Performance of Massive MIMO aided by Reflective Intelligent Surfaces

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Performance of Massive MIMO aided by Reflective Intelligent Surfaces

Andre Flaiban, Taufik Abrão

Abstract—Reflective intelligent surfaces (RIS) are large passive panels with hundreds or thousands of passive reflective meta-surface sensors, with the ability to electronically adjust the angle-of-departure (AoD) of the incident signal but not to apply any amplification and signal processing to the radio frequency signal. This technology is up-and-coming for networks beyond 5G (B5G). We evaluate the performance gains, including SINR and outage probability (OP) of RIS-aided massive MIMO systems regarding the conventional massive MIMO systems, highlighting the potential of beamforming performance and RIS element phase-shift optimization, aiming to deal with dense urban obstacles scenarios and high density of mobile users. This work aims to investigate the behavior of a RIS-aided MIMO system under different channel scenarios, considering the Rician factor.

Index Terms—Reflective Intelligent Surface (RIS); Massive MIMO; Outage Probability; evolutionary meta-heuristic.

I. INTRODUCTION

Wireless communication has become an essential part of modern life, enabling us to stay connected with the world around us. Wireless communications have revolutionized how we interact with our surroundings, from smartphones to smart devices. However, with the growing demand for high-speed and reliable wireless communication, there is an increasing need for better wireless systems. The current wireless networks, while capable of providing adequate service to a certain degree, are often unable to sustain high-quality service in highly crowded environments or areas where the base station (BS) to user link is frequently obstructed [1].

The reflective intelligent surface (RIS) is a promising technology that, when combined with massive multiple-input multiple-output (M-MIMO), is a promising solution to enhance 5G and beyond 5G (B5G) wireless communication systems. Passive RIS is a two-dimensional array of passive reflecting elements made of meta-materials that can be configured, changing the impedance of these meta-material elements by controlling the voltage applied to each element; hence, the direction of reflected signal can be controlled, while manipulating the phase of the signal to enhance the performance of the wireless system. By selecting an angle of reflection, a RIS can create additional paths between the transmitter and receiver, which can increase the signal strength and reduce the fading effect on the radio channel.

The integration between RIS and M-MIMO involves placing one or more RISs between the transmitter and receiver in the original M-MIMO system. The intelligent surface creates additional paths that can improve the performance of the system. Moreover, by changing the phase and amplitude of the reflected signal, the RIS elements allow the system to mitigate the deleterious channel effects on the signal, improving communication reliability.

A. Related Works

There are several challenges involving beamforming and phase shift design and optimization in a RIS-aided multi-user MIMO and massive MIMO scenarios with different objectives [2]–[11], including the maximization of the system sum-rate [2], [3], spectral efficiency [4] and energy efficiency [5], [6], or minimization of the transmission power [7], MAX-MIN SINR problem [8], [9], and the exposure to electromagnetic fields [10], [11]. Moreover, a more sophisticated setup involving multiple RIS is investigated in [12]. The authors investigate the SINR maximization problem in the downlink (DL) transmission of a multi-user massive MIMO system assisted with multiple RISs. In this scenario, they assume that the BS directly serves some of the UEs, while others have no direct channel to the BS and are served through the RISs. Each RIS serves several UEs in a specific geographic area, forming a cluster [12]. A zero-forcing (ZF) beamforming approach is deployed at the BS, completely canceling the interference, allowing the asymptotic analysis, and facilitating the RIS phase-shift matrices design.

B. Contributions

The contributions of this work are threefold. i) formulation and analysis of the performance and complexity of a RIS-aided multi-user massive MIMO system operating under different system configuration setups. ii) propose to solve three different optimization problems by formulating three different objective functions aiming to improve the system SINR by selecting the suitable RIS elements’ phase shift angles. iii) For that, we have evoked an evolutionary heuristic optimization method, namely the Particle swarm optimization (PSO), to solve the non-convex optimization problems associated with the complex RIS-aided M-MIMO systems. The three different objective functions evaluated are a) maximization of the sum of the individual (UE) SINR; b) maximization of the minimum individual SINRs (Max-Min); c) maximization of the geometric mean of the product of logarithm of SINRs for all users (Avg Max-Geometric). Moreover, we have proposed a hybrid method (Hyb Meth), by combining the Max-Min and Avg scheme. Also, we have characterized the average maximum geometric SINR concept, generating the Avg. Max-Geom optimization method. Also, we have analyzed the system performance under different linear precoders/combiners at the BS / UE terminal, respectively.
II. RIS-AIDED MASSIVE MIMO SYSTEM MODEL

