PSO-based Optimization of STAR-RIS aided NOMA Wireless Communication Networks

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***Abstract*—This paper considers a wireless communication system assisted by a Simultaneous Transmission and Reflection Reconfigurable Intelligent Surface (STAR-RIS) aided by Non-Orthogonal Multiple Access (NOMA) technique. The STAR-RIS is a new technology that, different from the traditional RIS, is capable of not only reflecting but also transmitting the incident signal. However, due to the large number of elements at the STAR-RIS, acquiring Channel State Information (CSI) may require considerable training overhead, which is limiting in practice. Therefore, we aim to jointly optimize the power allocation, the beamforming at the BS, and the STAR-RIS transmitting and reflecting beamforming vectors without full CSI, by maximizing the achievable sum rate, subject to a minimum achievable reate at each user. To solve this problem, a method based on the Particle Swarm Optimization (PSO) technique is proposed. Results show that the new solution outperforms STAR-RIS-assisted orthogonal multiple access (OMA) systems.**

***Index Terms*—STAR-RIS, NOMA, Beamforming, Particle Swarm Optimization.**

I. Introduction

Reconfigurable Intelligent Surfaces (RIS) have attracted the attention of the industry and the scientific community and are considered a key technology to achieve the stringent requirements of future wireless communication networks [1]. RIS is a two-dimensional (2D) meta-surface equipped with a large number of low-cost passive elements which is able to reflect the incident signal by intelligently controlling the amplitude and phase shift of each RIS' element [1]. The deployment of RISs into future wireless networks allows diverse applications [2] such as multi-user support, visible light communication, and millimeter wave and terahertz communication. Despite its advantages, the RIS acts only as pure reflective surfaces, and the served users must be on the same side of the RIS, i.e., the RIS provides only half-space coverage which limits the flexibility and performance of the RIS-assisted wireless network [1].

To mitigate this issue, recently, a novel concept of RIS named, Simultaneous Transmission and Reflection RIS (STAR-RIS), has been developed [3]. STAR-RIS can simultaneously transmit and reflect the incident signal by smartly controlling the transmission-reflection coefficients of each STAR-RIS' element. This provides an extra degree of freedom and enhances the performance of the wireless communication system. In addition, by deploying a STAR-RIS, a 360º smart radio environment coverage can be realized [3].

Another promising technology to satisfy the stringent requirements of low latency, high reliability, massive connectivity, improved fairness, and high throughput of future wireless communication networks is the non-orthogonal multiple access (NOMA) technique [4]. Differently from the conventional orthogonal multiple access (OMA) techniques, NOMA exploits the power domain to serve multiple users in the same resource block, where successive interference cancellation (SIC) is applied [4]. Considering these advantages, the integration of NOMA technique with the STAR-RIS technology can increase the coverage, the number of users served simultaneously, and, consequently, the spectrum efficiency.

Motivated by the above, some recent works studied STAR-RIS-assisted wireless communication systems aided by NOMA [5]–[9]. In [5], the authors evaluated a STAR-RIS wireless system assisted by NOMA and proposed a new approach to maximize the system sum rate by optimizing sub-channels, decoding orders, beamforming-coefficient vectors, and power allocation. In addition, the authors in [6] consider a STAR-RIS-assisted wireless communication system aided by NOMA and developed a novel machine learning (ML)-based approach to maximize the sum rate by jointly optimizing the power allocation and the STAR-RIS reflection/transmission coefficients. The energy efficiency maximization problem was investigated in [7] for a STAR-RIS-aided NOMA downlink network. The authors proposed a Deep Deterministic Policy Gradient (DDPG)-based approach to jointly optimize the beamforming at the BS and the transmission and reflection coefficients of the STAR-RIS' elements.

Moreover, Ni et al. [8] evaluated a NOMA STAR-RIS-aided uplink of the wireless communication network. In this paper, a mixed-integer nonlinear programming (MINLP) problem was formulated by jointly optimizing the power allocation and the transmission and reflection of the STAR-RIS' elements. To finish, Hou et al. [9] proposed a STAR-RIS-aided coordinated multi-point transmission (CoMP) assisted NOMA system, where the active and passive beamforming vectors and the detection vectors are jointly designed for signal power enhancement and interference cancellation.

