Enhancing the Energy Efficiency Utilizing Reconfigurable Intelligent Surfaces in Next Generation Communication Networks

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***Abstract*—Next generation networks (5G and beyond) face significant challenges in improving energy efficiency without sacrificing performance. This paper investigates the enhancement of energy efficiency (EE) in a Multi-Input Single-Output (MISO) system under Rician fading channels using Reconfigurable Intelligent Surfaces (RIS). Unlike traditional fully-active models, we investigate a different optimization framework combining Maximum Ratio Transmission (MRT) beamforming, genetic algorithms, and RIS phase shift optimization under selective RIS element activation. Two activation schemes are evaluated: random ON/OFF and Top-contributing 30% element selection based on channel gain to balance reflection gain against hardware power overhead. Simulations using MATLAB demonstrate that activating only the Top-contributing 30% of RIS elements achieves high EE with acceptable SNR. Among all techniques, phase shift optimization with selective RIS activation yields the highest EE of 5.3 × 10^6 bits/Joule, highlighting its potential for energy-efficient 6G communications.**

***Index Terms*—Beamforming, Reconfigurable Intelligent Surfaces, Energy Efficiency, Signal-to-Noise Ratio, Genetic algorithm GA, Multi-Input Single-Output (MISO).**

I. Introduction

The exponential growth in wireless data demand, driven by the proliferation of Internet of Things (IoT) devices, mobile applications, and smart environments, has necessitated the evolution of communication networks towards the sixth generation (6G) [1]. A critical requirement of 6G networks is to support massive connectivity while ensuring ultra-reliability, low latency, and most importantly, high energy efficiency (EE) [2]. Traditional approaches, such as deploying more base stations or using advanced Multiple Input Multiple Output (MIMO) systems, have shown limitations in scalability and energy consumption [2], [3].

As a promising solution, Reconfigurable Intelligent Surfaces (RIS) have emerged as a transformative technology capable of reconfiguring the wireless propagation environment intelligently, thereby enhancing signal strength and reducing energy consumption [4], [5].

RIS is an important technology and innovation for improving data transmission quality [6]. RIS enables easy and intelligent control of radio wave propagation [7]. RIS is able to convert wireless channels from non-line-of-sight (NLOS) to line-of-sight (LOS) by reflecting signals as needed [8]. This application significantly improves signal quality, enhances transmission efficiency, and reduces signal loss caused by obstacles and environmental interference. In addition, RIS reduces interference between different signals by controlling the formation of precise waveform patterns, allowing for the isolation of desired signals and reducing interference from other users or neighboring devices. RIS thus improves spectrum efficiency and increase network capacity, making them ideal for use in congested communications environments [9].

Despite the potential of RIS, most existing studies have primarily focused on maximizing spectral efficiency or signal-to-noise ratio (SNR) through full activation of all RIS elements with optimal phase shift designs [10]. However, the impact of selective activation of RIS elements on energy efficiency remains underexplored [11]. RIS design often relies on metamaterial unit cells, which can be miniaturized and optimized for millimeter-wave (mmWave) applications to fit future compact 6G scenarios [12]. This leaves a notable research gap: how can we balance RIS activation (e.g., partial ON/OFF control) with EE maximization, without compromising acceptable SNR levels?

This paper addresses the above gap by proposing a novel RIS-assisted framework that optimizes energy efficiency through selective RIS element activation combined with advanced optimization strategies. Specifically, it has been evaluated three main categories: first, Digital Beamforming Optimization at the transmitter, adapted to reflect the altered channel structure induced by RIS configurations. Second, Genetic Algorithm (GA)-based optimization, employed to maximize EE by tuning transmit power and RIS phase shifts across different ON/OFF scenarios [11], [13], [14]. Third, RIS phase shift optimization, which enhances signal reflection via intelligent adjustment of active element phases.