In a typical uplink (UL) reconfigurable intelligent surface (RIS)-aided communication system, we consider the existence of a base-station (BS) with $M$ antennas, a RIS with $N$ reflecting elements, and $K$ single-antenna user equipment (UE). Assuming a RIS was deployed in a position with an exclusive LoS link with the BS, it’s possible to compute only the path loss in this sub-channel. But, in the UE-RIS link, we adopt a Rician fading model since there should be a partial blockage due to some people, trees, or objects obstructing the signal propagation. Hence, the received signal at the BS can be formulated as follows [13]:

$$ y = G\Theta Hx + n $$

where $G \in \mathbb{C}^{M \times N}$ is the channel matrix for the RIS-BS link, $\Theta \in \mathbb{C}^{N \times N}$ is the phase-shift diagonal matrix for the $N$ RIS elements, and $H \in \mathbb{C}^{N \times K}$ is the channel matrix for UE-RIS link, as shown in Fig. 2. Also, $x \in \mathbb{C}^{K \times 1}$ denotes the simultaneously transmitted signal from $K$ single-antenna users, and $n \sim \mathcal{C}\mathcal{N}(0,1)$ is the vector of samples of additive white Gaussian noise (AWGN).

$$ G = \begin{bmatrix} g_{1,1} & g_{1,2} & \ldots & g_{1,N} \\ g_{2,1} & g_{2,2} & \ldots & g_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ g_{M,1} & g_{M,2} & \ldots & g_{M,N} \end{bmatrix} $$

$$ \Theta = \text{diag} \left( \begin{bmatrix} \alpha_1 e^{j\theta_1} \\ \alpha_2 e^{j\theta_2} \\ \vdots \\ \alpha_N e^{j\theta_N} \end{bmatrix} \right) $$

$$ H = \begin{bmatrix} h_{1,1} & h_{1,2} & \ldots & h_{1,K} \\ h_{2,1} & h_{2,2} & \ldots & h_{2,K} \\ \vdots & \vdots & \ddots & \vdots \\ h_{N,1} & h_{N,2} & \ldots & h_{N,K} \end{bmatrix} $$

where

$$ L_{\text{LoS}}^{n,m} = \frac{G_m \lambda^2}{(4\pi b_m)^2} $$

with $G_m$ being the $m$th antenna gain, $\lambda$ is the carrier wavelength, and $b_m$ being the distance between the $m$th antenna from the RIS and the $m$th antenna of the BS [13].

Similarly, the path loss coefficients $\beta_k$ associated with the $k$-th UE in the uplink UE-RIS NLoS channel, $h_{n,k}$ from matrix $H$ is different because the distance $\alpha_k$ varies according to the position of each UE. Notice that in the UE-RIS link, we are assuming a partial fading, described by the contribution of an LoS ($h_{n,k}$) and an NLoS ($\tilde{h}_{n,k}$) components:

$$ h_{n,k} = \sqrt{\beta_k} \left( \frac{1}{\epsilon_k + 1} b_{n,k} + \sqrt{\frac{1}{\epsilon_k + 1}} \tilde{h}_{n,k} \right) $$

$$ \beta_k = \frac{G_k \lambda^2}{(4\pi)^2 \alpha_k^2} $$

where $h_{n,k}$ divided by $\sqrt{\beta_k}$ follows a RICE distribution and $\epsilon_k$ is the Rician factor as described in [1] and without loss of generality, it is assumed to be the same for all $K$ users, i.e., $\epsilon_k = \epsilon$, $\forall k$. Typical values for $\epsilon \in \{1; 5; 10; 20\}$. Besides, $G_k$ is the $k$th UE single-antenna gain, and $\alpha_k$ is the distance between the $n$th antenna from the RIS and the antenna of the $k$th UE. The diagonal RIS transfer matrix $\Theta$ is described by the controllable magnitude ($\alpha_n$), and the phase response ($\phi_n$), i.e., $\theta_n = \alpha_n e^{j\phi_n}$ for $n = 1, \ldots, N$ antenna-elements. In this work, we assumed $\alpha_n = 1$, $\forall n$.

A. Massive MIMO Channel

We consider an M-MIMO antenna array with $M$-antenna ULA, so $M$ antennas serve $K$ UEs simultaneously. The ULA antennas in BS are separated by a distance $d$. The height of the ULA structure and the NLoS and the probabilistic LoS/NLoS channel vectors associated with the $k$th UE and ULA, while $\alpha_k$ is a Bernoulli random variable indicating the presence ($\alpha_k = 1$) or absence ($\alpha_k = 0$) of a LoS component between the $k$th UE and the ULA antennas, assuming that all UEs are located far from BS antennas, characterizing the far-field propagation, under planar wavefront propagation conditions.

