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Dynamic and Adaptive GA-based Optimization of Active Reconfigurable Intelligent Surface Assisted MU-MISO Networks

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Abstract—This paper investigates spectral efficiency enhancement in active reconfigurable intelligent surface (RIS)-assisted multi-user multiple-input single-output (MU-MISO) systems. Unlike conventional passive RIS, active RIS can mitigate the multiplicative fading effect by employing reflection-type amplification, at the cost of increased optimization complexity and strict power constraints. To address the resulting non-convex joint optimization problem, a genetic algorithm (GA)-based framework is proposed for the simultaneous design of base station precoding and active RIS configuration. Two constraint-handling strategies are developed, namely Dynamic-GA-RIS and Adaptive-GA-RIS, which regulate power constraints through generation-dependent and feasibility-driven penalty mechanisms, respectively. Simulation results demonstrate that the proposed GA-based approaches outperform baseline systems without RIS assistance. In particular, the adaptive strategy achieves higher spectral efficiency, while the dynamic strategy provides faster convergence and improved power regulation. These results confirm the effectiveness of evolutionary optimization techniques for enhancing the performance of active RIS-assisted wireless networks.

Index Terms—Active RIS, 6G Networks, Genetic Algorithm, Spectral Efficiency, MU-MISO, Beamforming.

I. Introduction

Nowadays, both 5G and the upcoming 6G network must meet the significant increase in high data rates, reliable connections, and scalable connectivity due to the increase in devices, which make the interconnected, data-intensive applications like virtual reality, autonomous vehicles, remote health (e-health), and smart cities increasingly demanding seamless, ultrafast, and reliable wireless communication. This rise in expectations creates considerable pressure on network providers to improve the capacity, coverage, and efficiency of their infrastructure [1]. As a result, innovations in technologies like massive multiple-input multiple-output (massive MIMO) and millimeter wave (mm-wave) communications are being rapidly developed and implemented swiftly to meet these increasing demands. Furthermore, meeting these demands poses a real challenge because spectral efficiency (SE) is limited, and it is very difficult to use it to accommodate the increasing number of the interconnected and data-intensive applications [2].

Reconfigurable Intelligent Surface (RIS) represents a transformative solution in the evaluation toward sixth-generation (6G). RIS can manipulate the propagation of electromagnetic waves [3]. This leads us to improve the capacity, coverage, and efficiency of their infrastructure. Unlike conventional systems that adapt to channel conditions, this feature often leads to increased system complexity and higher computational requirements. While RIS adapting to the channel condition of wireless communication can improve the performance and reliability [4].

RIS comprises numerous passive elements and can dynamically manage the wireless channel to enhance performance in communication systems; this form of technology is referred to as passive RIS [5]. A passive element offers several advantages, including the ability to reflect a signal without amplification. Additionally, it provides high gain, low cost, low power consumption, and negligible noise introduction, making it a promising technique for the future 6G generation [6]. However, passive RIS has two fundamental drawbacks: it achieves negligible capacity gain in typical scenarios and experiences the multiplicative fading effect [7]. This disadvantage occurs because the channel gain between the transmitter and receiver is approximately equal to the channel gain between the transmitter, RIS, and user. To address these fundamental drawbacks, a recent paper has introduced active RIS technology [8]. This technology integrates a reflection-type amplifier into each element, enabling a reflected signal with amplification thanks to the use of power amplifiers; thus, it achieves notable capacity gain in typical and atypical scenarios and overcomes the multiplicative fading effect [9].

The active RIS technology initially faces challenges primarily related to the joint optimization problem that involves both BS precoding and RIS configuration [10]. It consists of the optimization of both amplification coefficients and phase shifts. Moreover, the fundamental objective of sum-rate maximization leads to non-convex optimization because it is characterized by the fractional signal-to-interference-plus-noise ratio (SINR) [10], [11], [12]. Additionally, the problem is consistently constrained by a dual power constraint that must be simultaneously

satisfied subject to the restrictions imposed, which are BS transmit power and the active-RIS amplification power budget. These constraints create a complex feasibility region that traditional convex optimization techniques have difficulty working effectively with [10], [11], [12].

In this paper, we present a novel Genetic Algorithm (GA) framework specifically designed for Active-RIS optimization of MU-MISO systems. The GA is adept at navigating high-dimensional, non-convex solution space. Our methodology facilitates true joint optimization of both BS precoding and RIS configuration variables through simultaneous evaluation.

Contributions: The main aspect of our approach is found in several essential contributions

- Approach involves introducing two advanced constraint-handling strategies. Dynamic-GA-RIS acts as an exponentially increasing penalty coefficient to facilitate rapid convergence to feasible regions, and Adaptive-GA-RIS is used as a dynamically adjusted penalty parameter based on the feasibility rates of the populations, effectively balancing constraint satisfaction with objective optimization throughout the evolutionary process.
- Create specific genetic operators, including a circular-aware crossover for phase shifts, that properly handle the angular nature of the variables.
- Exposed to constraint-preserving mutation operations that ensure all offspring satisfy both BS and active RIS power constraints while exploring the solution space effectively.

Organization: The remainder of this paper is organized as follows. Section II introduces the system model of the active RIS-aided downlink multi-user multiple-input single-output (MU-MISO) network, including the channel relationships and signal formulation. Section III presents the spectral efficiency formulation by deriving the signal-to-interference-plus-noise ratio (SINR) and sum-rate expressions. Section IV formulates the joint optimization problem of maximizing the sum-rate under both base station (BS) and RIS power constraints and highlights its non-convex nature. Section V details the proposed genetic algorithm (GA)-based optimization framework, including chromosome encoding, penalty-based fitness functions, namely Dynamic-GA-RIS and Adaptive-GA-RIS, as well as the designed genetic operators. Section VI describes the simulation setup and discusses the numerical results, comparing the performance of the proposed schemes with a baseline system without RIS. Finally, Section VII concludes the paper by summarizing the main findings and outlining potential directions for future research.

Notations: The mathematical notations used throughout this paper are defined as follows. Scalar quantities are denoted by italic letters. Vectors and matrices are represented by boldface lowercase and boldface uppercase letters, respectively. The superscripts $(\cdot)^T$ and $(\cdot)^H$ denote the transpose and Hermitian (conjugate transpose) operations, respectively. The expectation operator is denoted by $\mathbb{E}[\cdot]$. For vector and matrix norms, $\|\cdot\|$ signifies the

vector ℓ_2 -norm, while $\|\cdot\|_F$ represents the Frobenius norm. The operators $\Re(\cdot)$ and $\Im(\cdot)$ extract the real and imaginary parts of a complex number, respectively. The $\text{diag}(\cdot)$ operator forms a diagonal matrix from its vector argument, and $\angle(\cdot)$ returns the phase angle of a complex number. The sets of complex, real, and positive real numbers are denoted by $\mathbb{C}$, $\mathbb{R}$, and $\mathbb{R}_+$, respectively. The notation $\mathcal{CN}(\mu, \Sigma)$ refers to the complex circularly symmetric Gaussian distribution with mean μ and covariance matrix Σ , and $\mathcal{U}[a, b]$ denotes a continuous uniform distribution over the interval $[a, b]$. Within the context of the Genetic Algorithm, $\mathcal{P}$ represents the population set, and $\mathcal{F}$ denotes the fitness function used to evaluate candidate solutions.

