# Solving Indefinite Communication Reliability Optimization for RIS-Aided Mobile Systems by an Improved Differential Evolution

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## ABSTRACT

This paper exploits the applications of evolutionary algorithms to solve a challenging category of optimization problems in 6G mobile networks, particularly focusing on communication reliability with modulated signals of reconfigurable intelligent surface (RIS)-assisted multiple input multiple output (MIMO) systems. By deriving the analytical downlink symbol error rate (SER) of each user as a multivariate function of both the phase-shift and beamforming vectors, we introduce a novel average SER minimization problem subject to the transmitted power budget and phase shift coefficients, which is NP-hard. By incorporating the differential evolution (DE) algorithm as a pivotal tool and an efficient local search to overcome the local optimum for optimizing the intricate active and passive beamforming variables, the non-convexity of the considered SER optimization problem can be effectively handled. Numerical results indicate that the proposed joint active and passive beamforming design is superior to the other benchmarks.

## CCS CONCEPTS

• **Networks** → **Network reliability**; • **Theory of computation** → *Probabilistic computation*; *Nonconvex optimization*; *Evolutionary algorithms*.

## KEYWORDS

RIS-assisted MIMO, beamforming design, communication reliability, differential evolution

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## 1 INTRODUCTION

The emergence of sixth-generation (6G) communication is paving the way for pervasive connectivity in networks. A strategic collaboration between reconfigurable intelligent surfaces (RISs) and multiple-input multiple-output (MIMO) systems [6] is transforming networks beyond 5G. This collaboration addresses propagation environment challenges, introducing adaptability, efficiency, and resilience through controllable multi-paths. The passive array of scattering elements in an RIS dynamically adjusts the phase and amplitude of incoming signals, facilitating constructive combinations at receivers. This integration leads to significant enhancements in throughput, coverage extension, and energy efficiency. RIS-assisted MIMO systems optimize resource allocation by dynamically adjusting transmit power, beamforming, and time-frequency slots. Communication reliability is crucial in wireless systems, evaluated through metrics like symbol error rate (SER). Achieving low SER for each user requires effective error control mechanisms, modulation schemes, and sophisticated channel coding strategies. Research efforts have emphasized enhancing communication reliability as a critical metric for resilience in fading channels. However, RIS-assisted networks face challenges in optimizing error probability, even in single-user scenarios. From an algorithmic standpoint, evolutionary computing involves efficient population-based search algorithms called evolutionary algorithms (EAs), which are known for their rapidity, effectiveness, and ability to tackle diverse optimization challenges. In 6G communications, EAs have been used to maximize total throughput [5], select cluster centers [2] in cloud optimization, and address uncovered areas in network routing [7]. However, there is still room for improvement in designing EAs, as they may encounter challenges in escaping local optima solutions.

This paper discusses the communication reliability of modulated RIS-assisted MIMO systems under active and passive beamforming designs. We first present a closed-form expression for the SER for each user in multi-downlink data transmission using Quadrature Amplitude Modulation (QAM) and formulate a non-convex problem to minimize the average SER for modulated communication systems. We encode optimization variables into individuals and propose

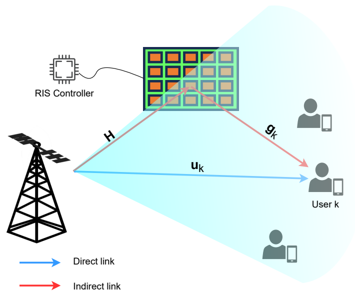



**Figure 1: The RIS-assisted MIMO system model where a BS serves multiple users.**

an enhanced DE algorithm with local search. Numerical results confirm the effectiveness of the approach, highlighting the superior capabilities of passive and active beamforming designs.