The associated channel model with probabilistic LoS components can be expressed as:

$$ h_{kl} = \alpha_k h_{k|l}^{\text{LoS}} + h_{k|l}^{\text{NLoS}} $$

where $h_{k|l}^{\text{LoS}}, h_{k|l}^{\text{NLoS}}, h_{kl} \in \mathbb{C}^N$ denote, respectively, the LoS, the NLoS, and the probabilistic LoS/NLoS channel vectors between UE $k$ and ULA, while $\alpha_k$ is a Bernoulli random variable indicating the presence ($\alpha_k = 1$) or absence ($\alpha_k = 0$) of a LoS component between the $k$th UE and the ULA antennas, assuming that all UEs are located far from BS antennas, characterizing the far-field propagation, under planar wavefront propagation conditions.

The LoS channel vector between the $k$-th UE and the ULA is given by [15]

$$ h_{kl}^{\text{LoS}} = G_k G_l z_{k|l}^{\text{UL}} z_{k|l}^{\text{LA}} e^{-j2\pi d_k} a(\varphi_{k|l}, \theta_{k|l}) $$

where $G_k$ and $G_l$ denote the antenna gain at the $k$th UE and the ULA antennas, respectively; $\lambda = c/f$ is the wavelength, being $c$ the speed of light and $f$ the carrier frequency; $A_k^{\text{LoS}}$ is

![Figure 1: UL system model for the RIS-aided multiuser communication with $K$ users, $M$ BS antennas and $N$ RIS elements.](image)
the shadow fading of the LoS component; and \( \mathbf{a}(\bar{\varphi}_k, \bar{\theta}_k) \) is the array response vector of the ULA, regarding to the LoS ray. The azimuth and elevation angles of the LoS path between the 4th UE and the center of ULA are denoted by \( \varphi_k \) and \( \theta_k \), respectively.

The array response vector, as a function of the azimuth and elevation angles \( \varphi \) and \( \theta \), is given by

\[
\mathbf{a}(\varphi, \theta) = \left[ 1, e^{-j2\pi \frac{d}{\lambda} \sin \varphi \sin \theta}, \ldots, e^{-j2(N-1)\pi \frac{d}{\lambda} \sin \varphi \sin \theta} \right]^T
\]  

(11)

and accounts for the phase differences among the signal that arrives in different antennas of the same uniform linear array (ULA).

B. Near-field vs. Far-field

An important issue on M-MIMO and XL-MIMO arrays is that the wavefront propagation can result in spherical or planar wavefront propagation, since some users may be in the near-field or far-field condition, respectively. Such a condition is defined by the distance w.r.t. the entire M-MIMO array, namely Rayleigh distance, given by [16]

\[
d_{\text{Rayl}} = \frac{2D^2}{\lambda} \text{ [m]}
\]

(12)

where \( D \) is the antenna array aperture and Hence, when \( d_{kl} < d_{\text{Rayl}} \) the near-field condition occurs. This results in different propagation scenarios, since distances along the ULA, UPA or subarrays (SAs) in XL-MIMO vary dependent on the application scenario.

Since in this work, we have considered that all UEs are in far-field propagation condition, it is equivalent to assume that the ULA aperture is small compared to the propagation distance, i.e., \( d_{kl} > d_{\text{Rayl}} \); hence, we can assume that the wavefront propagation is planar to the ULA BS point of view. The implication is that the difference between the propagation distance for two antennas belonging to the same ULA is negligible, such that the corresponding large-scale fading (LSF) coefficients are nearly the same. However, even this negligible difference is sufficient to produce phase differences among these antennas. Such phase differences are accounted for by the array response (steering) vector in [11].

III. SELECTING THE \( \Theta \) MATRIX IN MULTIUSER SPATIAL CORRELATION CHANNELS

One of the RIS effects is its capacity to modify the channel response by controlling the phase-shift introduced by each antenna element of the array, hence affecting the signal phase that is being reflected. Mathematically this effect is described by the transfer matrix \( \Theta \) that is composed by the controllable magnitude \( \alpha_n \), and the phase response \( \varphi_n \), i.e., \( \theta_n = \alpha_n e^{j\varphi_n} \) for \( n = 1, \ldots, N \) antenna-elements. Considering that the elements of the RIS are passive \( \alpha_n \), such a factor will always be set as a constant; in this paper, it was considered to be \( \alpha_n = 1 \), \( \forall n \). Oppositely the RIS phase response matrix can be controlled by varying the input voltage on the metamaterial and in doing so, one can modify and control the channel behavior. The challenge is to determine what is the effect of the channel on the signal phase and optimize the phase response to maximize, for instance, the sum-rate or the sum of the SINR of the \( K \) users, considering that such phase response matrix \( \varphi_n \) needs to be updated in a very high rate, i.e., in time-interval smaller than the channel coherence time, \( (\Delta t)_c \) and using the minimal amount of energy and bandwidth possible.