II. Methods

This study proposes a genetic algorithm-based optimization framework to enhance spectral efficiency in active RIS-assisted MU-MISO wireless communication systems. The proposed approach jointly optimizes the base station precoding vectors and the RIS reflection parameters, including amplification coefficients and phase shifts. Two constraint-handling strategies are implemented within the GA framework:

- Dynamic-GA-RIS, which uses generation-dependent penalty functions to enforce power constraints.
- Adaptive-GA-RIS, which dynamically adjusts penalty coefficients according to the feasibility rate of the evolving population..

The system performance is evaluated using Monte Carlo simulations under realistic wireless channel conditions. Spectral efficiency (sum-rate) is used as the main performance metric to compare the proposed methods with baseline systems without RIS assistance.

III. System model

Active RIS in typical communication scenarios: we consider an active RIS-aided downlink MU-MISO system as shown in Figure 1, where an M-antenna base station (BS) serves K single-antenna users simultaneously with the aid of an N-element active RIS [11].

Let $\mathbf{s} = [s_1, \dots, s_K]^T \in \mathbb{C}^K$ represent the vector of transmitted symbols for K users, where the symbols are assumed to be mutually uncorrelated with $\mathbb{E}[\mathbf{s}\mathbf{s}^H] = \mathbf{I}_K$. The base station utilizes multi-user linear precoding for downlink transmission. Consequently, the received signal $r_k \in \mathbb{C}$ at user k can be expressed as [8]:

$$r_k = \left(\mathbf{h}_k^H + \mathbf{f}_k^H \mathbf{\Psi} \mathbf{G} \right) \sum_{j=1}^K \mathbf{w}_j s_j + \mathbf{f}_k^H \mathbf{\Psi} \mathbf{v} + z_k, \quad (1)$$

Where $\mathbf{G} \in \mathbb{C}^{N \times M}$, $\mathbf{h}_k^H \in \mathbb{C}^{1 \times M}$, and $\mathbf{f}_k^H \in \mathbb{C}^{1 \times N}$ denote the channel matrix between the BS and the RIS, the channel vector between the BS and user k, and the channel vector between the RIS and user k, respectively [13]. The vector $\mathbf{w}_k \in \mathbb{C}^{M \times 1}$ represents the BS beamforming vector associated with the symbol s_k , while z_k denotes the additive white Gaussian noise (AWGN)

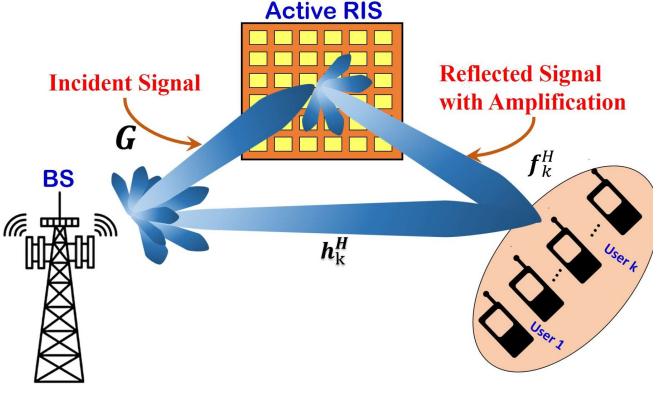


Fig. 1: Illustration of the downlink transmission in an active RIS aided MU-MISO system.

at user k , assumed to have zero mean and variance σ^2 . $\Psi = \text{diag}(p_1 e^{j\theta_1}, \dots, p_N e^{j\theta_N})$ is the reflection coefficient matrix of the active RIS, in which $p_n \in \mathbb{R}_+$ denotes the amplification factor of the n -th active element and p_n must be larger than one thanks to the integrated reflection-type amplifier and $\Psi \mathbf{v}$ is the noise introduced and amplified by the reflection-type amplifier [10].

IV. Spectral Efficiency (SE) Formulation

The signal-to-interference-plus-noise ratio (SINR) for user k can be obtained from the MU-MISO transmission model in (1).

$$\gamma_k = \frac{|\hat{\mathbf{h}}_k^H \mathbf{w}_k|^2}{\sum_{j=1; j \neq k}^K |\hat{\mathbf{h}}_k^H \mathbf{w}_j|^2 + \|\mathbf{f}_k^H \Psi\|^2 \sigma_v^2 + \sigma^2} \quad (2)$$

where $\hat{\mathbf{h}}_k = \mathbf{h}_k + \mathbf{f}_k^H \Psi \mathbf{G} \in \mathbb{C}^{1 \times M}$ denotes the equivalent channel from the BS for user k , γ_k represents the SINR for user k , σ_v^2 indicates the variance of dynamic noise from the active RIS, and σ^2 signifies the variance of AWGN.

From the obtained γ_k in equation Eq (2), the achievable spectral efficiency for that user is given by Shannon's formula as $R_k = \log_2(1 + \gamma_k)$. Consequently, the total system sum-rate, which serves as the key performance metric for evaluating the overall network capacity, is derived by summing spectral efficiencies of all K users [14]. This sum-rate is expressed as

$$R_{\text{sum}} = \sum_{k=1}^K \log_2(1 + \gamma_k), \quad (3)$$

This final sum-rate is direct function of RIS configurations Matrix Ψ through the equivalent channel $\hat{\mathbf{h}}_k^H$ embedded within each γ_k .

V. Joint transmit precoding and perfect beamforming design

The fundamental objective of this work is to maximize the overall network capacity systems by jointly precoding at the BS and the beamforming configuration at the active RIS. This goal is formally cast as a sum-rate maximization

problem, subject to the critical power constraints of both the BS and the RIS, and it can be formulated as follows [15]:

$$\begin{aligned} \max_{\mathbf{w}, \Psi} \quad & R_{\text{sum}}(\mathbf{w}, \Psi) = \sum_{k=1}^K \log_2(1 + \gamma_k) \\ \text{s.t.} \quad & \\ & \text{C1: } \sum_{k=1}^K \|\mathbf{w}_k\|^2 \leq P_{\text{BS}}^{\text{max}} \\ & \text{C2: } \sum_{k=1}^K \|\Psi \mathbf{G} \mathbf{w}_k\|^2 + \|\Psi\|_{\text{F}}^2 \sigma_v^2 \leq P_{\text{RIS}}^{\text{max}} \end{aligned} \quad (4)$$

where R_{sum} denotes the system sum-rate. Constraint C1 ensures that the total transmit power from all precoding vectors $\mathbf{w}_k$ at the base station (BS) does not exceed the maximum power budget, denoted as $P_{\text{BS}}^{\text{max}}$ [11], [15]. Constraints C2 enforces the power limitation at the active RIS, where the total power consumption includes two components: the power required to amplify the reflected BS signals in the first term of C2 ($\sum_{k=1}^K \|\Psi \mathbf{G} \mathbf{w}_k\|^2$) and the power required to amplify the dynamic noise at the RIS ($\|\Psi\|_{\text{F}}^2 \sigma_v^2$) in the second term of C2. The variables $\mathbf{w}$ and Ψ must be coupled with each other, making the solved problem highly challenging [11], [16].