To simulate and validate these categories, it has been utilized a MATLAB as the core tool, allowing for flexible system modeling and integration of optimization routines. The simulation incorporates realistic channel modeling, RIS parameterization, and EE computation under varying conditions. It has been investigated two RIS element activation schemes: First, random ON/OFF selection, where a subset of RIS elements is randomly chosen to be active. Second, Top-

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contributing 30% ON elements based on channel gain, where only the highest-gain RIS elements are activated.

The paper results indicate that activating only the top-contributing 30% of RIS elements yields the highest energy efficiency while still maintaining satisfactory SNR performance. This demonstrates that full RIS activation is not always necessary, and selective control can significantly reduce power consumption without degrading communication quality.

The main contributions of this paper can be listed as:

- A novel RIS-assisted energy-efficient MISO framework that incorporates partial ON/OFF activation of RIS elements to reduce power consumption while maintaining acceptable SNR levels.
- Comparative evaluation of three key optimization strategies: digital beamforming at the BS, Genetic Algorithm (GA)-based power and phase optimization, and RIS phase shift optimization.
- Proposal and validation of a gain-based RIS element selection strategy, where only the top contributing 30% of RIS elements (ranked by composite channel gain) are activated to achieve better energy efficiency.
- Integration of selective RIS activation with GA-based optimization, showing its effectiveness in improving energy efficiency under realistic channel and power constraints.
- Comprehensive MATLAB-based simulation, incorporating realistic Rician fading channels, digital beamforming, and hardware-aware power models to validate performance metrics (EE, SNR).
- Demonstration that full RIS activation is not necessary, and selective activation yields near-optimal SNR performance with significantly lower power consumption, improving RIS scalability for future 6G networks.

While this study focuses on Rician (LOS) channels typical of urban micro-cell deployments, the performance of selective RIS activation in Rayleigh (NLOS) environments may differ. In pure NLOS scenarios, the absence of a dominant LOS component reduces the 'ranking' gap between elements, potentially requiring a higher activation ratio to achieve the same SNR gains. Furthermore, selective activation may be sub-optimal in high-mobility scenarios where the CSI fluctuates rapidly, making the overhead of the Genetic Algorithm's re-convergence prohibitive. These multi-path and high-mobility challenges represent a distinct research direction that aim to explore in future work.

The remainder of this paper is organized as follows. Section II Reviews the most important and latest related references. Section III describes the system model and problem formulation beside details the optimization techniques. Section IV presents the simulation setup and results. Finally, Section V concludes the paper with insights and future research directions.

II. Related Work

Several RIS has emerged as a groundbreaking solution to address the challenges of spectral and energy efficiency in 5G and forthcoming 6G communication systems. Basically, a Reconfigurable Intelligent Surface (RIS) is a smart, flat panel made of many small elements. These elements act like a "programmable mirror" for radio waves, letting steer and shape signals to improve wireless coverage. Unlike traditional active relays, RISs consume minimal power and introduce negligible noise, making them ideal for green communications. In 5G, RIS has been investigated to enhance coverage and capacity in dense urban environments and mmWave bands, where signal blockages are frequent. Looking ahead to 6G, RISs are envisioned to play a central role in enabling programmable radio environments, intelligent signal routing, and context-aware resource allocation [4][11]. Their ability to support smart environments with high reliability, low latency, and minimal energy footprint positions them as a key enabler of future wireless networks.

Several recent studies have addressed RIS-assisted optimization in wireless communications. Wu et al. [4] introduced RIS-aided MISO systems and formulated joint beamforming and RIS phase optimization to enhance spectral efficiency. Zhang et al. [2] investigated RIS placement and element phase configuration to improve coverage and throughput. More recently, Fotock et al. [15] proposed EE-maximizing strategies under RIS configurations, yet still assumed all elements were active, ignoring hardware power consumption due to element switching. Similarly, Long et al. [16] presented a genetic algorithm-based solution for RIS phase optimization but considered no ON/OFF selection of elements. These works confirm the performance benefits of RIS, but they lack a fine-grained evaluation of partial RIS activation strategies in the context of EE.