IV. OPTIMIZATION IN RIS-AGED M-MIMO SYSTEMS

How to select and optimize the RIS phase-shift elements, the \( \Theta \) matrix? Initially, let’s consider a quasi-static scenario, i.e., the UE or UEs present very low mobility. The \( N \times N \) matrix \( \Theta \) in eq. (3) is composed by the controllable magnitude \( \alpha \) and phase shift \( \varphi \), where the amplitude is assumed \( \alpha_n = 1, \forall n \), and controllable phase shift \( \varphi_n \) is the phase response of the \( n \)-th RIS element that should be optimized aiming to reduce the effect of the fading radio channel on the received signal.

A. Optimal \( \Theta \) matrix – Single-User Case

Considering the positioning of the user (single-user (SU) scenario), BS, and RIS are known, while both the UE and BS are assumed in a far-field condition. Hence, it is possible to calculate the angles of arrival (AoA) of the signal. In view of the planar wavefront propagation condition, the phase shift in each RIS element can be easily calculated. Hence, knowing the phase shift in each RIS element one can calculate the \( n \)-th optimal RIS-element phase response as:

\[
\theta_n^* = -(\phi_n + \varphi_n)
\]

(13)

where \( \phi_n \) is the phase caused by the RIS-BS sub-channel \( g_{mn} \), and \( \varphi_n \) is the phase caused by the UE-RIS sub-channel \( h_{n,k} \) in the uplink mode. The problem is that each single UE-RIS element and RIS element -BS composite subchannel needs to be known at BS to proceed with the detection at the UL.

B. Combiner (Rx-ULA) Design

The optimal precoder vector is given by solving the following problem:

\[
\max_k \min \text{SINR}_k \\
\text{s.t. } \| \mathbf{\chi}_k \| = 1; \forall k \in \{ 1, \ldots, K \}.
\]

(14)

**MMSE Precoder/Combiner.** Following the steps in [17], the solution for the above problem is given by the minimum mean squared error (MMSE):

\[
\mathbf{\chi}_k = \left( \mathbf{\Sigma}_k + \sigma^2 \mathbf{I} \right)^{-1} \mathbf{q}_k \left\| \mathbf{\Sigma}_k + \sigma^2 \mathbf{I} \right\|^{-1} \mathbf{q}_k
\]

(15)

where \( \mathbf{\Sigma}_k = \sum_{i=1,i\neq k}^{K} \frac{p_i}{K} \mathbf{q}_i \mathbf{q}_i^H \) and \( \mathbf{q}_k = \mathbf{GR}_{\text{RS}} \mathbf{\Theta}_k \).

For this choice of the precoder set \( \{ \mathbf{\chi}_k \} \), the SINR of the \( k \)-th user is given by:

\[
\text{SINR}_k = \frac{p_k}{K} \mathbf{q}_k^H \left( \mathbf{\Sigma}_k + \sigma^2 \mathbf{I} \right)^{-1} \mathbf{q}_k
\]

(16)
Maximum Ratio Transmission/Combiner (MRT/MRC): the MRT/MRC is a suboptimal precoding/combiner matrix described as:
\[ X_{k,t} = q_k^* \]  
(17)

Zero Forcing (ZF) is a suboptimal low-complexity Precoder/Combiner described by the vectors:
\[ X_{k,t} = q_k^* (q_k^T q_k^*)^{-1} \]  
(18)

C. Optimizing Θ and Power Allocation – MultiUser Case

In the multi-user scenarios, we consider the correlation coefficient between RIS elements, defined experimentally by ΘC. Optimizing Zero Forcing (ZF) is a suboptimal low-complexity Pre-

users. Note that the received signal at the BS (UL) in (22) can be described as:
\[ r_k = \chi_k^H y \]  
(25)

Then, the decoded symbol from user k can be represented as
\[ r_k = \chi_k^H y \]
where \( \chi_k \) is the k-th row of the matrix \( \chi \). Finally, the SINR for user k at the BS is hence given by
\[ SINR_k = \frac{p_k}{\sum_{i=1,i\neq k}^{K} p_i} \frac{||\chi_k^H \Theta h_k||^2}{\sigma^2 ||\chi_k||^2} \]  
(26)

where \( \sigma^2 = \sigma_n^2 \). The SINR experienced by each user is thus a function of the power allocation, type of precoder/combiner at the BS, and the phase shift induced by the RIS elements.