The original sum-rate maximization problem, formulated in (4), is a non-convex optimization problem due to the coupled variables, specifically, the tight interdependence between the BS precoding vectors $\mathbf{w}_k$ and the RIS precoding matrix Ψ and the complex fractional form of the SINR (γ_k) within the objective function [11], [17], [18], [19]. The introduction of the active RIS further increase the challenge by adding a non-linear power constraint (C2) that involves both the amplified transmitted signals and the amplified noise. Traditional optimization techniques struggle to efficiently solve this joint design problem [15], [11], [20], [21]. To solve this complexity and adeptly traverse the extensive, non-convex solution space, we propose utilizing a metaheuristic strategy based on a Genetic Algorithm (GA) [22]. We develop two distinct techniques, Dynamic-GA-RIS and Adaptive-GA-RIS, which leverage the evolutionary principles of genetic algorithms to enhance the base station precoding vectors $\mathbf{w}_k$ and the reconfigurable intelligent surface precoding matrix Ψ . These methodologies facilitate simultaneous design, resulting in a robust and high-performance solution to the complex beamforming challenge.

VI. Proposed Genetic Algorithm (GA) Framework

The GA is a heuristic search method inspired by the natural selection process. It proves to be particularly effective for addressing the Active-RIS problem because it can explore the non-convex SINR space without needing gradient calculations, which often prove inadequate in high-dimensional wireless scenarios [22], [23].

A. Chromosome Representation and Encoding

The first step in our GA framework is "encoding" the optimization variables into a single chromosome. The chromosome structure comprehensively represents all optimization variables: The BS precoding vectors, denoted as $\mathbf{w}_k \in \mathbb{C}^{M \times 1}$, and the RIS precoding matrix, denoted as $\mathbf{\Psi} = \text{diag}(p_1 e^{j\theta_1}, p_2 e^{j\theta_2}, \dots, p_N e^{j\theta_N}) \in \mathbb{C}^{N \times N}$, are included in the chromosome structure. These variables are encoded in a single chromosome that represents an individual in the population $\mathcal{P}$ [24]. The single chromosome vector ($\mathbf{c}$) consists of three distinct components, which are detailed below:

$$\mathbf{c} = [\mathbf{c}_{\text{BS}}^T, \mathbf{c}_P^T, \mathbf{c}_\theta^T]^T \in \mathbb{R}^{N_c}, \quad (5)$$

where $\mathbf{c}$ is the single chromosome vector with chromosome size $N_c = 2MK + 2N$, $\mathbf{c}_{\text{BS}} = [\Re(\mathbf{w}_1^T), \Im(\mathbf{w}_1^T), \dots, \Re(\mathbf{w}_K^T), \Im(\mathbf{w}_K^T)]^T \in \mathbb{R}^{2MK}$ represents the BS precoding vector component of the chromosome, and $\mathbf{c}_P = [p_1, p_2, \dots, p_N]^T \in \mathbb{R}_+^N$ denotes the amplification coefficients component of the chromosome, and $\mathbf{c}_\theta = [\theta_1, \theta_2, \dots, \theta_N]^T \in \mathbb{R}^N$ signifies the phase shifts component of the chromosome.

In this study, we will define the population in terms of a set of chromosomes. Specifically, we will denote the population at generation t as $\mathcal{P}^{(t)}$, defined as:

$$\mathcal{P}^{(t)} = \{\mathbf{c}_1^{(t)}, \mathbf{c}_2^{(t)}, \dots, \mathbf{c}_{N_p}^{(t)}\}, \quad (6)$$

where $\mathcal{P}^{(t)}$ represents the population at generation (t) , while the symbol $\mathbf{c}_i^{(t)} \in \mathbb{R}^{N_c}$ signifies the i^{th} individual chromosome vector at generation (t) .

B. Fitness Function

The formulation of the fitness function is crucial to directing the genetic algorithm toward optimal solutions that adhere to system restrictions. The principal objective function is to maximize the sum-rate $R_{\text{sum}} = \log_2(1 + \gamma_k)$ for all K users [14]. However, the GA must simultaneously enforce strict adherence to the transmit power constraint in both the BS and the active RIS. A constraint violation occurs when a candidate solutions power allocation exceeds the predetermined budget [24]. Specifically, the BS power violation is quantified as $\mathcal{B}(\mathbf{w}) = \sum_{k=1}^K \|\mathbf{w}_k\|^2 - P_{\text{max}}^{\text{BS}}$, and the active RIS power violation as $\mathcal{Q}(\mathbf{w}, \mathbf{\Psi}) = \sum_{k=1}^K \|\mathbf{\Psi} \mathbf{G} \mathbf{w}_k\|^2 + \|\mathbf{\Psi}\|^2 \sigma_v^2 - P_{\text{max}}^{\text{RIS}}$ to integrate these critical system constraints into evolutionary optimization process, we employ a penalty function approach. The fitness function is formulated as

$$F^{(i,t)} = R_{\text{sum}}^{(i,t)} - \lambda_1(t)[\mathcal{B}^{(i,t)}(\mathbf{w}_i)]^+ - \lambda_2(t)[\mathcal{Q}^{(i,t)}(\mathbf{w}_i, \mathbf{\Psi}_i)]^+ \quad (7)$$

where $F^{(i,t)}$ represents the fitness value of chromosome i at generation t , $\mathcal{B}^{(i,t)}(\mathbf{w}_i)$ denotes the BS power constraint violation for individual i at generation t , $\mathcal{Q}^{(i,t)}(\mathbf{w}_i, \mathbf{\Psi}_i)$ denotes RIS power constraint violation for individual i at generations t , $[x]^+ = \max(0, x) \in \mathbb{R}_+$ ensures only violations are penalized, and where $\lambda_1(t)$ and $\lambda_2(t)$ are adjusted penalty coefficients every generation (or iteration

t). To this end, we propose and investigate two penalty strategies, Adaptive-GA-RIS and Dynamic-GA-RIS, that leverage this penalty framework in fundamentally different ways. In the next subsection, we will propose how these approaches employ the penalty mechanism to achieve their optimization objectives. The adaptive penalty strategy emphasizes long-term performance through a thorough search, while the dynamic strategy focuses on achieving rapid convergence via effective constraint management.