## 2 RIS-ASSISTED SYSTEM MODEL AND DOWNLINK SYMBOL ERROR RATE

An RIS-assisted MIMO system consists of a base station (BS) with $M$ antennas serving $K$ single-antenna users in the coverage area as illustrated in Figure 1. The system is supported by an RIS consisting of $N$ scattering elements with phase shift matrix denoted as $\mathbf{\Phi} = \mathrm{diag}\left([e^{j\theta_1}, \dots, e^{j\theta_N}]^T\right)$ where $j^2 = -1$. Let us denote $\mathbf{H} \in \mathbb{C}^{M\times N}$ the channel matrix between the BS and the RIS, while $\mathbf{g}_k \in \mathbb{C}^N$ denotes the channel vector between the RIS and user $k$ and the channel between the BS and user $k$ is $\mathbf{u}_k \in \mathbb{C}^M$. In the downlink data transmission, all the users simultaneously receive signals from the BS with the assistance of the RIS. Let us denote $s_k$ with $\mathbb{E}\{\|s_k\|_2^2\} = 1$ the data symbol transmitted from the BS to user $k$, which is steered to user $k$ by a beamforming vector $\mathbf{w}_k \in \mathbb{C}^M$ with $\|\mathbf{w}_k\|_2 = 1$. Consequently, the received signal at user $k$ is

$$y_k = (\mathbf{u}_k + \mathbf{H\Phi g}_k)^H \sum\nolimits_{k'=1}^{K} \sqrt{\rho}\mathbf{w}_{k'} s_{k'} + n_k, \tag{1}$$

where $\rho > 0$ is the transmit power allocated to each data symbol, and $n_k \sim \mathcal{CN}(0, \sigma^2)$ is additive noise. Let us introduce a new variable $\mathbf{z}_k = \mathbf{u}_k + \mathbf{H\Phi g}_k$ and utilize the coefficient $\sqrt{\rho}\mathbf{z}_k^H\mathbf{w}_k$, the symbol interested by user $k$ is defined from

$$r_k = s_k + \sum_{k'=1, k'\neq k}^{K} \frac{\mathbf{z}_k^H \mathbf{w}_{k'}}{\mathbf{z}_k^H \mathbf{w}_k} s_{k'} + \frac{n_k}{\sqrt{\rho}\mathbf{z}_k^H\mathbf{w}_k}. \tag{2}$$

In this paper, we investigate $m$-QAM with $m$ being the modulation index, to modulate the binary data sequence before transmitting the signals over the medium. Let us consider a scenario where the BS sends equiprobable symbols so that $\Pr(s_k = s_t) = 1/m, \forall s_t \in \mathcal{M}$ (a modulation constellation set by using the $m$-QAM). Mutual interference in user $k$'s SER can introduce random fluctuations in amplitude and phase, potentially contaminating decoding quality. In multiple-user networks, this interference from other users sharing the same time and frequency resources significantly impacts the received signal quality. Conditioned on channel gains and under the assumption of Gaussian signaling, the analytical downlink SER of a user can be computed as in Lemma 1.

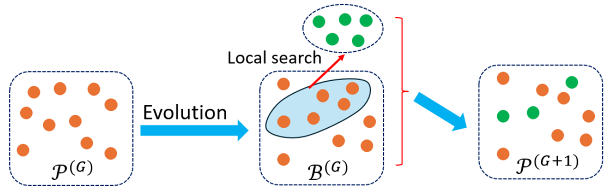



**Figure 2: The overall process of the joint active and passive beamforming designs by the improved DE algorithm with a local search.**

Lemma 1. *The analytical downlink SER of user $k$ is*

$$\overline{\mathrm{SER}}_k(\{\mathbf{w}_k\}, \mathbf{\Phi}) = 2\left(1 - \frac{1}{\sqrt{m}}\right) \mathrm{erfc}\left(\sqrt{\frac{3\mathrm{SINR}_k(\{\mathbf{w}_k\}, \mathbf{\Phi})}{m-1}}\right) - \left(1 - \frac{1}{\sqrt{m}}\right)^2 \mathrm{erfc}^2\left(\sqrt{\frac{3\mathrm{SINR}_k(\{\mathbf{w}_k\}, \mathbf{\Phi})}{m-1}}\right), \tag{3}$$

*where the signal-to-interference-and-noise ratio of user $k$, denoted by $\mathrm{SINR}_k(\{\mathbf{w}_k\}, \mathbf{\Phi})$, is driven based on the received signal in (2) as*

$$\mathrm{SINR}_k(\{\mathbf{w}_k\}, \mathbf{\Phi}) = \frac{\rho \left|\mathbf{z}_k^H \mathbf{w}_k\right|^2}{\sum_{k'=1,k'\neq k}^{K} \rho \left|\mathbf{z}_k^H \mathbf{w}_{k'}\right|^2 + \sigma^2}, \tag{4}$$