This work proposes a method based on the Particle Swarm

Optimization (PSO) technique to jointly design the beamforming at the BS, the reflection and transmission coefficients of the STAR-RIS' elements, and the power allocation for all UEs by considering a minimum achievable rate constraint without explicitly estimate the CSI. We aim to maximize the achievable sum rate while meeting a minimum achievable rate requirement through beamforming optimization. Different from the previously cited work, in this paper, we do not consider explicit CSI estimation [5], [6], [9] and the proposed solution is not dependent on data for training [7], [8] and presents low computational complexity. The main contribution of this work is to show that it is possible to achieve a close-to-optimal performance, without requiring CSI acquisition.

The rest of this paper is organized as follows. Section II presents the system model and the optimization problem. Section III describes the PSO operation and its principles. Section IV reports the proposed approach. Section V presents simulation results. Finally, Section VI concludes the paper.

Notations: Italic letters like x denote a variable, $\mathbf{X}$ denotes a matrix, and bold-faced lower case $\mathbf{x}$ denotes a vector, where $[\mathbf{x}]_i$ is the i-th element of $\mathbf{x}$. Moreover, $(\cdot)^{\mathrm{H}}$ is the conjugate transpose, $|\cdot|$ is the absolute value and $||\cdot||$ represents the norm.

II. System Model

As illustrated in Figure 1, we consider the downlink of a wireless system including a BS equipped with a Uniform Linear Array (ULA) with N transmit antennas, a STAR-RIS equipped with M reflecting/transmitting elements, and two single-antenna UEs each on one side of the STAR-RIS (UE$_{\mathrm{t}}$ and UE$_{\mathrm{r}}$, where t and r denote transmission and reflection plane, respectively). We assume that mobility is limited or very limited so that the channels change slowly and that there is no direct link between the BS and the UE$_{\mathrm{t}}$ as the STAR-RIS is blocking the link.

In addition, STAR-RIS can operate according to three different protocols [10]: Mode Switching (MS), Time Switching (TS), or Energy Splitting (ES). In the MS, the STAR-RIS is split into two sets of elements where one is composed of a set of elements that operate in the transmission mode while the elements belonging to the second set operate in the reflection mode. Then, since only a set of the STAR-RIS' elements are selected for transmission or reflection mode, the MS protocol cannot achieve the maximum beamforming gain. Different from the MS protocol, the TS protocol periodically switches between the transmit and reflect modes. More specifically, in each orthogonal time slot, all STAR-RIS' elements operate in the transmit or reflect mode. However, the TS protocol considerably increases the hardware complexity of the STAR-RIS. To finish, in the ES protocol, each STAR-RIS' element operates simultaneously in the transmit and reflect modes by splitting the signal energy between the transmitted and reflected signals. In this work, in order to achieve full beamforming gain and reduce the hardware complexity, we consider a STAR-RIS operating on the ES protocol.

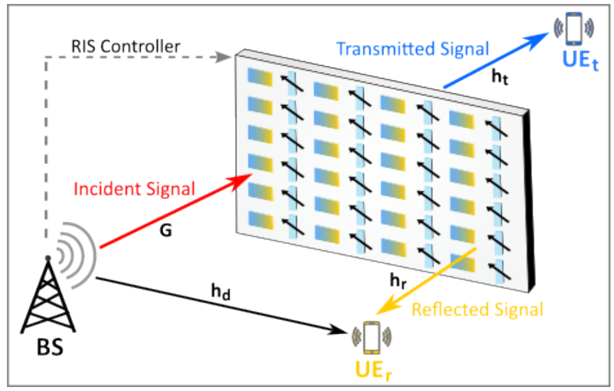


Figure 1: System model: multiple antenna BS, single antenna UEs, and STAR-RIS operating on the ES protocol.