1) **Dynamic Penalty for Constraint Handling:** Integrating a dynamic penalty function into the fitness evolution is essential for addressing the challenging power constraints present in the active RIS-assisted MU-MISO system, referred to as Dynamic-GA-RIS. The dynamic penalty mechanism is mathematically formulated through an exponentially increasing penalty coefficient that evolves across generations [25]. Integrating a dynamic penalty function into the fitness evolution is essential for addressing the challenging power constraints present in the active RIS-assisted MU-MISO system, referred to as Dynamic-GA-RIS. The dynamic penalty mechanism is mathematically formulated through an exponentially increasing penalty coefficient that evolves across generations. We can rewrite the fitness evolution for the dynamic-GA-RIS approach using equation (7) as follows:

$$F_D^{(i,t)} = R_{\text{sum}}^{(i,t)} - \lambda_1^D(t)[\mathcal{B}^{(i,t)}(\mathbf{w}_i)]^+ - \lambda_2^D(t)[\mathcal{Q}^{(i,t)}(\mathbf{w}_i, \mathbf{\Psi}_i)]^+ \quad (8)$$

where $\lambda_1^D(t)$ and $\lambda_2^D(t)$ are the penalty coefficients for both the BS and IRS power constraints, respectively, at generation t and are defined as:

$$\lambda_j^D(t) = \lambda_{j,o}^D(1 + \alpha)^t, \quad \forall j \in \{1, 2\} \quad (9)$$

where $\lambda_{j,o}^D$ represents the initial penalty coefficient for both the BS and IRS power constraints, denotes the growth rate parameter that controls the exponential increase of penalties, and t indicates the current generation number.

2) **Adaptive Penalty for Constraint Handling:** Integrating an adaptive penalty function into the fitness evolution is essential for addressing the challenging power constraints present in the active RIS-assisted MU-MISO system, referred to as Adaptive-GA-RIS [25], [26]. The adaptive-GA-RIS approach implements a sophisticated penalty adjustment mechanism that dynamically responds to the population feasibility rate $\mathcal{X}$. Based on equation (7), we can reformulate the fitness evolution for the Adaptive-GA-RIS approach as follows:

$$F_A^{(i,t)} = R_{\text{sum}}^{(i,t)} - \lambda_1^A(t)[\mathcal{B}^{(i,t)}(\mathbf{w}_i)]^+ - \lambda_2^A(t)[\mathcal{Q}^{(i,t)}(\mathbf{w}_i, \mathbf{\Psi}_i)]^+ \quad (10)$$

where λ_1^A, λ_2^A are the penalty coefficients of the adaptive penalty function, we can as follows:

$$\lambda_j^A(t+1) = \begin{cases} \lambda_j^A(t) \cdot \alpha_{\text{inc}} & \text{if } \mathcal{X}^{(t)} \leq \mathcal{X}_L \\ \lambda_j^A(t) & \text{if } \mathcal{X}_L < \mathcal{X}^{(t)} < \mathcal{X}_H \\ \lambda_j^A(t) \cdot \alpha_{\text{dec}} & \text{if } \mathcal{X}^{(t)} \geq \mathcal{X}_H \end{cases} \quad (11)$$

where $\mathcal{X}^{(t)}$ represents the feasibility rate of the current population, $\mathcal{X}_L$ denotes the lower threshold for penalty intensification, $\mathcal{X}_H$ indicates the higher threshold for penalty relaxation, α_{inc} refers to the penalty intensification factor (where $\alpha_{\text{inc}} > 1$), and α_{dec} signifies the penalty relaxation factor (with $0 < \alpha_{\text{dec}} < 1$). The adaptive mechanism, as delineated in (11), works using a threshold-based methodology. Initially, when the feasible rate $\mathcal{X}^{(t)}$ drops below the lower threshold $\mathcal{X}_L$, the algorithm enters high constraint pressure mode. In this mode, penalty coefficients are significantly increased by a factor of α_{inc} , creating dedicated evolutionary pressure that drives the population toward the feasible region $\mathcal{X}^{(t)}$. This method generates considerable evolutionary pressure focused on meeting power constraints rather than maximizing the sum-rate. The term $\lambda_j^A(t) \cdot \alpha_{\text{inc}}$ reduces the fitness of solutions that exceed the power limits of the base station (BS) and reconfigurable intelligent surface (RIS), enabling the genetic algorithm to converge rapidly to the feasible region $\mathcal{X}$.

Secondly, when the feasible rate is between the interval of $\mathcal{X}_L < \mathcal{X}^{(t)} < \mathcal{X}_H$, the penalty coefficient remains unchanged. Consequently, $\lambda_j^A(t+1) = \lambda_j^A(t)$, enabling the algorithm to change into Moderate Constraint Pressure mode. This mode agrees with the simultaneous optimization of both sum-rate and power constraints.

Finally, when the feasible rate exceeds both high, the algorithm activates the Lower Constraint Pressure Mode. In this mode, penalty coefficients are significantly decreased by a factor of α_{dec} , shifting focus toward sum-rate maximization. The term $\lambda_j^A(t) \cdot \alpha_{\text{dec}}$ increases the fitness of solutions that do not exceed the power limits of base station (BS) and reconfigurable intelligent surface (RIS), enabling the GA to improve the sum-rate.

C. Genetic Algorithm GA Operators

1) Tournament Selection: Tournament selection is a widely used method in genetic algorithms [27]. In this approach, individuals are randomly chosen from the population, and the one that wins is selected for reproduction for the next generation; therefore, the selection-encoded chromosome population is $\mathcal{P}^{(t)} = \{\mathbf{c}_1^{(t)}, \mathbf{c}_2^{(t)}, \dots, \mathbf{c}_{N_{\text{pop}}}^{(t)}\}$ where each chromosome $\mathbf{c}_i$ is defined as (5). For each selection operation required to create a mating process, the tournament process $\mathcal{T}^{(t)}$ is formed by randomly sampling (or selecting) $N_{\mathcal{T}}$ individuals from the population every generation t according to a discrete uniform distribution:

$$\mathcal{T}^{(t)} = \left\{ \mathbf{c}_{r_1}^{(t)}, \mathbf{c}_{r_2}^{(t)}, \dots, \mathbf{c}_{r_{N_{\mathcal{T}}}}^{(t)} \right\} \subset \mathcal{P}^{(t)} \quad (12)$$

The tournament winner is determined by selecting the individual with highest fitness value from the tournament pool:

$$\mathbf{c}_{\text{winner}}^{(t)} = \arg \max_{\mathbf{c} \in \mathcal{T}^{(t)}} \mathcal{F}(\mathbf{c}, t) \quad (13)$$

where $\mathcal{F}(\mathbf{c}, t)$ denotes the fitness function evaluated for chromosome $\mathbf{c}$ at generation t .

2) Crossover: After selecting chromosome pairs from the population using tournament selection, the crossover operation begins to create offspring. The exchange of genetic material between selected parents is straightforward [28]. Given we have to parent a chromosome, $\mathbf{c}^{\text{Parent 1}}$, $\mathbf{c}^{\text{Parent 2}}$ are selected through tournament selection, and the crossover generates two new offspring:

$$[\mathbf{c}^{\text{Child 1}}, \mathbf{c}^{\text{Child 2}}] = \text{Crossover}(\mathbf{c}^{\text{Parent 1}}, \mathbf{c}^{\text{Parent 2}}), \quad (14)$$