In the multi-user (MU) scenario, the optimal RIS phase-shift selection problem gets more complex because interference – the first term in the denominator of eq. (26) – needs to be accounted for. Thus turning the selection of the Θ matrix into a harder process, in this case, strictly speaking, there is no optimal solution to maximize the combined signal-to-interference-plus-noise ratio SINR of the system since the problem in its original form becomes non-convex.

Hence the basic problem of optimizing the sum of SINR in a RIS-aided communication can be formulated as:
\[ (P_1) \ \text{maximize} \ \sum_{k=1}^{K} \text{SINR}_k \]  
\[ \text{s.t.} \ \left\{ \begin{array}{l} 0 < \theta_n < 2\pi; \forall n \in \{1, \ldots, N\} \\
p_k \leq p_{\text{max}}; \forall k \in \{1, \ldots, K\} \end{array} \right. \]  
(27)

where \( p_{\text{max}} \) is the maximum power available at the the k-th UE.

In [9], the SINR maximization problem is formulated as a Max-Min problem:
\[ (P_2) \ \max_{(p_k)_{k=1}^{K}, \Theta, \chi} \ \min_k \text{SINR}_k \]  
\[ \text{s.t.} \ \left\{ \begin{array}{l} 0 \leq \theta_n \leq 2\pi; \forall n \in \{1, \ldots, N\} \\
||\chi_k|| = 1; \forall k \in \{1, \ldots, K\} \\
\Theta_{\chi} = 1; \forall n \in \{1, \ldots, N\} \end{array} \right. \]  
(28)

1 The most used linear precoders include MRT, ZF, and MMSE. Note that in the UL, the BS executes the combiner, while in the DL, the BS implements the precoder. Popular linear precoders include maximum ratio transmitter (MRT), zero forcing (ZF), and minimum mean squared error (MMSE) precoder, while the corresponding combiners implementing the same rule are the maximum ratio combiner (MRC), zero forcing (ZF) combiner, and the minimum mean squared error (MMSE) combiner. Moreover, we have the equal gain combiner (EGC) and the empirical rule combiner (ERC), as well as the singular value decomposition-based (SVD) precoder/combiner.

Now, let \( \chi \in \mathbb{C}^{K \times M} \) be the combiner (Rx) / beamformer (Tx) matrix at the BS. Hence, the received symbols can be decoded as
\[ r_k = \chi_k^H y \]  
(25)

where \( r_k \) is the k-th row of the matrix \( \chi \). Finally, the SINR for user k at the BS is hence given by
\[ SINR_k = \frac{p_k}{\sum_{i=1,i\neq k}^{K} p_i} \frac{||\chi_k^H \Theta h_k||^2}{\sigma^2 ||\chi_k||^2} \]  
(26)
rate for some of UEs [18]. The GM for RIS-aided M-MIMO context can be formulated as problem 3 (P₃):

$$\max_{\{p_k\}_{k=1}^{K}} \left( \sum_{k=1}^{K} \log_2 (1 + \text{SINR}_k) \right)$$

s.t. $0 \leq \frac{p_k}{K} \leq p_{\text{max}}; \forall k \in \{1, \cdots, K\},$

$$||x_k|| = 1; \forall k \in \{1, \cdots, K\},$$

$$\Theta_n = 1, \forall n \in \{1, \cdots, N\}.$$  \hspace{1cm} (29)

In [19], alternating maximization and majorization-minimization (AMM) methods were combined to maximize the sum achievable rate in typical MU scenarios. In another attempt to optimize the solution of problem (34), a weighted sum-rate (wSR) maximization approach is adopted in [20]. With many other suboptimal solutions associated with RIS-aided communication, the problem in (34) is still relevant and deserves effective, low-complexity, practical quasi-optimal solutions inspired by a plethora of methods and tools.