In addition, we consider NOMA transmission. Therefore, by adopting superposition coding, the received signal at the UE$_k$ is given by [5]

$$y_{\mathrm{k}} = C_k\left(\sum_{j}^{j\in\{\mathrm{r,t}\}} \sqrt{\rho_j}\mathbf{w}_j s_j\right) + n_{\mathrm{k}}, \tag{1}$$

in which $k, j \in \{\mathrm{r,t}\}$ and $C_{\mathrm{r}} = (\mathbf{h}_{\mathrm{r}}^{\mathrm{H}}\boldsymbol{\Theta}_{\mathrm{r}}\mathbf{G}+\mathbf{h}_{\mathrm{d}})$, $C_{\mathrm{t}} = (\mathbf{h}_{\mathrm{t}}^{\mathrm{H}}\boldsymbol{\Theta}_{\mathrm{t}}\mathbf{G})$ where $\mathbf{G} \in \mathbb{C}^{N\times M}$ denotes the channel matrix from the BS to the STAR-RIS; $\mathbf{h}_k^{\mathrm{H}} \in \mathbb{C}^{1\times M}$ denotes the channel vector from the STAR-RIS to the UE$_k$; $\mathbf{h}_{\mathrm{d}} \in \mathbb{C}^{1\times N}$ is the channel vector from the BS and the UE$_{\mathrm{r}}$; ρ_j denotes the transmit power allocated to user j; $\mathbf{w}_j \in \mathbb{C}^{N\times 1}$ is the beamforming vector at the BS for the UE$_j$; s_j, modeled as an independent random variable with zero mean and unit variance, is the transmitted data for UE$_k$; while n_k denotes the additive white Gaussian noise at the UE$_k$ with power σ^2. Moreover, $\boldsymbol{\Theta}_k = \mathrm{diag}\big(\beta_1^k e^{j\theta_1^k}, ..., \beta_M^k e^{j\theta_M^k}\big)$ where $\boldsymbol{\theta}_k = \big[\theta_1^k, ..., \theta_M^k\big]$ denotes the transmitted/reflected phase shift vector with $\theta_m^k \in [0, 2\pi)$ for $m = 1, \dots, M$, and $\beta_m^k \in [0,1]$ is the amplitude coefficient. The phase shifts for the reflection and transmission mode (i.e. θ_m^{t} and θ_m^{r}) can be independently defined. However, the amplitude coefficients need to obey the law of energy conservation, i.e. $\beta_m^{\mathrm{t}} + \beta_m^{\mathrm{r}} = 1\ \forall m$, consequently, the β_m^{t} and β_m^{r} are coupled and cannot be optimized independently [10].

In addition, we assume Rician fading and log-distance path loss for all channels, as in [11]. Thus, $\mathbf{h}_k$ are given by

$$\mathbf{h}_l = \sqrt{PL(d_l)}\left(\sqrt{\frac{\kappa_l}{1+\kappa_l}}\mathbf{h}_l^{\mathrm{LoS}} + \sqrt{\frac{1}{1+\kappa_l}}\mathbf{h}_l^{\mathrm{NLoS}}\right), \tag{2}$$

where

$$PL(d_j) = C_0\left(\frac{d_j}{d_0}\right)^{-\alpha_j} \tag{3}$$

in which $l \in \{\mathrm{t, r, d}\}$ and $j \in \{\mathrm{G, t, r, d}\}$ denote the channel links related to $\mathbf{G}$, $\mathbf{h}_{\mathrm{t}}$, $\mathbf{h}_{\mathrm{r}}$, and $\mathbf{h}_{\mathrm{d}}$. The $\mathbf{G}$ channel matrix is generated in the same way as (2). Moreover, C_0 is the path loss at the reference distance d_0; α_j is the path loss exponent of the channel links; $d_j \geq d_0$ denotes the distance between the BS and the STAR-RIS, the BS and the UE_r, or between the STAR-RIS and UE_k; $\mathbf{G}^{\text{LoS}}$ and $\mathbf{h}_k^{\text{LoS}}$ denote the deterministic LoS components; $\mathbf{G}^{\text{NLoS}}$ and $\mathbf{h}_k^{\text{NLoS}}$ are the Rayleigh fading; and κ_{G} and κ_{k} are the corresponding Rician factors.