More recently, Huang, et al. [17] presented a hybrid RIS architecture that combines a subset of active and passive elements to balance performance and cost, while Tang et al. [18] proposed a machine learning-based RIS control scheme for minimizing energy consumption under QoS constraints. Pala et al. [19] investigated low-resolution RIS elements to reduce hardware complexity, but their model still assumed uniform activation of all elements.

A particularly relevant study by He et al. [20] investigated energy-efficient communication in multi-user, multi-antenna networks supported by multiple RISs, where they jointly optimized RIS phase shifts, BS beamforming, and active RIS selection to minimize total power consumption under QoS constraints. They further introduced a user admission control mechanism to handle infeasibility when all QoS constraints could not be satisfied. While their work provides a comprehensive optimization framework, it focuses on multi-RIS and multi-user scenarios, whereas our work emphasizes selective RIS element activation and EE maximization in a single-user setup, highlighting the gains of partial RIS control strategies. These studies confirm the strong potential of RIS in future networks but also highlight a common limitation: the assumption of full RIS activation, which may not be optimal in power-constrained environments. Our work fills this gap by evaluating selective RIS element activation (e.g., top contributing 30% based on composite channel gain) and its joint optimization with beamforming and phase shifts to maximize energy efficiency without sacrificing SNR.

III. System Model and Problem Formulation

In this paper, it has been considered a Multiple-Input Single-Output (MISO) downlink communication system where a Base Station (BS) equipped with M transmit antennas serves a single-antenna user terminal with the assistance of a Reconfigurable Intelligent Surface (RIS). The RIS comprises N passive reflecting elements and is deployed strategically between the BS and the user to enhance the signal strength and energy efficiency.

A. System Setup and Channel Modeling

The locations of the BS, RIS, and user are randomly generated within a 3D coordinate space that represents a realistic urban environment [4]. The BS is elevated and centrally positioned, while the user is randomly located within a coverage area. The RIS is placed on a building facade or wall to ensure a dominant LOS or strong reflected path between the BS and the user. It can be defined two channel matrices [21]:

$F \in C^{N\times M}$: channel from the BS to the RIS,

$G \in C^{1\times N}$: channel from the RIS to the user.

Both channels are modeled using Rician fading to account for the presence of LOS and scattered components [22], [23]. The overall received signal y at the user can be expressed as:

$$y = h_{eff}\, W\, x + n \tag{1}$$

where $h_{\mathrm{eff}} = G\Phi F$, $W \in C^{M\times 1}$ is the digital beamforming vector at the BS, x is the transmitted symbol with $E[|x|^2] = 1$, and $n \sim CN(0, \sigma^2)$ is the additive white Gaussian noise (AWGN).

B. RIS Configuration and Selection

The RIS reflection matrix is defined as:

$$\Phi = \mathrm{diag}(S_1 e^{j\theta 1}, S_2 e^{j\theta 2}, \dots, S_N e^{j\theta N}) \tag{2}$$

where $Sn \in \{0,1\}$is a binary state indicating whether the n-th RIS element is ON or OFF, and $\theta n \in [0,2\pi]$ is the adjustable phase shift [14]. Two RIS activation strategies are considered:

1. Random ON/OFF: A random subset of RIS elements is activated.
2. Top contributing 30% ON: Only the top contributing 30% of RIS elements are turned ON based on the magnitude of the composite channel gain $|Gn \cdot Fn|$, where high-gain elements are prioritized for activation [24][14].

C. Problem Formulation

The primary objective is to maximize the system's energy efficiency (EE), defined as:

$$EE = R / P_{total} \tag{3}$$

where P_{total} is the total power consumption defined as: $P_{total} = P_T + P_{static} + N_{on} P_{RIS}$. Here, P_T represents the dynamic transmit power, P_{static} is the fixed hardware dissipation of the Base Station, N_{on} is the number of active (ON) RIS elements, and P_{RIS} is the power consumed by a single active RIS element [13].

This optimization is subject to the following constraints:

- Power budget: Transmit power $P_T \le P_{\max}$,
- Minimum SE requirement: $R \ge R_{\min}$,
- RIS constraint: Only 30% of RIS elements can be active at any time.