D. Meta-Heuristic Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a metaheuristic optimization algorithm used to find a "low-cost/complexity" solution as close to the optimal solution as possible, which demonstrates efficiency in effectively solving non-convex optimization problems. In PSO, the swarm of particles is initialized randomly in the search space, each with a random position, and then moves through the search space iteratively, adjusting their position and velocity based on their past positions (personal best) and the experience of the other particles in the swarm and their best positions (global best). The effect of the personal best and global best in the particle is adjusted using the cognitive coefficient and social coefficient, $c_1$ and $c_2$, respectively. The particle position vector and particle velocity vector updating, at the $(t + 1)$-th iteration, can be expressed respectively as:

$$x_{t+1} = x_t + v_{t+1}$$

$$v_{t+1} = w \cdot v_t + c_1 \cdot r_1 \odot (p_t - x_t) + c_2 \cdot r_2 \odot (p_g - x_t)$$  \hspace{1cm} (30)

where the operator $\odot$ is the Hadamard product, $w$ is the inertia factor, $c_1$ and $c_2$ is the individual and global weight factor, $r_1$ and $r_2$ are random vectors with elements uniformly distributed $r_i \sim U[0; 1]$; finally, the particle position, velocity and random vectors, respectively $x = [x_1, x_2, \cdots, x_N]$ and $v = [v_1, v_2, \cdots, v_N]$, and $r_1 = [r_1, r_2, \cdots, r_N]$, are composed by $N$ particles.

Based on the algorithm described in [21] we have constructed a new version of PSO algorithm adapted to solve the non-convex optimization problem in (34).

V. NUMERICAL RESULTS

The main parameter values adopted in this section are shown in Table I. In this section, we have analyzed the performance of downlink (DL) single-user (SU) and multi-user (MU) RIS-aided M-MIMO systems under different channel and system configurations.

Table I: Adopted Simulation Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of mobile users</td>
<td>$K = 1$ (SU)</td>
</tr>
<tr>
<td>$K \in [2; 10; 20]$ (MU)</td>
<td></td>
</tr>
<tr>
<td>Carrier frequency</td>
<td>$f_c = 3$ GHz</td>
</tr>
<tr>
<td>Wave length</td>
<td>$\lambda = 10$ cm</td>
</tr>
<tr>
<td>PSD, $(f)$</td>
<td>$S_0 = -196$ dBm/Hz</td>
</tr>
<tr>
<td>Noise power (variance)</td>
<td>$\sigma^2 = \text{BW} \cdot S_0 = 80$ FW</td>
</tr>
<tr>
<td>Transmit power $k$th user</td>
<td>$p_k = p_{\text{max}}$ (uniform allocation)</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>$\text{BW} = 20$ MHz</td>
</tr>
<tr>
<td>Antennas at BS (ULA)</td>
<td>$\mathcal{M} \in [1, 20, 64]$</td>
</tr>
<tr>
<td># RIS elements</td>
<td>$N \in [40, 60, 100]$</td>
</tr>
<tr>
<td>Distance between RIS elements</td>
<td>$d = 5$ cm</td>
</tr>
<tr>
<td>$T_x$, $R_x$ antenna gain</td>
<td>$G_1 = 4$ dB, $G_2 = 0$ dB</td>
</tr>
<tr>
<td>Combiner: MRC, ZF, MMSE</td>
<td>$\chi$, eq. (17), (15), (15)</td>
</tr>
<tr>
<td>Monte-Carlo Simulation</td>
<td>$J = 100$ realizations</td>
</tr>
</tbody>
</table>

A. Single-user Scenario (SU): $K = 1$

In the first simulation scenario, the system was modeled considering one user, $N = 40$ elements on the RIS, and $M = 1$ antenna at the BS receiver. The elements of the RIS in this case were separated by $\frac{d}{2}$, considering $f_{\text{carrier}} = 3$ GHz, we have 5 cm between each element. Fig. 2 reveals the physical channel scenario adopted in the simulation. Notice that RIS panel is positioned in $(x, y, z) \equiv (x, 0, 0)$, i.e., along the $x$-axis in the range $x \in [\pm 200]$ m. The adopted UE and RIS channels consider the urban environment, i.e., a Non-line-of-sight (NLoS); while for the RIS-BS link we consider a line-of-sight (LoS) link.

![Figure 2: Positioning of the system components. The direct BS-UE₁ channel is totally obstructed.](image)

Fig. 3 depicts the SNR at the BS as a function of RIS panel positions and considering four different Rician NLoS channel factors, $\epsilon \in [1, 2, 5, 10]$.
where the n-th optimal RIS phase shift is given by:
\[ \theta_n = - (\phi_n + \varphi_n) \]  
(33)
with \( \phi_n \) and \( \varphi_n \) are, respectively, the phase shift caused by the \( g_{m,n} \) and \( h_{n,k} \) subchannels. The positioning of the system components was known, and the phase shift was calculated using that data. Interestingly, the results of Fig. 3 reveal that the best RIS placement, maximizing SNR is obtained when the RIS panel is near to UE \((\approx -150\text{m}, \forall \epsilon)\), minimizing the deleterious effect of NLoS channel.