Finally, for NOMA decoding, SIC is used [4]. The decoding order depends on the channel gain, i.e., the UE with the strongest channel gain can first decode the signals of the other UEs and, consequently, cancel their contributions before decoding its own signal. Therefore, without loss of generality, we assume that the user in the reflection side has a better channel condition than the user in the transmission side, i.e., $G_\text{r} > G_\text{t}$ where $G_\text{r} = |(\mathbf{h}_\text{r}^{\text{H}}\mathbf{\Theta}_\text{r}\mathbf{G}+\mathbf{h}_\text{d})\mathbf{w}_\text{r}|^2$ and $G_\text{t} = |(\mathbf{h}_\text{t}^{\text{H}}\mathbf{\Theta}_\text{t}\mathbf{G})\mathbf{w}_\text{t}|^2$, then the achievable rate of each user is [12]

$$R_\text{r}^{\text{NOMA}} = \log_2\left(1 + \frac{\rho_\text{r} G_\text{r}}{\rho_\text{t} G_\text{t} + \sigma^2}\right) \tag{4}$$

$$R_\text{t}^{\text{NOMA}} = \log_2\left(1 + \frac{\rho_\text{t} G_\text{t}}{\sigma^2}\right) \tag{5}$$

where σ^2 denotes the noise power. Moreover, the achievable rates in an OMA system, more specifically Time Division Multiple Access (TDMA), with total transmit power P_T, are

$$R_k^{\text{OMA}} = \frac{1}{2}\log_2\left(1 + \frac{P_\text{T} G_k}{\sigma^2}\right) \tag{6}$$

To finish, we assume that there is no *a priori* CSI knowledge at the BS and/or the STAR-RIS.

A. Optimization Problem

The main goal of this paper is to maximize the achievable sum rate by jointly optimizing the beamforming at the BS, the reflection/transmission coefficients of the STAR-RIS' elements, and the power allocation by considering a minimum rate constraint, without explicit CSI estimation. This non-convex optimization problem can be formulated as [11]

$$\begin{aligned}
\underset{\mathbf{w}_k, \mathbf{\Theta}_k, \rho_k}{\text{Maximize}} \quad & \sum_{k}^{k\in\{\text{r, t}\}} R_k \\
\text{Subject to} \quad & R_k \geq \gamma_k \ \forall k, \\
& ||\mathbf{w}_k||^2 \leq P_\text{T}, \\
& \sum_k \rho_k = P_\text{T} \ \forall k, \\
& 0 \leq \theta_m^k \leq 2\pi, \quad 0 \leq \beta_m^k \leq 1, \\
& \sum_k \beta_m^k = 1 \ \forall m, k, \quad m = 1, \ldots, M.
\end{aligned} \tag{7}$$

where γ_k is the minimum rate constraint for each UE. Since this optimization problem is non-convex, there is no standard method to solve it. Therefore, in this paper, we propose a novel solution based on the PSO technique. In addition, we consider that $\mathbf{W} = [\mathbf{w}_\text{r}, \mathbf{w}_\text{t}]$, $\mathbf{\Phi} = [\Theta_\text{r}, \Theta_\text{t}]$, and $\boldsymbol{\rho} = [\rho_\text{r}, \rho_\text{t}]$.

III. Particle Swarm Optimization

PSO is a stochastic optimization approach that tries to mimic the social behavior of animal species which presents the capacity to work collectively [13]. It is a simple approach with low computational complexity, but it presents high effectiveness in non-convex optimization and it has been widely applied in several problems in the telecommunication area [14]. PSO considers the following terminologies: particle, swarm, velocity, position, g_{best}, and p_{best}. A "particle" is a possible solution to the optimization problem and represents a "position" in the search space. The "swarm" represents all possible solutions in the current iteration. The "velocity" is the speed from which one particle changes its position in the search space and depends on g_{best} and p_{best}. The g_{best} defines the collective experience and p_{best} is the individual experience. These parameters are obtained by evaluating the position of each particle through a fitness function. In addition, each particle presents its own (p_{best}) value and all particles present the same (g_{best}) value. For each iteration, the velocity ($\mathbf{v}$) and position ($\mathbf{x}$) of each particle are updated based on [13]

$$\begin{aligned}
[\mathbf{v}]_i^g = \omega[\mathbf{v}]_i^g + \ell_1 \text{rand}() * ([p_{\text{best}}]_i^g - [\mathbf{x}]_i^g) \ldots \\
\ell_2 \text{rand}() * ([g_{\text{best}}]^g - [\mathbf{x}]_i^g),
\end{aligned} \tag{8}$$