It's well known that the process of finding optimal values SNR, interference reduction, etc. depends on many factors, including the user's location, distance, the angles they form, the number of users, and the presence of obstructions and motion in the environment. This leads to the problem of non-convexity. Modern communications face this problem, which is the existence of more than one optimal solution. To solve this non-convex problem, it is vital to apply digital beamforming at the BS using Maximum Ratio Transmission (MRT). Given the single-user setup, MRT is the optimal strategy to maximize the received SNR by matching the transmitted signal to the effective channel vector, which in turn enhances the system's Energy Efficiency (EE), and employ a Genetic Algorithm (GA) to jointly optimize:

- The RIS phase shift vector θ,
- The binary ON/OFF state vector s,
- The BS beamforming vector W (via heuristic or closed-form approach).

This hybrid optimization framework ensures high EE while satisfying SNR and SE constraints under realistic RIS hardware limitations [25] - [27].

D. Simulation Setup

To evaluate the proposed energy-efficient RIS-assisted MISO system, simulations are conducted in MATLAB using the parameters summarized below. The Base Station (BS) is equipped with M=4 transmit antennas and serves a single-antenna user. The number of RIS elements N is varied across a range: $N \in \{16, 36, 64, 100, 144, 169\}$ to study the impact of RIS size on system performance. The thermal noise power is set to $\sigma^2 = -90$ dBm. The total transmit power is limited to $P_{\max}$=10W (30 dBm), and each simulation is averaged over 100 independent channel realizations. The Genetic Algorithm (GA) is run for 50 epochs per simulation with a population size of 30.

For the 30% ON scheme, the RIS elements are sorted based on the product of their individual channel gains, computed as $|Gn \cdot Fn|$, where Gn and Fn are the channel coefficients between the RIS and the user and between the BS and the RIS, respectively. Only the top contributing 30% of these elements are activated (set to 1 in the RIS state vector), while the rest are turned OFF (set to 0), significantly reducing power consumption while retaining strong signal paths [24].

The effective end-to-end channel is computed using the expression:

$$H = G.diag(1 - 2\theta).F \quad (4)$$

where $G \in C^{1\times N}$ and $F \in C^{N\times M}$ are the RIS-user and BS-RIS channels, respectively, and $\theta \in [0,1]$. N is the binary ON/OFF vector. The term $(1-2\theta_n)$ maps ON elements to +1 and OFF elements to -1, simulating a binary phase reflection [24].

The SNR at the user is calculated as:

$$SNR = \left|h_{eff} W\right|^2 / \sigma^2 \quad (5)$$

where $h_{\text{eff}}=H$ and W is the digital beamforming vector (e.g., MRT). The achievable Spectral Efficiency (SE) is then given by:

$$R = log_2(1 + SNR) \quad (6)$$

Then the Energy Efficiency (EE) is calculated as eq. (3).

The Genetic Algorithm (GA) is used to optimize the RIS phase shifts and ON/OFF state vector [28][29]. A specialized Genetic Algorithm (GA) created to manage a hybrid discrete-continuous search space is used to mimic the optimization of the active RIS setup. Every member of the population is represented by a dual-encoded chromosome, which consists of a real-valued vector that represents the continuous phase shifts and a binary string that controls the ON/OFF states of the RIS elements. The fitness function is defined as the negative of the Energy Efficiency (EE) in order to conform to typical GA minimization methods. A population of 30 individuals is used throughout 50 generations in the evolution process. An elitism technique has used that keeps the top two solutions in each generation in order to preserve high-performing genetic features. To enable global exploration, a crossover operation with a chance of 0.8 is done after selection through a tournament process. A mutation rate of 0.1 is used, permitting random perturbations in both the element states and phase values, to avoid stagnation in local optima, a frequent problem in non-convex RIS surfaces. This heuristic approach converges within G.Np iterations, whereas an optimal search across N elements requires 2^N evaluations. The ZF precoding, which has a cost of $O(K^3 + NK^2)$ per chromosome, is the main computational bottleneck in the fitness function evaluation. This methodical technique balances computing complexity and guarantees a reliable search for the ideal RIS configuration. This setup allows robust exploration of the RIS configuration space, balancing energy consumption and SNR performance effectively. The standard mid-band spectrum for 5G/6G installations is represented by the carrier frequency, which is set to 3.5 GHz. The normalized performance increases and the qualitative behavior of the Genetic Algorithm-based activation method are essentially independent of the particular frequency band, even if higher frequencies (such as 28 GHz or 60 GHz) would bring increased path loss. We maintain the generalizability of the suggested optimization methodology while ensuring that our power consumption model for the active RIS elements reflects current state-of-the-art hardware capabilities by concentrating on the 3.5 GHz domain.

