO can be expressed as $\mathcal{O}(GPN_tN_rN)$, where G denotes the number of generations and P denotes the population size. This indicates that the complexity of EO scales linearly with the principal system and algorithm parameters. In contrast, the computational complexity of the SDR-based method, when solved using practical convex optimization solvers, is approximately $\mathcal{O}(N^3)$. Moreover, the complexity of the DQN-based approach proposed in [3] is given by $\mathcal{O}(ET\,(W + N_tN_rN))$, while that of the MPC-TD3 method in [4] is $\mathcal{O}(ET\,(W + H_rN_tN_rN))$. Here, E denotes the number of training episodes, T denotes the number of time steps, W represents the number of neural network parameters, and H_r is the MPC prediction horizon, which specifies the number of future time steps considered during control optimization. Owing to these additional training and prediction-related parameters, the DQN- and MPC-TD3-based methods generally incur higher computational complexity than the proposed EO-based approach.

IV. Conclusion

This paper investigated EO-based RIS phase shift optimization in an RIS-assisted MIMO system, with particular emphasis on the effect of the crossover probability P_c and mutation probability P_m. A systematic hyperparameter sweep was carried out for both 1-bit and 2-bit quantized RIS phase configurations over 100 Monte Carlo channel realizations. The results showed that EO is highly sensitive to the mutation probability, with $P_m = 0.01$ yielding the best SNR performance, while the effect of the crossover probability was relatively small within the tested range. The best hyperparameter setting was identified as $P_c = 0.9$ and $P_m = 0.01$. Compared to the SDR-based benchmark, the proposed EO scheme achieved SNR gains of 1.91 dB and 2.88 dB for the 1-bit and 2-bit RIS cases, respectively, while also providing lower outage probability. These results demonstrate that EO is an effective and practical approach for quantized RIS phase optimization in RIS-assisted wireless systems.

References

[1] A. N. S. Hamadou, C. W. Maina, and M. M. Soidridine, "A Grey Wolf Optimiser (GWO)-based RIS Phase Shift Design for a RIS-assisted Multi-Antenna System," *IEEE Communications Letters*, 2024.

[2] M. Z. Siddiqi, A. Munir, S. A. H. Mohsan, S. Shah, S. Chaudhary, P. Sangwongngam, and L. Wuttisittikulkij, "Low-complexity Beamforming Design for a Cooperative Reconfigurable Intelligent Surface-aided Cell-free Network," *Sensors*, vol. 23, no. 2, p. 903, 2023.

[3] P. Chen, X. Li, M. Matthaiou, and S. Jin, "DRL-based RIS Phase Shift Design for OFDM Communication Systems," *IEEE Wireless Communications Letters*, vol. 12, no. 4, pp. 733–737, 2023.

[4] W. Zhang and K. Cao, "Beamforming Design for Active RIS-aided ISAC systems: A Deep Reinforcement Learning Approach," *IEEE Communications Letters*, pp. 1–1, 2025.

[5] H. Fang, H. Hu, Y. Zhang, L. Yang, and H. Zhu, "Joint Design of Pilot Power and Phase Shifts in RIS-aided Cell-Free Massive MIMO URLLC Systems," *IEEE Internet of Things Journal*, 2024.

[6] L. Jiang, X. Li, M. Matthaiou, and S. Jin, "Joint User Scheduling and Phase Shift Design for RIS-assisted Multi-Cell MISO Systems," *IEEE Wireless Communications Letters*, vol. 12, no. 3, pp. 431–435, 2022.

[7] X. Wang, Z. Fei, J. Huang, and H. Yu, "Joint Waveform and Discrete Phase Shift Design for RIS-assisted Integrated Sensing and Communication System Under Cramer-Rao Bound Constraint," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 1, pp. 1004–1009, 2021.

[8] T.-H. Vu and S. Kim, "Performance Analysis of Full-Duplex Two-Way RIS-based Systems with Imperfect CSI and Discrete Phase-Shift Design," *IEEE Communications Letters*, vol. 27, no. 2, pp. 512–516, 2022.

[9] J. Cheng, G. Wang, and Q. Zhang, "On the Optimal Discrete Phase Values of Reconfigurable Intelligent Surfaces," *IEEE Antennas and Wireless Propagation Letters*, vol. 23, no. 7, pp. 2111–2114, 2024.

[10] I. Burtakov, A. Poyda, A. Kureev, and E. Khorov, "Simultaneous RIS Adjustment and Transmission Based on Markov Chain Monte Carlo and Simulated Annealing," *IEEE Open Journal of the Communications Society*, 2025.

[11] Z. Xing, R. Wang, and X. Yuan, "Joint active and passive beamforming design for reconfigurable intelligent surface enabled integrated sensing and communication," *IEEE Transactions on Communications*, vol. 71, no. 4, pp. 2457–2474, 2023.

[12] Z.-M. Jiang, M. Rihan, P. Zhang, L. Huang, Q. Deng, J. Zhang, and E. M. Mohamed, "Intelligent reflecting surface aided dual-function radar and communication system," *IEEE Systems Journal*, vol. 16, no. 1, pp. 475–486, 2021.