$$[\mathbf{x}]_i^{g+1} = [\mathbf{x}]_i^g + [\mathbf{v}]_i^{g+1} \tag{9}$$

where $g \in \{1, ..., N_{\text{it}}\}$ is the current iteration of particle $i \in \{1, ..., L\}$ where L is the number of particles in the swarm and N_{it} denotes the total number of iterations. $[\mathbf{v}]_i^g$ and $[\mathbf{x}]_i^g$ denote the velocity and the position of particle i at iteration g, respectively, ℓ_1 and ℓ_2 are the particle learning factors, which determine the influence of individual and collective experience on the velocity of the particle, respectively, while the function rand() returns a random number between 0 and 1 with uniform distribution [13]. Moreover, ω is the inertia velocity weight, which defines the influence of the current velocity on the update velocity of each particle, being [13].

$$\omega = \left[\omega_{\max} - \frac{(\omega_{\max} - \omega_{\min})g}{N_{\text{it}}}\right] \tag{10}$$

where $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum of ω.

IV. Proposed Solution

Motivated by the advantages of the PSO technique, we propose a novel approach based on PSO to solve (7). For a better understanding, the proposed method is presented in **Algorithm 1** and its steps are detailed next.

1. Randomly generate L particles, i.e., the beamforming vector pairs and the power allocation, $(\mathbf{W}_l, \mathbf{\Phi}_l, \boldsymbol{\rho}_l)$, $l = 1, \ldots, L$ which denotes the "positions" of the particles.
2. For each particle, if the R_k at the UE_k is larger than γ_k for $k \in \{\text{r, t}\}$, then the fitness of that particle is $\sum_k^{k\in\{r,t\}} R_k$.
3. Update p_{best} and g_{best} from the fitness computed in the previous step: p_{best} is the best fitness obtained for each particle till the current iteration, and g_{best} is the best fitness obtained for all particles till the current iteration.

4. Update the velocity and position of each particle using (8) and (9), respectively.
5. Check if the stop criterion is met. If so, return the fittest particle ($\mathbf{W}_{\text{best}}, \mathbf{\Phi}_{\text{best}}, \boldsymbol{\rho}_{\text{best}}$). Otherwise, go to Step 2.

Algorithm 1: Proposed approach based on PSO.

Input : System parameters: N, M
PSO parameters: L, N_{it}, ℓ_1, ℓ_2, ω_{min}, ω_{max}
Output: $\mathbf{W}_{\text{best}}, \mathbf{\Phi}_{\text{best}}, \boldsymbol{\rho}_{\text{best}}$

```
Initialize position x_BS = W, x_SR = Φ, and x_P = ρ;
Initialize velocity v_BS, v_SR, and v_P;
[x]_i = ([x_BS]_i, [x_SR]_i, [x_P]_i);
[v]_i = ([v_BS]_i; [v_SR]_i; [v_P]_i);
Find the global g_best and local p_best best solutions.
for g = 1 : N_it do
    Calculate ω following (10)
    for i = 1 : L do
        Update [v]_i^g based on (8).
        Update [x]_i^g based on (9).
        Update p_best
    end
    Update g_best = x_best
end
W_best = g_best,  Φ_best = g_best, ρ_best = g_best
return W_best, Φ_best, ρ_best
```

In this work, the main parameters used in **Algorithm 1** are: $N_{\text{it}} = 1000$, $L = 10$, $\ell_1 = \ell_2 = 1.0$, $w_{\text{min}} = 0.2$, and $w_{\text{max}} = 0.9$. These parameters have been selected after extensive simulations. In our proposed method, the pairs of beamforming vectors at the BS and STAR-RIS to be tested are defined at the BS, while the STAR-RIS beamforming is sent by the BS to the controller shown in Figure 1. Then, for each beamforming pair, the feedback of the SINR at the UE is received at the BS/STAR-RIS, and the current beamforming pair is evaluated based on $\sum_{k}^{k\in\{\text{r, t}\}} R_k$. This process is performed for all pairs. Note that the BS/STAR-RIS/UE channels are not explicitly estimated.