For the BS precoding matrix we have $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_N] \in \mathbb{C}^{M \times K}$, where it represents the beamforming weights for user k across M BS antennas. In BS precoding crossover begins with parent chromosome through tournament selection. each chromosome contains the BS precoding vectors, RIS amplification coefficients, and RIS phase shifts. We focusing on BS precoding vector part. Let $\mathbf{c}^{\text{Parent 1}}$ and $\mathbf{c}^{\text{Parent 2}}$ denotes the two chromosome selected from the population using the tournament selection process. From these chromosomes, we extract the BS precoding components:

$$\begin{aligned} \mathbf{c}_{\text{precoding}}^{\text{Parent 1}} &= [\Re(\mathbf{w}_1^{\text{P1}^T}), \Im(\mathbf{w}_1^{\text{P1}^T}), \dots, \Re(\mathbf{w}_K^{\text{P1}^T}), \Im(\mathbf{w}_K^{\text{P1}^T})] \\ \mathbf{c}_{\text{precoding}}^{\text{Parent 2}} &= [\Re(\mathbf{w}_1^{\text{P2}^T}), \Im(\mathbf{w}_1^{\text{P2}^T}), \dots, \Re(\mathbf{w}_K^{\text{P2}^T}), \Im(\mathbf{w}_K^{\text{P2}^T})] \end{aligned} \quad (15)$$

For this chromosome, extract the BS precoding component:

$$\begin{aligned} \mathbf{W}^{\text{Parent 1}} &= [\mathbf{w}_1^{\text{P1}}, \mathbf{w}_2^{\text{P1}}, \dots, \mathbf{w}_K^{\text{P1}}] \in \mathbb{C}^{M \times K} \\ \mathbf{W}^{\text{Parent 2}} &= [\mathbf{w}_1^{\text{P2}}, \mathbf{w}_2^{\text{P2}}, \dots, \mathbf{w}_K^{\text{P2}}] \in \mathbb{C}^{M \times K} \end{aligned} \quad (16)$$

where each column vector $\mathbf{w}_k \in \mathbb{C}^{M \times 1}$ represents beamforming weights for user k across M BS antennas. The crossover operation generates convex combinations of the parent precoding matrices to produce two offspring:

$$\begin{aligned} \mathbf{W}^{\text{Child 1}} &= \alpha_w \mathbf{W}^{\text{Parent 1}} + (1 - \alpha_w) \mathbf{W}^{\text{Parent 2}} \\ \mathbf{W}^{\text{Child 2}} &= \alpha_w \mathbf{W}^{\text{Parent 2}} + (1 - \alpha_w) \mathbf{W}^{\text{Parent 1}} \end{aligned} \quad (17)$$

These child precoding components are then integrated with the corresponding RIS amplification and phase shift components to form complete child chromosome for next generation.

Then we can apply bidirectional angular interpolation, to generate new offspring phase vector as follow

$$\begin{aligned} \boldsymbol{\theta}^{\text{Child 1}} &= \boldsymbol{\theta}^{\text{Parent 1}} + \alpha_{\theta} \boldsymbol{\delta} \\ \boldsymbol{\theta}^{\text{Child 2}} &= \boldsymbol{\theta}^{\text{Parent 2}} + (1 - \alpha_{\theta}) \boldsymbol{\delta}, \end{aligned} \quad (18)$$

where $\alpha_{\theta} \sim \mathcal{U}[0, 1]$ is the mixing parameter that governs the degree of interpolation, and $\boldsymbol{\delta}$ is the circular difference between parent phases. At some point we may reconstruct a novel offspring matrix in (18), as defined below:

$$\begin{aligned} \boldsymbol{\Theta}^{\text{Child 1}} &= \text{diag} \left(e^{j\boldsymbol{\theta}^{\text{Child 1}}} \right) \\ \boldsymbol{\Theta}^{\text{Child 2}} &= \text{diag} \left(e^{j\boldsymbol{\theta}^{\text{Child 2}}} \right) \end{aligned} \quad (19)$$

3) Mutation: Mutation is a major step in GA that introduces random perturbations into the population generated by previous operations, such as crossover. Therefore, it serves as a mechanism for maintaining population diversity and enabling exploration of the solution space. In this paper, we are performing a mutation operation on RIS-assisted MU-MISO systems [29], [30]. As a stage of GA, we see its effect on the performance of the algorithm and our system models and how it plays a critical role in optimizing the complex interplay between BS precoding $\mathbf{W} \in \mathbb{C}^{M \times K}$ and RIS configuration $\Psi = \mathbf{P}\Theta$ parameters [29], [30], [31]. The BS precoding mutation operation is a mechanism to explore the complex beamforming space on RIS-assisted MU-MISO systems. Therefore, this mutation applies to the BS precoding matrix $\mathbf{W} \in \mathbb{C}^{M \times K}$; each column vector $\mathbf{w}_k \in \mathbb{C}^{M \times 1}$ represents the beamforming weight for user k across all M BS antennas.

Firstly, we can apply a Complex Gaussian Perturbation to the BS precoding matrix $\mathbf{W} \in \mathbb{C}^{M \times K}$ yielding $\mathbf{W}'$ as shown below:

$$\mathbf{W}' = \mathbf{W} + \Delta\mathbf{W}, \quad (20)$$

where the mutation matrix $\Delta\mathbf{W} \in \mathbb{C}^{M \times K}$ follows:

$$\Delta\mathbf{W} = \sigma_w(\mathbf{X} + j\mathbf{Y}), \quad \mathbf{X}, \mathbf{Y} \sim \mathcal{CN}(0, \mathbf{I}_{M \times K}), \quad (21)$$

with σ_w controlling mutation strength. After adding complex perturbation on the BS precoding matrix, we must verify that the total power of $\|\mathbf{W}'\|_F^2$ is less than the total BS power constraint $P_{\max}^{\text{BS}}$, and this requirement is specified in constraint C1 of equation (4). In other words, the solution must be projected to a feasible set, as specified below:

$$\mathbf{W}_{\text{Mut}} = \begin{cases} \mathbf{W}' \cdot \sqrt{\frac{P_{\max}^{\text{BS}}}{\|\mathbf{W}'\|_F^2}} & \text{If } \|\mathbf{W}'\|_F^2 > P_{\max}^{\text{BS}} \\ \mathbf{W}' & \text{If otherwise} \end{cases} \quad (22)$$

For the RIS amplification coefficient matrix $\mathbf{P} = \text{diag}(p_1, p_2, \dots, p_N)$, where the amplification coefficients must satisfy the active RIS constraints $p_n > 1 \quad \forall n \in \{1, 2, \dots, N\}$. Now we extract diagonal elements of the RIS amplification coefficient matrix to vector $\mathbf{p} = [p_1, p_2, \dots, p_N]^T$. now we can apply a Gaussian Perturbation to the RIS precoding vector to $\mathbf{p} \in \mathbb{R}^{N \times 1}$ yielding $\mathbf{p}'$ as shown below:

$$\mathbf{p}' = \mathbf{p} + \Delta\mathbf{p}, \quad (23)$$

where $\Delta\mathbf{p}$ denotes the perturbation power, represented as a minor increment of amplification coefficients, as explained in the subsequent equation:

$$\Delta\mathbf{p} = \sigma_p \cdot \boldsymbol{\epsilon}, \sim \mathcal{N}(0, \mathbf{I}_N) \quad (24)$$

where $\boldsymbol{\epsilon} \in \mathbb{R}^{N \times 1}$ is the vector of independent standard normal random variables, and σ_p controls the mutation strength. And then must ensure each element the RIS precoding vector perturbation $\mathbf{p}' \in \mathbb{R}^{N \times 1}$ is grater than