Table I includes the system simulation parameters which have used in the system modeled by MATLAB codes.

TABLE I
THE SYSTEM SIMULATION PARAMETERS

PARAMETER	VALUE
Carrier frequency (fc)	3.5 GHz
Bandwidth (BW)	10 MHz
Wavelength (λ\lambda)	λ =c/fc=0.0857 m
Simulation area	100 m × 100 m × 10 m (urban 3D scenario)
BS position	[0, 0, 10] m
User position	Random in XY-plane at height 1.5 m
RIS position	[50, 50, 5] m
Number of BS antennas (M)	4
Number of users	1
Noise power (σ2)	-90 dBm
RIS sizes (N)	16, 36, 64, 100, 144, 169
RIS activation strategies	Random ON/OFF, Top gain 30% ON elements
Transmit power (Pmax)	10 W (40 dBm)
Path loss model	Rician fading + distance-based path loss
Rician K-factor	5 dB (typical urban LOS)
Number of channel realizations	100
Beamforming	Digital beamforming
RIS phase shift control	Optimized using Genetic Algorithm (GA)
RIS ON/OFF control	Binary vector $\theta \in \{0,1\}^N$
GA population size	30
GA generations (epochs)	50
GA crossover rate	0.8
GA mutation rate	0.1
Minimum SE constraint	1 bps/Hz (can be adjusted)

IV. RESULTS AND DISCUSSION

In this section, the system performance of the proposed RIS-assisted MISO downlink communication setup has been analyzed under three different schemes: (1) Random beamforming with ON/OFF RIS states, (2) Genetic Algorithm (GA) for optimizing Energy Efficiency (EE), and (3) GA-based Phase Shift Optimization with 30% ON elements. The metrics of interest are Energy Efficiency (EE), Signal-to-Noise Ratio (SNR), and the distribution of ON/OFF RIS elements. The flowchart of phase shift optimization process can be represented in the Fig.1.

A. EE vs. Number of RIS Elements

Fig. 2 illustrates the variation of EE as a function of the number of RIS elements N under the three approaches when randomly activate the RIS elements. While Fig. 3 illustrates the variation of EE at 30% of RIS elements are ON. All schemes show a clear improvement in EE as N increases, helps to enhanced reflection diversity and stronger end-to-end channel gains. However, this increase saturates beyond N=100, especially in the random beamforming and EE-optimized cases. The saturation is due to two main factors:

- Diminishing marginal returns in effective channel gain from additional reflecting elements.
- Power constraints, where additional elements increase passive circuit power without proportionally boosting the signal.