*and* $\mathrm{erfc}(\cdot)$ *is the complementary error function.*

Proof. The detailed proof is omitted due to space limitations. □

## 3 ACTIVE AND PASSIVE BEAMFORMING DESIGNS FOR COMMUNICATION RELIABILITY OPTIMIZATION

We formulate the SER minimization problem by treating $\mathbf{\Phi}$ and $\{\mathbf{w}_k\}$ as optimization variables, aiming to minimize the average error probability as

$$\underset{\{\mathbf{w}_k\}, \mathbf{\Phi}}{\text{minimize}} \ \frac{1}{K}\sum_{k=1}^{K} \overline{\mathrm{SER}}_k(\{\mathbf{w}_k\}, \mathbf{\Phi}) \tag{5a}$$

$$\text{subject to } \rho\|\mathbf{w}_k\|_2^2 = P_{\max}, \forall k, \tag{5b}$$

$$-\pi \leq \theta_n \leq \pi, \forall n. \tag{5c}$$

where $P_{\max}$ is the maximum transmit power allocated to data symbols. The objective function of problem (5) represents the average SER of each user for multi-user systems. In this context, the constraints (5b), $\forall k$, guarantees that the transmit power does not exceed the limit power budget by steering the waveform to user $k$ with a beamforming technique.

### 3.1 Improved DE with Local Search

*3.1.1 Solution representation and population initialization.* To identify individuals, which represent potential solutions, within the population across generations, we designate the $i$-th individual of the population in the $G$-th generation, denoted by $\mathbf{x}^{(iG)} \in \mathbb{R}^{N+2MK}$ as:

$$\mathbf{x}^{(iG)} = \left[x_1^{(iG)}, x_2^{(iG)}, \dots, x_N^{(iG)}, x_{N+1}^{(iG)}, \dots, x_{N+2MK}^{(iG)}\right]^T, \tag{6}$$

where $x_n^{(iG)} \in [-1, 1]$ if $n \in \{1, \ldots, N\}$ represents the $n$-th phase shift coefficient, and $x_n^{(iG)} \in [-1, 1]$ with $n \in \{N + 1, \ldots 2MK\}$ model either the real or imaginary of the beamforming coefficients. Additionally, we denote $\mathbf{x}^{(\text{best}\, G)}$ as the individual with the minimum fitness in the $G$-th generation.

*3.1.2 Mutation and Crossover.* In the $G$-th generation, every individual $\mathbf{x}^{(iG)}$ generates a mutant vector, denoted as $\mathbf{u}^{(iG)} \in \mathbb{R}^{N+2MK}$. In this study, we employ the $DE/best/1$ operator with its mathematical representation is as follows

$$\mathbf{u}^{(iG)} = \mathbf{x}^{(\text{best}\, G)} + \mathsf{F}^{(iG)} \left( \mathbf{x}^{(r_1 G)} - \mathbf{x}^{(r_2 G)} \right), \tag{7}$$

where $\mathsf{F}^{(iG)}$ denotes the scale factor parameter assigned to the $i$-th individual to augment the differential vectors. Because (7) might generate some elements of $\mathbf{u}^{(iG)}$ that violate the value domain constraint, we employ normalization procedures to ensure that the elements of each individual fall within the range of $[-1, 1]$.

Following the mutation, a trial vector $\boldsymbol{\omega}^{(iG)} \in \mathbb{R}^{N+2MK}$ is formed by combining $\mathbf{x}^{(iG)}$ and $\mathbf{u}^{(iG)}$ through the crossover operator. The $n$-th element, represented as $\omega_n^{(iG)}$, is defined as

$$\omega_n^{(iG)} = \begin{cases} u_n^{(iG)}, & \text{if } \mathcal{U}[0,1] \leq \ \mathsf{CR}^{(iG)} \ \text{ or } n = n_{\text{rand}}, \\ x_n^{(iG)}, & \text{otherwise}, \end{cases} \tag{8}$$

where $\mathcal{U}[0, 1]$ introduces a random variable uniformly distributed in the range $[0, 1]$. The parameter $\mathsf{CR}^{(iG)}$ is adaptively chosen to customize each individual $\boldsymbol{\omega}^{(iG)}$. A random position $n_{\text{rand}} \in \{1, \ldots, N + 2MK\}$ is preselected to ensure that $\boldsymbol{\omega}^{(iG)}$ has at least one dimension different from $\mathbf{x}^{(iG)}$.