### B. Multiuser scenario (MU): \( K > 1 \)

We modified the previous system, positioning the users randomly at \((x, z, y) \equiv (x, z, 0)\), along the x-axis in the range \(x \in [-150, -300] \text{ m}\), and z-axis in the range \(z \in [-50, -150]\) m, Fig. 4. Under the MU scenarios, the positioning of the UEs, RIS, and BS follows Fig 4 where the selection of the RIS phase response is based on the optimal \( \Theta \) for the user of interest.

**Figure 3:** System SNR \((K = 1 \text{ user})\) moving the RIS under different Rician factors \((\epsilon)\) in the NLoS channels. \(M = 1 \text{ antenna and } N = 40 \text{ RIS elements.}\)

**Figure 4:** Generic positioning of the system components, with UE\(_1\), UE\(_2\), ..., UE\(_K\) randomly distributed in a specific area.

**Increasing the number of BS antennas and RIS elements:** in the second and third simulations setup, the RIS was fixed at \((x, y, z) \equiv (-150, 0, 0), \epsilon = 2\) and a MMSE combiner was deployed. Both simulations were meant to analyze different configurations of antennas at the BS and the number of elements in the RIS. In Fig. 5(a), we explore the SNR of single-user scenarios \((K = 1)\), and in Fig. 5(b) the SINR multi-user scenarios \((K = 10)\) is revealed. Initially, we assume \(N = [40, 60, 100]\) and \(M\) varied from 1 to 64, then \(M\) was fixed at \([1, 20, 64]\) and \(N\) increases from 1 to 100. In both single user configurations, the SNR was used to analyze the performance of the RIS-aided M-MIMO system. As expected, the SNR increases substantially when the number of antennas in BS or RIS grows from 1 to 20 antennas, becoming more modest with the increase in the SNR from 20 to 64 antennas. On the other hand, in multi-user scenarios, Fig 5(b), the SINR vs. # RIS elements increases just marginally with the increase of the number of BS \(M\).

**Figure 5:** a) SNR \((K = 1 \text{ user})\) and b) SNR \((K = 10 \text{ user})\) under Rician factor \(\epsilon = 2\) by varying the # antennas at the BS \((M)\), parameterized in \(N \in [40, 60, 100]\) elements; and # RIS elements \((N)\), considering \(M \in [1, 20, 64]\) BS antennas. \(\Theta\) is optimized for just UE\(_1\), that is fixed at position \((x, z, y) \equiv (-150, -50, 0)\).
C. PSO Input Parameters Optimization

In this subsection, we present numerical results for the PSO input parameters calibration. The adopted PSO input parameter values in multi-user scenarios analyzed herein are summarized in Table II. Notice that since the problem dimension increases with $K$, the population size of the PSO must increase accordingly. Fig. 5 demonstrates that a population size value of $n_{\text{pop}} = 40$ particles represents the best trade-off between PSO performance vs. complexity for the SINR maximization problem in the context of RIS-aided M-MIMO systems. Notice that the average SINR across the PSO iterations does not increase substantially when $n_{\text{pop}} = 40$ increases to 60 particles for a problem with dimensionality 10 ($K = 10$ users).

Table II: Adopted PSO Input and Simulation Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inertia weight</td>
<td>$u = 0.9$</td>
</tr>
<tr>
<td>Cognitive coefficient ($c_1$)</td>
<td>$c_1 = [0.2, 0.5, 1, 1.5, 1.8]$</td>
</tr>
<tr>
<td>Social coefficient ($c_2$)</td>
<td>$c_2 = [0.2, 0.5, 1, 1.5, 1.8]$</td>
</tr>
<tr>
<td>Population size</td>
<td>$n_{\text{pop}} = [20, 40, 60, 80]$</td>
</tr>
<tr>
<td>Random coefficient ($r_1, r_2$)</td>
<td>$r_1, r_2 \sim U[0; 1]$</td>
</tr>
<tr>
<td>Maximum iterations</td>
<td>$\mathcal{I}_{\text{max}} \in [40, 100]$</td>
</tr>
<tr>
<td>Monte-Carlo Simulation</td>
<td>$\mathcal{T} = 50$ realizations</td>
</tr>
</tbody>
</table>

![Figure 6](image_url)  
Figure 6: The average SINR across the PSO iterations, where $M = 64$, $K = 10$, $N = 40$, and $\epsilon = 2$. ($\mathcal{T} = 50$ trials, $\mathcal{I}_{\text{max}} = 100$).