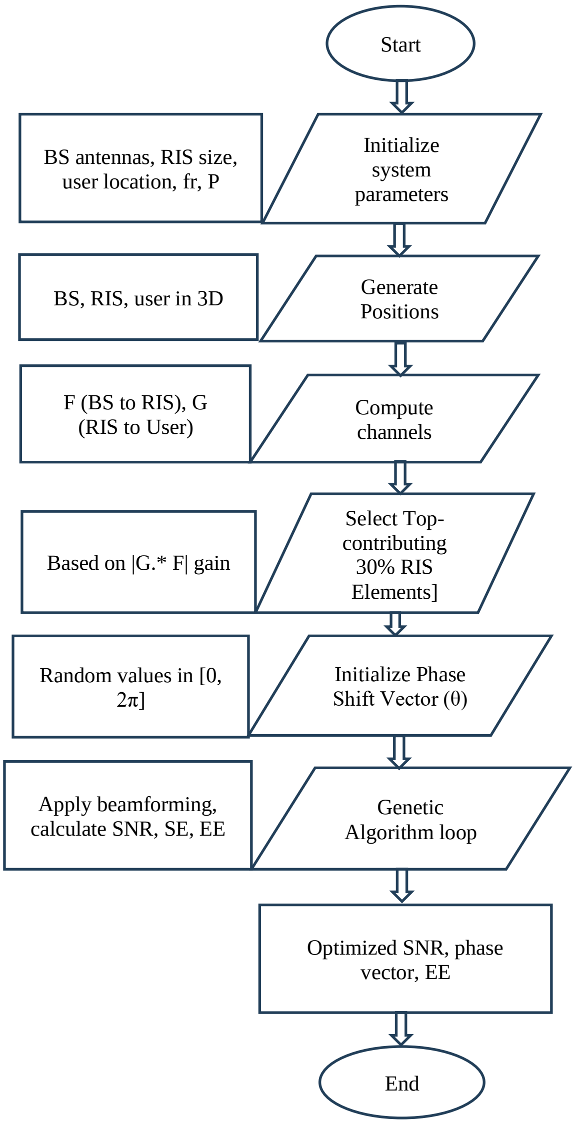


Fig. 1. Flowchart for the phase shift optimization approach in a RIS-assisted MISO system using a Genetic Algorithm

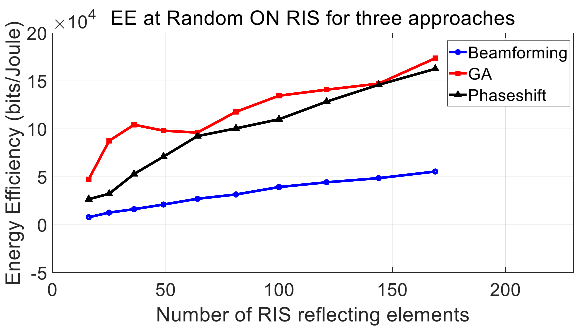


Fig. 2. Energy Efficiency (EE) vs. Number of RIS Elements for all three approaches (Beamforming, Genetic Algorithm GA, and Phase shift_GA) at random ON/OFF RIS

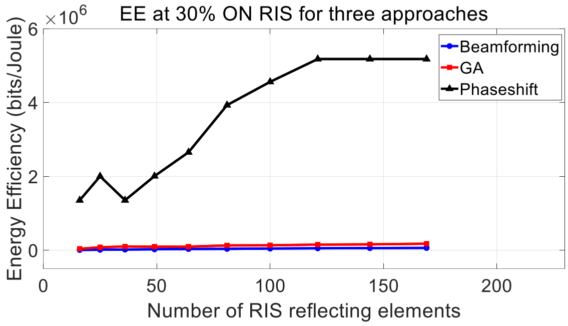


Fig. 3. Energy Efficiency (EE) vs. Number of RIS Elements for all three approaches (Beamforming, Genetic Algorithm GA, and Phase shift_GA) at 30% ON RIS

Notably, phase shift optimization with 30% ON elements achieves the highest EE of approximately 5.3×10^6 bits/Joule at N=169, outperforming the full-ON strategy due to smarter use of resources. However, as the RIS size increased, the outcomes of the beamforming and GA approaches behaved similarly.