*3.1.3 Selection.* Following the generation of each trial vector $\boldsymbol{\omega}^{(iG)}$, the associated phase shift coefficients $\boldsymbol{\Phi}^{(iG)}$ and beamforming vectors $\mathbf{w}_k^{(iG)}$ are derived. The evaluation of these potential solutions involves using a fitness function expressed as

$$f(\{\mathbf{w}_k^{(iG)}\}, \boldsymbol{\Phi}^{(iG)}) = \frac{1}{K} \sum_{k=1}^{K} \overline{\mathsf{SER}}_k(\{\mathbf{w}_k^{(iG)}\}, \boldsymbol{\Phi}^{(iG)}). \tag{9}$$

If the fitness value obtained by the pair $\{\mathbf{w}_k^{(iG)}, \boldsymbol{\Phi}^{(iG)}\}$ is better than that of individual $\mathbf{x}^{(iG)}$, $\boldsymbol{\omega}^{(iG)}$ will replace $\mathbf{x}^{(iG)}$ in the population.

Algorithm 1's performance depends on hyperparameters like $\mathsf{F}^{(iG)}$ and $\mathsf{CR}^{(iG)}$. Instead of keeping these fixed, we utilize success-history-based parameter adaptation (SHADE) [4], enabling automatic adjustment for improved performance.

*3.1.4 Local search.* Despite DE algorithm's fast solution-finding ability, it's prone to being trapped in local optima. This study suggests preventing premature convergence by adding a local search technique. After selection, $\lambda_G$ individuals are randomly chosen for potential relocation, determined as follows

$$\lambda_G = \left\lfloor \frac{f^{(cG)}(G_{\max} - G)I}{f^{(\text{best}(G-1))} G_{\max}} \right\rfloor, \tag{10}$$

where $f^{(cG)}$ represents the best fitness value after selection in the $G$-th generation, $f^{(\text{best}(G-1))}$ is the best fitness value in the $(G-1)$-th generation. In (10), the fraction $(G_{\max} - G)I/G_{\max}$ implies that the maximum number of local search operations will decrease gradually over generations. Along the generations, the number of conducted local search operations is inversely proportional to the improvement achieved by DE in Algorithm 1.

To move the solution to a neighbor location, we create a Gaussian vector $\boldsymbol{\xi}^{(iG)} \sim \mathcal{N}(\mathbf{0}, \tilde{\sigma}^2 \mathbf{I}_{N+2MK})$ with the small variance $\tilde{\sigma}^2$ effective in exploring the neighborhoods. For an individual $\boldsymbol{\omega}^{(iG)}$, the neighboring individual is generated as $\tilde{\boldsymbol{\omega}}^{(iG)} = \boldsymbol{\omega}^{(iG)} + \boldsymbol{\xi}^{(iG)}$. In this case, $\tilde{\boldsymbol{\omega}}^{(iG)}$ is a potential solution and its fitness value is computed accordingly. If the fitness value is better than that of $\boldsymbol{\omega}^{(iG)}$, then $\tilde{\boldsymbol{\omega}}^{(iG)}$ is chosen for $Q^{(G)}$, conversely $\boldsymbol{\omega}^{(iG)}$ is chosen.

## 3.2 Convergence Analysis and Computational Complexity

We now probabilistically analyze the convergence of Algorithm 1 to an optimal solution, which is determined as follows.