one, that is $\mathbf{p}' = [p'_1, p'_2, \dots, p'_N]^T$, This can be confirmed using the following equation:

$$p'_n = \max(p'_n, 1), \quad \forall n \in \{1, 2, \dots, N\} \quad (25)$$

Finally, The total RIS power constraint is enforced by scaling to ensure the total perturbation power of $P^{\text{RIS}}(\mathbf{p}'') = \sum_{k=1}^K \|\Psi'' \mathbf{G} \mathbf{w}_k\|^2 + \|\Psi''\|_F^2 \sigma_v^2 \leq P_{\max}^{\text{RIS}}$, where $\Psi'' = \text{diag}(\mathbf{p}'' \Theta)$. In other words, the solution must be projected to a feasible set, as specified below:

$$\mathbf{p}_{\text{Mut}} = \begin{cases} \mathbf{p}'' \cdot \sqrt{\frac{P_{\max}^{\text{RIS}}}{P^{\text{RIS}}(\mathbf{p}'')}} & \text{If } P^{\text{RIS}}(\mathbf{p}'') > P_{\max}^{\text{RIS}} \\ \mathbf{p}'' & \text{If otherwise} \end{cases} \quad (26)$$

The current phase configuration $\boldsymbol{\theta}$ for the RIS phase shift can also be extracted from each element of the RIS phase shift matrix Θ , as shown below:

$$\boldsymbol{\theta} = \angle(\text{diag}(\Theta)) \in [0, 2\pi)^N, \quad (27)$$

where $\Theta = \text{diag}(e^{j\theta_1}, e^{j\theta_2}, \dots, e^{j\theta_N})$ is the current phase shift matrix, and $\boldsymbol{\theta} = [\theta_1, \theta_2, \dots, \theta_N]^T$ represents the current phase angles. Then the mutation of RIS phase shift is formulated as an angular perturbation in circular domain as given:

$$\boldsymbol{\theta}' = \boldsymbol{\theta} + \Delta\boldsymbol{\theta}, \quad (28)$$

where $\boldsymbol{\theta} = [\theta_1, \theta_2, \dots, \theta_N]^T \in [0, 2\pi)^N$ denotes the current phase shifts. The vector $\Delta\boldsymbol{\theta} \sim \mathcal{N}(0, \sigma_\theta^2 \mathbf{I}_N)$ represents the Gaussian angular perturbation. The σ_θ (in radians) controls the mutation strength within the angular domain. It is essential to ensure that all phase shifts remain within the fundamental interval $[0, 2\pi)$ while preserving the circular continuity of the phase space. This equation explains that:

$$\boldsymbol{\theta}_{\text{Mut}} = \text{mod}(\boldsymbol{\theta}', 2\pi), \quad \forall n \in \{1, 2, \dots, N\} \quad (29)$$

Algorithm 1 delineates the proposed GA-RIS framework for the joint optimization of the base station (BS) precoding matrix and the active RIS configuration within a downlink MU-MISO system. The algorithm offers an evolutionary solution to the non-convex sum-rate maximization problem delineated in (4), with stringent enforcement of power constraints for both the BS and RIS.

VII. Simulation setup

Figure 2 illustrates the simulation setup for downlink transmission in an active RIS-assisted MU-MISO system. The base station (BS) is situated at coordinates (0 m, -40 m), and the reconfigurable intelligent surface (RIS) is located at (200 m, 30 m). Users are moving along a distance L , ranging from 0 m to 300 m. The objective of this simulation is to evaluate the performance of the system. To efficiently evaluate the performance of the proposed Dynamic-GA-RIS and Adaptive-GA-RIS approaches, we conduct Monte Carlo simulations using a geometric channel model. The spectral efficiency of the active RIS-assisted system is evaluated compared to a traditional baseline without RIS. The total system power

Algorithm 1 GA-RIS: Joint BS Precoding and Active RIS Optimization

Require: Channel matrices $\mathbf{G}, \mathbf{h}_k, \mathbf{f}_k$; $P_{\text{BS}}^{\text{max}}, P_{\text{RIS}}^{\text{max}}$; $N_{\text{pop}}, G_{\text{max}}$
 Ensure: Optimized $\mathbf{W}^*, \Psi^*$
 1: Initialize population $\mathcal{P}(0)$ using (5)–(6)
 2: for $t = 1$ to G_{max} do
 3: Compute SINR γ_k using (2)
 4: Compute sum-rate R_{sum} using (3)
 5: Evaluate fitness using Dynamic-GA-RIS via (8)–(9) or Dynamic-GA-RIS via (10)–(11)
 6: Select parents via tournament selection (12)–(13)
 7: Apply crossover:
 BS precoding via (15)–(17)
 RIS phase via (18)–(19)
 8: Apply mutation:
 BS precoding via (20)–(22)
 RIS amplification via (23)–(26)
 RIS phase via (27)–(29)
 9: Form next population $\mathcal{P}(t+1)$
 10: end for
 11: Select best chromosome
 12: Decode $\Psi^* = \text{diag}(p_n e^{j\theta_n})$
 return $\mathbf{W}^*, \Psi^*$

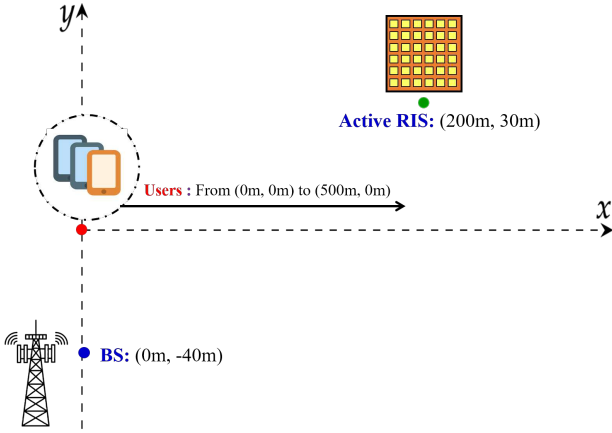


Fig. 2: The simulation setup where one BS assisted by one Active RIS serve four users.

budget P_{total} remains constant for a fair comparison. In RIS-aided scenarios, the power allocation is defined as $P_{\text{max}}^{\text{BS}} = 0.99 P_{\text{total}}$ for the base station (BS) and $P_{\text{max}}^{\text{RIS}} = 0.01 P_{\text{total}}$ for the RIS. In contrast, the baseline (without RIS) system employs the entire power budget, $P_{\text{total}} = P_{\text{max}}^{\text{BS}}$, for BS transmission. The simulation parameters are categorized into the physical system model and the GA framework, detailed in Table I. The wireless channel model utilized in this simulation adopts a composite structure that integrates both large-scale path loss and small-scale Rician fading. For any channel matrix $\mathbf{H}$, which may represent $\mathbf{G} \in \mathbb{C}^{N \times M}$, $\mathbf{h}_k \in \mathbb{C}^{M \times 1}$, or $\mathbf{f}_k \in \mathbb{C}^{N \times 1}$, the generation proceeds as follows:

TABLE I: Simulation Parameters for Active RIS-Aided MU-MISO System Evaluation

Parameter	Symbol	Value
Communication System		
BS Antennas	M	4
Active RIS Elements	N	256
Single-antenna Users	K	2
Carrier Frequency	f_c	5 GHz
Total Power Budget	P_{total}	10 dBm
BS Power (RIS-aided)	$P_{\text{max}}^{\text{BS}}$	9.9 dBm
RIS Power Budget	$P_{\text{max}}^{\text{RIS}}$	0.1 dBm
AWGN Variance at User	σ_v^2	-100 dBm
Dynamic Noise Variance at RIS	σ_v^2	-100 dBm
Genetic Algorithm		
Population Size	N_{pop}	50
Maximum Generations	G_{max}	100
Tournament Size	$N_{\mathcal{T}}$	5
Mutation Rate	p_m	0.1
Evaluated Scenarios		
	1)	Dynamic-GA-RIS
	2)	Adaptive-GA-RIS
	3)	Baseline (without RIS)

$$\mathbf{H} = \sqrt{\text{PL}} \left(\sqrt{\frac{\kappa}{\kappa+1}} \mathbf{H}_{\text{LoS}} + \sqrt{\frac{1}{\kappa+1}} \mathbf{H}_{\text{NLoS}} \right), \quad (30)$$

where PL denotes the distance-dependent path loss, $\kappa = 1$ is the Rician factor, $\mathbf{H}_{\text{LoS}}$ represents the deterministic line-of-sight (LoS) component, and $\mathbf{H}_{\text{NLoS}}$ models the Rayleigh-distributed non-LoS component with $\mathbf{H}_{\text{NLoS}} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I})$. The path loss is calculated using a 3GPP-TS 36.814 standard [32]:

$$\text{PL}_s = 37.3 + 22.0 \log d \quad (31)$$

$$\text{PL}_w = 41.2 + 28.7 \log d, \quad (32)$$

where d denotes the distance between the BS and users, PL_s represents a robust path loss model utilized to generate the strong BS-RIS and RIS-users channels, while PL_w signifies a weak path loss model employed to generate the weak BS-users channel.

VIII. Results

This section presents the simulation results used to evaluate the performance of the proposed optimization strategies for the active RIS-assisted MU-MISO system. The objective of these simulations is to examine how the proposed Dynamic-GA-RIS and Adaptive-GA-RIS approaches improve spectral efficiency under practical system conditions. The performance of the proposed methods is compared with a baseline system without RIS to highlight the benefits of RIS-assisted communication. The results focus on key performance metrics such as spectral efficiency convergence, system sum-rate, and power consumption under different user distances and system configurations. Figure 3 presents the spectral efficiency (in bps/Hz) versus the number of generations (or iterations) for two optimization strategies: The Dynamic-GA-RIS

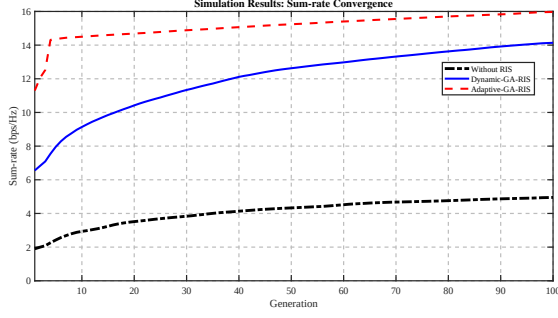


Fig. 3: Simulation spectral efficiency (in bps/Hz) versus the number of generations (or iterations) in an RIS-aided MU-MISO system.

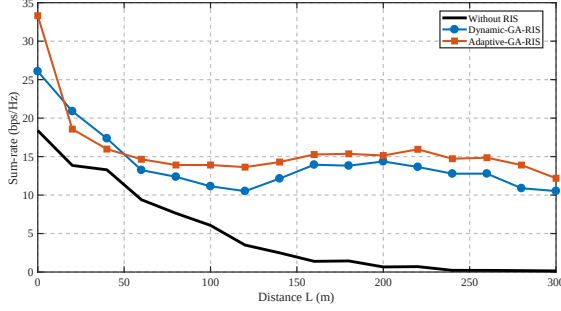
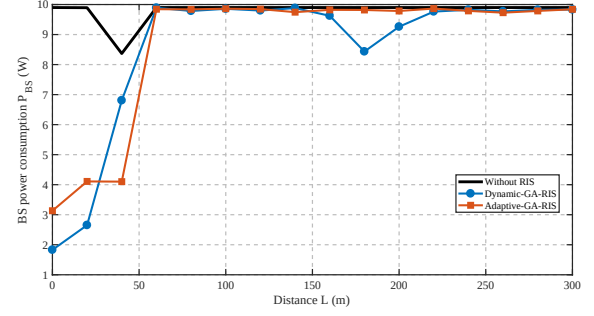


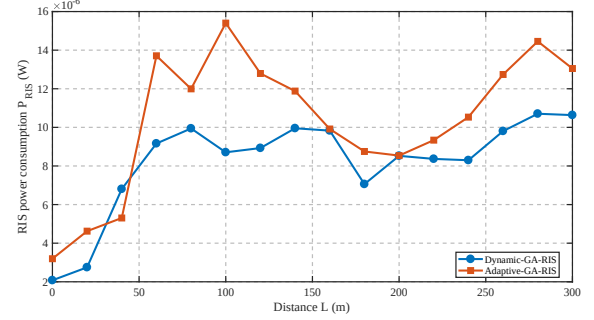
Fig. 4: Simulation results for the sum-rate (bps/Hz) as a function of distance L (m) in an RIS-aided MU-MISO system.

and the Adaptive-GA-RIS. The Dynamic-GA-RIS demonstrates a rapid initial rise in spectral efficiency, quickly achieving a moderate level of performance. In contrast, the Adaptive-GA-RIS may start at lower efficiency but exhibit a steeper and more sustained growth curve over the generations.

Figure 4 illustrates the sum-rate in bps/Hz for a user moving along distance L (from 0 m to 300 m). This comparison includes systems without RIS, those using a dynamic RIS approach, and those employing an adaptive RIS approach. The BS is fixed at coordinate (0 m, -40 m), and the RIS is deployed at (200 m, 30 m). Firstly, when the user is near the BS $L = 0$ m, the direct link distance is minimized, leading to the highest sum-rate for the systems without RIS. The performance gap between RIS-assisted systems and baseline (without RIS) is narrowest here, as the strength of the direct link diminished the relative benefit of the RIS assistance. Secondly, when $L = 200$ m, the users are near RIS, and the BS-RIS-user link becomes highly favorable. In this region, both approaches are dynamic-GA-RIS and adaptive-GA-RIS show a significant sum-rate peak. Furthermore, the adaptive RIS approach achieves the highest sum-rate of 15.98 bps/Hz, which corresponds to a 2296.8% improvement over the baseline (without RIS). The dynamic RIS approach also shows a substantial gain, with a sum-rate of 14.16 bps/Hz (1949.3% improvement). The adaptive RIS approach outperforms



(a) The comparisons of BS power consumption with respect to user distance L (m).



(b) The comparisons of RIS power consumption with respect to user distance L (m).