B. SNR vs. Number of RIS Elements

Figures 4 and 5 illustrate the impact of the number of RIS reflecting elements on the SNR performance under two distinct RIS activation strategies—random ON/OFF selection and top contributing 30% ON selection—for three optimization approaches: beamforming, genetic algorithm (GA), and phase shift optimization-based GA. As shown in Fig 4, SNR consistently improves with the number of RIS elements in all schemes. Interestingly, the 30% ON selection method achieves better SNR compared to full activation, proving that only a subset of well-placed, high-gain RIS elements are sufficient to maintain high signal quality. The phase shift + GA method demonstrates the highest SNR gains across all RIS sizes, confirming that intelligent phase adjustment further enhances signal focusing at the receiver. The SNR improvement becomes more pronounced as the number of RIS elements increases, though the gains taper slightly beyond 150 elements, suggesting diminishing returns under random activation. Fig. 5. illustrates that all three approaches experience a notable boost in SNR compared to the random activation case, validating the efficiency of channel-aware RIS element selection.

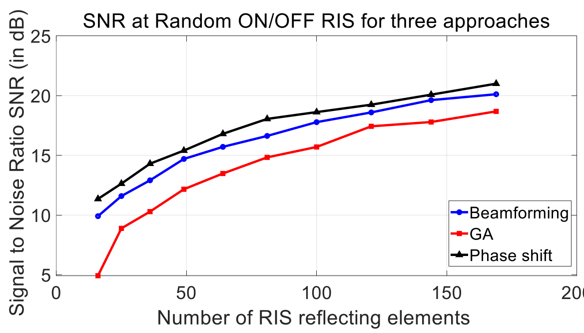


Fig. 4. Signal to Noise Ratio SNR (in dB) vs. Number of RIS Elements for all three approaches (Beamforming, Genetic Algorithm GA, and Phase shift_GA) at random ON/OFF RIS

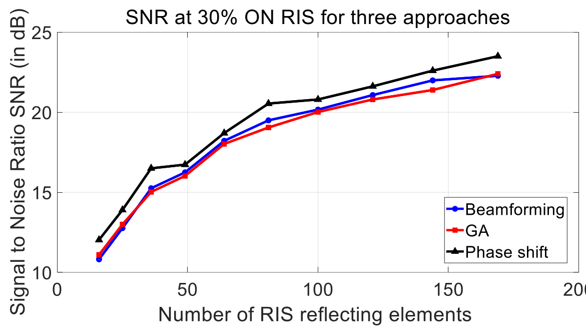
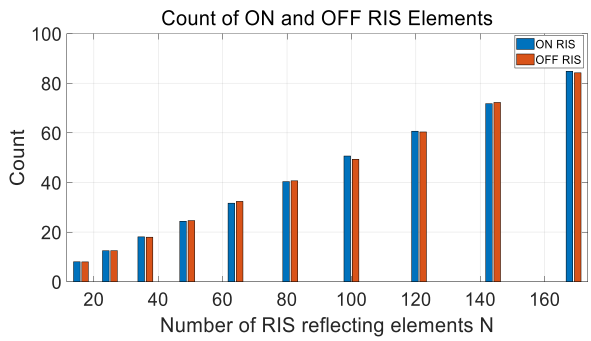


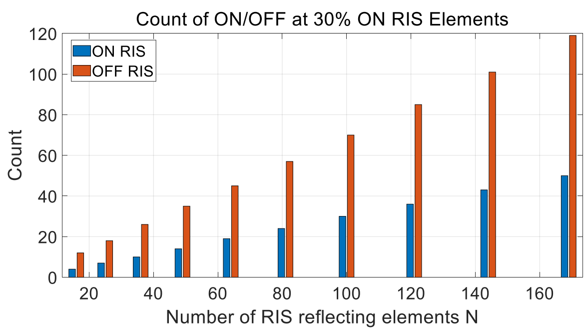
Fig. 5. Signal to Noise Ratio SNR (in dB) vs. Number of RIS Elements for all three approaches (Beamforming, Genetic Algorithm GA, and Phase shift_GA) at 30% ON RIS

C. ON/OFF State Distribution

To provide a clear baseline for the performance evaluations, Fig. 6 illustrates the statistical distribution of active (ON) and inactive (OFF) elements for the two benchmark strategies. In Figure 6a, the random configuration demonstrates a near-uniform 50% distribution across varying RIS sizes. This confirms the nature of baseline, ensuring that the observed energy efficiency is representative of a standard non-optimized deployment. For the 30% ON strategy, the number of active elements matches exactly 30% of N, as expected. This confirms the efficiency of gain-based selection, which retains only the most impactful elements based on the magnitude of |G·F|. This contrasts with the random strategy, where energy is wasted on low-contribution paths.