THEOREM 1. *Let $\mathcal{S}_\varepsilon^*$ be the space of the $\varepsilon$-optimal solution to* (5)

$$\mathcal{S}_\varepsilon^* = \Big\{ \{\mathbf{w}_k\}, \boldsymbol{\Phi} \,\Big|\, |f(\{\mathbf{w}_k\}, \boldsymbol{\Phi}) - f(\{\mathbf{w}_k^*\}, \boldsymbol{\Phi}^*)| < \varepsilon, \\ \{\mathbf{w}_k\}, \boldsymbol{\Phi} \in \mathcal{S} \text{ and } \{\mathbf{w}_k^*\}, \boldsymbol{\Phi}^* \in \mathcal{S} \Big\}, \tag{11}$$

*where $f(\cdot)$ is the objective function and $\mathcal{S}$ denotes the feasible region; $\{\mathbf{w}_k^*\}, \boldsymbol{\Phi}^*$ is the optimal solution and $\varepsilon$ is a small positive value. For a population $\mathcal{P}$ with $I$ individuals, the probability of $\mathcal{P}$ converging to an individual belonging to $\mathcal{S}_\varepsilon^*$ by exploiting Algorithm 1 is*

$$\Pr\left(\mathcal{P} \cap \mathcal{S}_\varepsilon^* \neq \emptyset\right) \geq 1 - \left(1 - \mu_1\left(\mathcal{S}_\varepsilon^*\right) P_{\text{ep}}\right)^I \times \\ \left(1 - \mu_2\left(\mathcal{S}_\varepsilon^*\right) \left(\frac{1}{\tilde{\sigma}\sqrt{2\pi}}\right)^{N+2MK} e^{\frac{-2(N+2MK)}{\tilde{\sigma}^2}}\right)^{\tilde{\lambda}}, \tag{12}$$

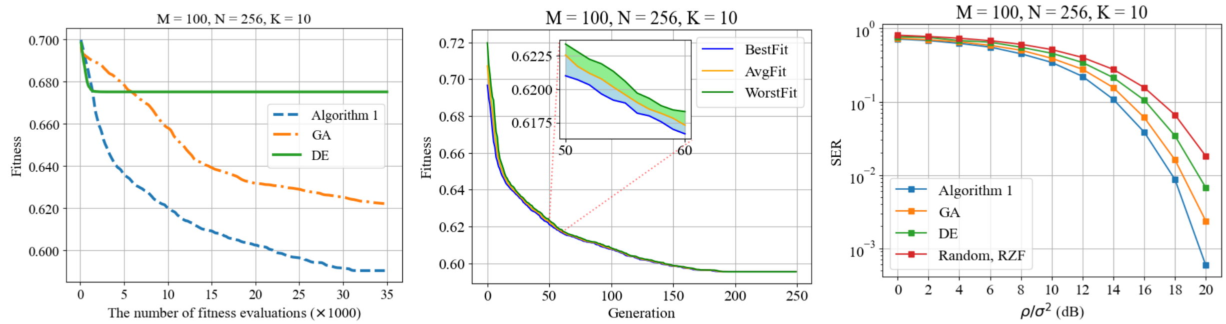
*where $P_{\text{ep}} \in [0, 1]$ is the mutation probability of each individual; $\mu_1\left(\mathcal{S}_\varepsilon^*\right)$ and $\mu_2\left(\mathcal{S}_\varepsilon^*\right)$ are the measures to the space $\mathcal{S}_\varepsilon^*$ regarding the mutation and the local search, respectively; and $\tilde{\lambda}$ as the number of individuals utilized for the local search step in each generation.*

PROOF. The proof is based on computing the probability that the optimal solution appears in the population as the generations grow. The detailed proof is omitted due to space limitations. □

Algorithm 1 with the local search has better convergence in probability than the standard DE. The local search improves the lower bound of the convergence probability. The computational complexity of Algorithm 1 is $O\left(GI\log(I) + 2GI(N + 2KM)\right)$, where $G$ is the number of generations and $I$ is the population size.