V. Simulation Results

All curves in this section are the average of 10^3 different realizations. We consider the simulation setup described in Figure 2, where d_{G} is the horizontal distance between the BS and STAR-RIS, d_{v} is the vertical distance, and d_{r} and d_{t} are the horizontal distance between the UE_{r} and the STAR-RIS and the STAR-RIS and the UE_{t}, respectively. Therefore, $d_{\text{St}} = \sqrt{d_{\text{t}}^2 + d_{\text{v}}^2}$, $d_{\text{Sr}} = \sqrt{d_{\text{r}}^2 + d_{\text{v}}^2}$, $d_{\text{Br}} = \sqrt{(d_{\text{G}} - d_{\text{r}})^2 + d_{\text{v}}^2}$, and $d_{\text{Bt}} = \sqrt{(d_{\text{G}} + d_{\text{t}})^2 + d_{\text{v}}^2}$ are the distance between the STAR-RIS and UE_{t}, the STAR-RIS and UE_{r}, the BS and UE_{r}, and the BS and UE_{t}, respectively. In addition, if not specified otherwise, the results presented in this section consider the following simulation parameters: $N = 10$, $M = 40$, $\kappa_{\text{G}} = 1.5$, $\kappa_{\text{d}} = 0.5$, $\kappa_k = 3.0$, $\kappa_{\text{Bt}} = 0.5$, $\alpha_{\text{G}} = 2.0$, $\alpha_{\text{d}} = 2.8$, $\alpha_k = 2.8$, $\kappa_{\text{Bt}} = 2.0$, $\lambda_k = 5$ bps/Hz, $d_0 = 1$ m, $C_0 = -30$ dBm, $\sigma^2 = -80$ dBm, $d_{\text{G}} = 70$ m, $d_{\text{v}} = 2$ m, $d_k = 20$ m.

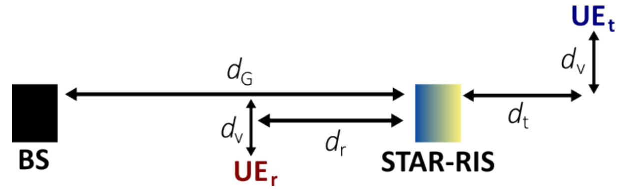
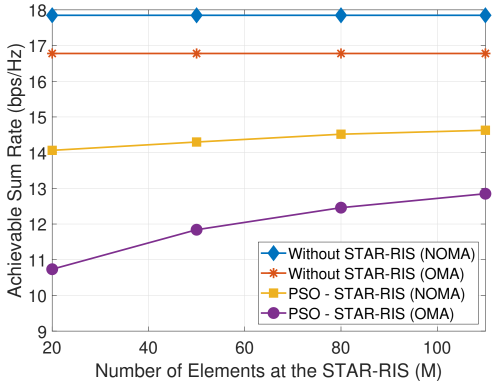


Figure 2: Simulation setup.

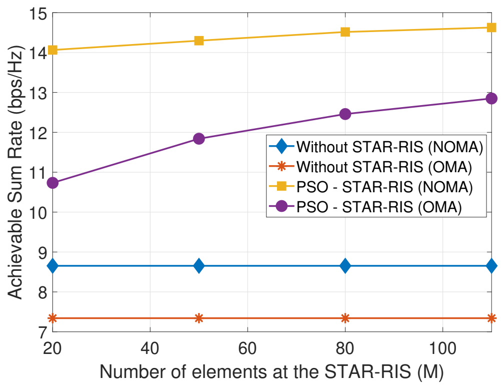
Furthermore, as benchmarks, we consider a scenario without the STAR-RIS, where the BS transmits to all users considering the perfect CSI knowledge and OMA or NOMA techniques. These benchmarks are defined as "Without STAR-RIS OMA" and "Without STAR-RIS NOMA", respectively. Moreover, for the sake of simplicity, in this work, we consider the number of iterations N_{it} as the stop criterion.