(a) Random configuration



(b) 30% ON configuration.

Fig. 6. Number of ON vs. OFF RIS elements for different N values.

D. Discussion and Insights

There is a clear trade-off between activating more RIS elements and the resulting EE. While SNR improves with more ON elements, the power consumption of each active element limits EE gains. The 30% ON scheme strikes an effective balance achieving strong SNR while consuming significantly less power.

Gain-based ON selection outperforms random selection across all metrics. By prioritizing RIS elements that contribute most to the effective channel, the system avoids wasting power on ineffective paths. This also leads to better convergence in GA-based optimization, as the search space is more meaningful. Within 50 generations, the algorithm achieves a stable Energy Efficiency (EE), as seen by the convergence performance. The computational feasibility of the selective activation technique for real-time reconfigurable surfaces with a large number of elements is confirmed by this linear scaling with N.

The proposed approach demonstrates that RIS scalability does not require full activation. Even for large N, activating just 30% of elements using channel gain ranking and phase optimization yields near-optimal performance. This supports the development of energy-efficient, scalable RIS systems for future 5G/6G deployments. The results clearly support the claim that full RIS activation is not always necessary; strategic activation of a fraction of elements (e.g., Top-contributing 30%) can achieve near-optimal SNR while reducing energy and hardware costs.

Table II presents a comparison with the state-of-the-art methods.

V. Conclusion

This paper explored the enhancement of Energy Efficiency (EE) in RIS-assisted MISO downlink communication systems using three key approaches: random beamforming, genetic algorithm (GA)-based EE optimization, and phase shift optimization with a 30% ON RIS element strategy. This paper presented a comprehensive system model that includes digital beamforming, RIS ON/OFF control, and intelligent phase adjustment, simulated using MATLAB. The results clearly demonstrate that activating only the top contributing 30% of RIS elements selected based on composite channel gain achieves near-optimal SNR and EE, outperforming random ON/OFF strategies and even full element activation in terms of efficiency. Selective activation of high-gain RIS elements significantly enhances SNR performance, even when fewer elements are active, indicating an effective tradeoff between complexity and performance. The phase shift optimization approach, in particular, achieved the best EE performance of 5.3×10^{6} bits/Joule, validating the effectiveness of joint phase and power control. By leveraging genetic algorithms for phase shift tuning, it's significantly reduced the computational burden while maintaining robust convergence toward energy-efficient configurations. These findings also highlight the scalability potential of RIS systems: performance can be preserved or enhanced even as RIS size increases, without incurring linear increases in power consumption. In summary, this work demonstrates that intelligent RIS control strategies particularly gain-based ON/OFF selection and optimized phase shifting are vital to achieving green and scalable next-generation wireless networks such as 5G and 6G.

TABLE II
COMPARISON OF THE RESEARCH WORK WITH STATE OF ART RELATED WORKS

Reference	System Model	RIS Type	Optimization Objective	Activation Strategy	Algorithm Used	Complexity
Wu & Zhang [4]	MISO / Multi-user	Passive	SNR / Sum-Rate	100% Passive	Alternating Opt. (AO)	Moderate O(IK3)
Fotock et al. [11, 15]	MISO / MIMO	Active	Energy Efficiency (EE)	100% Full Active	Fractional Programming	High (Matrix Inversion)
Huang et al. [17]	Multi-user	Hybrid	Energy Efficiency	Fixed Active Ratio	Heuristic / Iterative	Moderate
Javad-Kalbasi [29]	UAV-assisted	Passive	Energy Efficiency	100% Passive	Genetic Algorithm (GA)	O(G·Np·N)
Proposed Work	MISO (Rician)	Active	Global EE	Selective 30% (ON/OFF)	GA + MRT	Linear O(N)

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