# 4 NUMERICAL RESULTS

This section provides experimental results to evaluate the effectiveness of our proposed active and passive beamforming design. In particular, we consider a system where the BS is equipped with 100 antennas, and the RIS consists of 256 phase shift elements. The number of users is $K = 10$, up to the network density. The signal modulation and demodulation are the 16-QAM. The propagation channels $\mathbf{H}$, $\mathbf{u}_k$, and $\mathbf{g}_k$ are constructed as $\mathbf{H} = \sqrt{\beta_{\text{bsr}}}\tilde{\mathbf{H}}$, $\mathbf{g}_k = \sqrt{\beta_{rk}}\tilde{\mathbf{g}}_k$, $\mathbf{u}_k = \sqrt{\beta_k}\tilde{\mathbf{u}}_k$, where $\beta_{sr}$, $\beta_{rk}$, and $\beta_k$ are the large-scale fading coefficients between the BS and the RIS, the RIS and user $k$, and the BS and user $k$, respectively. Meanwhile, $\tilde{\mathbf{H}}$, $\tilde{\mathbf{g}}_k$, and $\tilde{\mathbf{u}}_k$ follow the Rayleigh fading.




(a) (b) (c)

**Figure 3: Evaluating the effectiveness of algorithm 1: (3a) Convergence of different benchmarks comprising Algorithm 1, GA, DE with $\rho/\sigma^2 = 5$ [dB], (3b) Convergence of Algorithm 1 as the behavior of individuals (the best, worst, and average) with $\rho/\sigma^2 = 5$ [dB], (3c) SER of different benchmarks comprising Algorithm 1, the GA, the DE, and the random phase shift together with the RZF technique.**

In order to show the benefits of Algorithm 1 with an additional local search, Figure 3a visualizes the convergence versus the number of fitness evaluations with the different benchmarks including the GA [3], and the DE [1]. The intial hyperparameters are $\mathsf{F}_{\text{init}} = 0.1$ and $\mathsf{CR}_{\text{init}} = 0.9$. The maximum number of generations is 350, which is equivalent to 35000 fitness evaluations.

Algorithm 1 and DE converge faster than GA. Initially, Algorithm 1 doesn't show much improvement over DE due to ineffective local search. However, as DE may prematurely converge after about 2000 evaluations, Algorithm 1's local search becomes crucial, significantly enhancing results. Though GA avoids early local minima, its solution improvement is slow. The numerical results point out a notable effectiveness of Algorithm 1 observed across all the considered settings.

Additionally, we analyze Algorithm 1's convergence within the population and its stability, as depicted in Figure 3b. Over time, the population stabilizes across all metrics, with decreasing differences in fitness indicating adaptability and gradual elimination of less competent individuals. Table 1 the improvement in solution quality before and after applying local search in each generation, demonstrating the effectiveness of the added technique, and the average number of individuals performing neighbors search is statistically analyzed including the average (**avg**) and standard deviation (**std**) of the generation duration.

| Generations | 10 users | |
|---|---|---|
| | **avg** | **std** |
| [1, 50] | 87.58 | 13.69 |
| [51, 100] | 69.6 | 5.77 |
| [101, 150] | 49.6 | 5.77 |
| [151, 200] | 29.6 | 5.76 |
| [201, 250] | 9.66 | 5.70 |

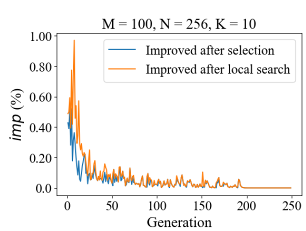



**Table 1: The number of individuals performing local search in each generation and the improvement of solution quality (*imp*%) in each generation with $\rho/\sigma^2 = 5$ [dB].**

In Figure 3c, we compare the effectiveness of Algorithm 1 with the GA, DE, and the baseline that involves the random phase shift selection and the RZF technique. Algorithm 1 outperforms all the remaining benchmarks over the different network settings. Furthermore, the SER of each user is significantly improved as the signal-to-noise ratio increases. With a small number of users, Algorithm 1 shows substantially better performance than the others.

## 5 CONCLUSION

The paper optimizes communication reliability in RIS-assisted MIMO systems by combining active and passive beamforming designs. It addresses propagation environment challenges and pioneers a method for RIS integration. The improved DE algorithm minimizes average downlink SER for modulated signals, demonstrating its adaptability and efficiency. Numerical results show the efficacy of the proposed evolutionary approach, highlighting its potential for RIS deployments in practice.

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