Analyzing Fig. 7 one can observe that the optimal Cognitive coefficient ($c_1$) and Social coefficient ($c_2$) values for this problem and configuration are $[c_1; c_2] = [1.5; 0.5]$.

D. Comparing Max-Min, Max-Avg, and GM Criteria

There are many ways one can describe a RIS-aided M-MIMO optimization process, as well as selecting an evolutionary heuristic tool, such as the PSO algorithm, to solve the problem. In this subsection, we discuss different approaches to optimizing system performance and the related performance-complexity trade-offs. We analyze four different approaches for optimizing the RIS-aided M-MIMO performance: a) Max-Min SINR; b) Max-Avg SINR; c) Hybrid method, combining the objective function of both Max-Min SINR and Max-Avg SINR methods; d) Geometric mean of UEs rate.

Max-Min SINR: In this optimization problem, the PSO algorithm solves in a quasi-optimal way the problem described in (29), where the user with the lowest SINR is prioritized.

Max-Average SINR: The second approach used to optimize the system performance deploys the average SINR as an objective function.

$$
\max_{\Theta} \quad \frac{1}{K} \sum_{k=1}^{K} \text{SINR}_k \\
\text{s.t.} \quad 0 < \theta_n < 2\pi; \forall n \in \{1, \cdots, N\} \quad (34)
$$

Hybrid Method: Combining the previous methods is an alternative form to optimize the system. In this proposed method, the first 75% of the PSO iterations are deployed to solve the second problem, Eq. (34), and in the following 25% the first one is deployed aiming to improve the system fairness.

Geometric Mean UEs rate: In the fourth approach, instead of maximizing the SINR, in the GM the product of logarithm of SINRs for all $K$ users, is maximized, eq. (29).

Figs. 8 a) - d) compare the minimum, maximum and average SINR values for each optimization strategy; one can observe that Max-Min design has the best performance from the fairness perspective, while under the Max-Avg SINR optimization, the system attains the highest spectral efficiency (SE) values. Indeed, the Max-Avg method presents both a greater maximum SINR and a lower inferior minimum SINR, prioritizing the UEs with favorable transmission paths, not wasting resources with a deteriorated link and achieving a better average value. The proposed Hybrid design is an alternative that by combining both methods can bring an...
intermediate performance in a data rate fairness perspective and also in terms of average SINR value. Besides, the Max-GM method performs similarly to the Hybrid method with a slightly higher average and a lower minimum SINR.

E. Outage Probability (OP) under $P_1$, $P_2$, and $P_3$ Optimization Criteria

The outage probability (OP) quantifies the likelihood of communication failure due to signal attenuation or interference beyond an acceptable threshold. In this context, the OP analysis becomes pivotal in understanding the reliability and robustness of communication links. The attainable outage probability of RIS-aided massive MIMO systems under the PSO-based optimization method and applying different $P_1$, $P_2$, and $P_3$ optimization criteria are analyzed in the following. The link reliability $R_k$ can be expressed as the complement of outage probability:

$$R_k = 1 - OP_k = 1 - Pr(SINR_k < \gamma_{th})$$  \hspace{1cm} (35)

where $\gamma_{th}$ is the SINR threshold.

The complementary OP, a statistical figure of merit for the link reliability as a function of the SINR threshold, is plotted in Fig. 8 (e). From the link reliability perspective, the Max-Min method demonstrates the best criterion, maintaining reasonable reliability against interference and noise, resulting in a higher threshold when compared to the other solutions. The Hybrid and Max-GM methods present similar reliability $R$ performances but slightly worse than the Max-Min. On the other hand, the Max-Avg criterion resulted in very poor reliability across the entire range of the SINR threshold, evidencing the prioritization of the UE with the best link to the detriment of all others.

VI. CONCLUSION

This work analyzed the performance of a RIS-aided MIMO system under different channel scenarios and system configurations, especially appropriate to deal with dense-obstacle (rich in scattering) urban scenarios and with a high density of mobile users. Our numerical results and setup evaluation consider the number of RIS antenna elements, UEs position, number of RIS elements, and the power ratio between the direct line-of-sight (LoS) path and the power in the other scattered non-line-of-sight (NLoS) paths. We have evaluated the performance gains, including SINR and outage probability (OP) of RIS-aided massive MIMO systems regarding the conventional massive MIMO systems. The SINR optimization problem involving the RIS phase-shift elements was solved by deploying a PSO evolutionary heuristic non-convex optimization technique, revealing the potential of controlling and reprogramming the channel response aided by RIS.

REFERENCES


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