Fig. 5: The comparison of power consumption (in watts) for each base station (BS) and reconfigurable intelligent surface (RIS) in relation to user distance L (in meters).

the dynamic RIS approach by 12.85%.

Figure 5a illustrates the comparisons of BS power consumption (in watts) with respect to user distance L for three scenarios: Dynamic-GA-RIS, Adaptive-GA-RIS, and Without-RIS, where the BS is located at (0, -40) m and the RIS at (200, 30) m. The results show that when the user is near the BS, the required transmit power is relatively low, but it increases as the distance from the BS grows. As the distance from the BS increases, the BS power consumption rises significantly due to path loss. Without RIS, the BS consumes more power, while RIS-assisted systems effectively mitigate this effect through intelligent signal reflecting, with dynamic-GA-RIS consistently providing stable savings and adaptive-GA-RIS competitive results.

Figure 5b illustrates the RIS power consumption (in watts) of Intelligence Reflecting Surface (RIS) for the Dynamic-GA-RIS and Adaptive-GA-RIS scenarios as a function of distance L (in meters). Firstly, the graph indicates that the Adaptive-GA-RIS scenario consistently consumes more power than the Dynamic-GA-RIS scenario for all measured distances because it's designed to push power limits when doing so improves sum-rate, and also the adaptive penalties create bias toward higher-power consumptions. The Dynamic-GA-RIS scenario, by contrast, treats power constraints as hard limits that must be respected, resulting in more energy efficiency but potentially lower sum-rate. Secondly, when the users are

close to BS, the direct link between BS and the user is strong. Consequently, the role of RIS is less critical, and both scenarios operate at the lower power level, as minimal intervention is required. The second power minimum occurs when users are located near the RIS. Here, the BS-RIS-user cascaded channel link is exponentially strong and efficient; therefore, the RIS can achieve a high sum-rate with relatively low power consumption in two scenarios.

IX. Discussion

The simulation results provide valuable insights into the effectiveness of the proposed GA-based optimization strategies in active RIS-assisted MU-MISO systems. The findings indicate that both Dynamic-GA-RIS and Adaptive-GA-RIS significantly improve spectral efficiency compared to traditional systems without RIS support. The Dynamic-GA-RIS strategy shows faster convergence due to a progressively increasing penalty mechanism that strictly enforces system constraints during the early stages of the optimization process. The Adaptive-GA-RIS approach achieves greater spectral efficiency through its adaptive penalty adjustment, which allows for more effective exploration of potential solutions during the evolutionary process. The results suggest that RIS-assisted communication is particularly beneficial when users are close to the RIS, as the cascaded BS-RIS-user channel enhances signal propagation. Overall, the findings highlight the effectiveness of evolutionary optimization methods in tackling complex non-convex optimization challenges in next-generation wireless communication systems.

X. Conclusions

This paper addresses the important challenge of optimizing spectral efficiency in the upcoming generation of wireless networks by utilizing active-RIS technology. The main goal is to reduce the "multiplicative fading effect" that is typical of passive RIS systems. The joint optimization of base station (BS) precoding and active RIS configurations, with a particular focus on amplification factors and phase shifts, achieves this. The study navigates a complex, non-convex solution space that is subject to dual power constraints. The paper presents a thorough genetic algorithm (GA) framework that includes two unique strategies: dynamic-GA-RIS and adaptive-GA-RIS models. The key findings are as follows: The Adaptive-GA-RIS approach achieves a maximum sum rate of 15.98 bps/Hz. This signifies a 2296.8% improvement over baseline systems that do not use RIS. Dynamic-GA-RIS quickly converges to feasible regions, but Adaptive-GA-RIS ultimately achieves better spectral efficiency, beating the dynamic method by 12.85%. The paper finds that RIS-assisted systems work best when users are close to the RIS, which makes the BS-RIS-user cascade link strong. Results demonstrated that Adaptive-GA-RIS expands power limits to optimize sum-rate, whereas Dynamic-GA-RIS treats power constraints as stringent limits, thereby enhancing energy efficiency. This study presents a novel methodology

for the concurrent design of active beamforming and reflection parameters. This study offers a practical framework for employing metaheuristic algorithms to address high-dimensional optimization challenges in 6G infrastructure through the effective application of circular-aware crossover and constraint-preserving mutation operators. Future research will expand on this framework by incorporating additional constraints to enhance the optimization of the balance between Spectral Efficiency (SE) and Energy Efficiency (EE). The incorporation of minimum Quality of Service (QoS) standards for each user, along with hardware impairment limitations for amplifiers, is anticipated to improve system reliability and authenticity. Furthermore, enhancing the Genetic Algorithm (GA) to directly optimize Energy Efficiency (EE) will facilitate the advancement of sustainable, "green" 6G communication systems.

XI. List of Abbreviations

Active RIS	Active Reconfigurable Intelligent Surface
Adaptive-GA-RIS	Adaptive Genetic Algorithm for RIS Optimization
AWGN	Additive White Gaussian Noise
BS	Base Station
BS-RIS	Base Station to RIS Link
CN	Complex Gaussian Distribution
Dynamic-GA-RIS	Dynamic Genetic Algorithm for RIS Optimization
EE	Energy Efficiency
GA	Genetic Algorithm
LoS	Line-of-Sight
MIMO	Multiple Input Multiple Output
MU-MISO	Multi-User Multiple Input Single Output
NLoS	Non-Line-of-Sight
PL	Path Loss
PLs	Strong Path Loss
PLw	Weak Path Loss
QoS	Quality of Service
RIS	Reconfigurable Intelligent Surface
RIS-User	RIS to User Link
SE	Spectral Efficiency
SINR	Signal-to-Interference-plus-Noise Ratio
SNR	Signal-to-Noise Ratio
$U[a, b]$	Uniform Distribution

XII. Declarations

A. Availability of data and materials

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

B. Competing interests

The authors declare that they have no competing interests.

C. Funding

The authors received no specific funding for this research.

D. Authors' contributions

Abdalahman Basheer conceived the research idea, developed the system model, designed the GA-based optimization framework, performed simulations, and wrote the manuscript. Ibrahim Khider contributed to validation, technical review, and manuscript editing. All authors read and approved the final manuscript.

E. Acknowledgements

Not applicable.

F. Authors' information

Not applicable.

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XIII. Figure Legends

Figure 1. Active RIS-assisted MU-MISO system model. Illustration of the downlink communication scenario where a multi-antenna base station serves multiple users with the assistance of an active reconfigurable intelligent surface (RIS).

Figure 2. Simulation setup of the active RIS-assisted system. The base station is located at (0 m, -40 m), the RIS is deployed at (200 m, 30 m), and users move along a distance range from 0 m to 300 m.

Figure 3. Spectral efficiency convergence versus generation number. Comparison of Dynamic-GA-RIS, Adaptive-GA-RIS, and the baseline system without RIS.

Figure 4. Sum-rate performance versus user distance. Performance comparison between the proposed optimization strategies and the baseline system without RIS.

Figure 5. Power consumption comparison of BS and RIS. (a) Base station power consumption. (b) Active RIS power consumption as a function of user distance.