A. Impact of the Number of Elements at the STAR-RIS

To illustrate the impact of the number of elements at the STAR-RIS (M), Figure 3 presents the achievable sum rate for different values of M. From Figure 3a, it can be noted that the use of NOMA increases the achievable sum rate for all values of M. However, it can be also evaluated that for a high M, the difference in performance between the OMA and NOMA approaches reduces, this can be explained due to the fact that, when M increases the complexity of the optimization problem in (7) increases, and the performance of the proposed method (PSO - STAR-RIS (NOMA)) decreases. This effect is softened for the "PSO - STAR-RIS (OMA)" as the power allocation optimization is not considered in this case. Moreover, it can be noted that increasing M, i.e., large STAR-RIS, increases the achievable performance of the system which demonstrates the importance of the STAR-RIS to achieve some stringent requirements of the future wireless communication systems. In addition, the proposed solution "PSO - STAR-RIS (NOMA)" can achieve a reasonable performance when compared to the "Without STAR-RIS (NOMA)" even without considering any explicit CSI estimation. Here, it is important to highlight that for the benchmarks "Without STAR-RIS (NOMA)" and "Without STAR-RIS (OMA)", it is assumed $\kappa_{\text{Bt}} = \kappa_{\text{d}} = 3.0$ for the link between the BS and UE_{t} and the link between the BS and UE_{t}, i.e., a high influence of the LoS components is considered which increases the performance of the benchmarks. In addition, a path loss exponent of 2.0 is considered for the link between the BS and UE_{t} (α_{Bt}) and 2.8 for the link between the BS and UE_{r} (α_{d}) which demonstrates that the benchmarks were evaluated considering favorable channel conditions and perfect knowledge of the CSI at the BS and perfect power allocation are also considered. However, in favorable propagation scenarios, the deployment of the STAR-RIS should not be considered. Then, Figure 3b demonstrates the influence of the STAR-RIS when there is no LoS for both links between the BS and UE_{k} for $k \in \{\text{r}, \text{t}, \}$. From Figure 3b, it is possible to show the importance of the deployment of STAR-RISs in this type of scenario.

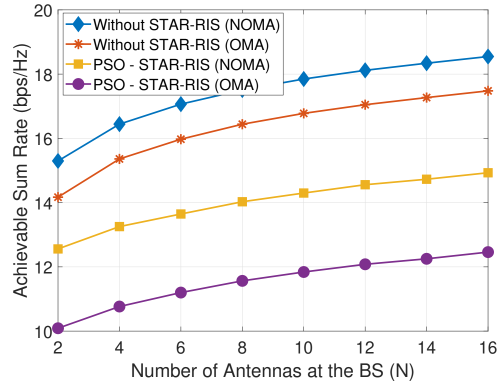


(a)

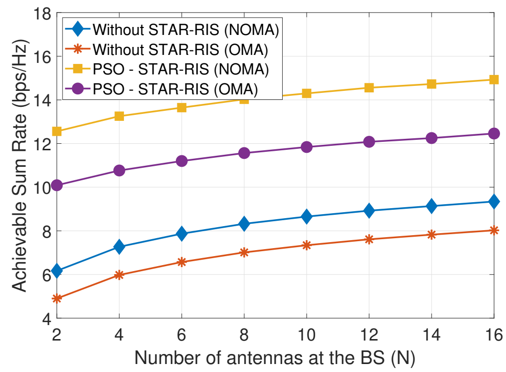


(b)

Figure 3: Achievable sum rate vs M analysis considering (a) *Favorable Propagation Scenario*, i.e., $\kappa = 3.0$, $\alpha_{\mathrm{Bt}} = 2.8$, and $\alpha_{\mathrm{d}} = 2.0$; and (b) *Unfavorable Propagation Scenario*, i.e., $\kappa_{\mathrm{Bt}} = \kappa_{\mathrm{Br}} = 0.5$, $\alpha_{\mathrm{Bt}} = 3.0$, and $\alpha_{\mathrm{d}} = 3.0$.



(a)



(b)

Figure 4: Achievable sum rate vs N analysis considering (a) *Favorable Propagation Scenario*; and (b) *Unfavorable Propagation Scenario*.

B. Impact of the Number of Antennas at the BS

Figure 4 shows the achievable sum rate for different values of N. It can be observed that increasing N, increases the achievable sum rate as the beamforming gain increases. In addition, it can also be noted that the NOMA approaches (“Without STAR-RIS (NOMA)” and “PSO - STAR-RIS (NOMA)”) presented a higher performance than the OMA, which demonstrates the importance of considering the NOMA technique to achieve a higher system's performance. Moreover, evaluating Figure 4a and Figure 4b, it can be concluded that the STAR-RIS deployment is essential in scenarios where there is no LoS between the BS and users.

C. Impact of the Distance between the STAR-RIS and UEs

Figure 5 illustrated the achievable sum rate for different values of d_{G} considering favorable and unfavorable propagation scenarios. In this analysis, when d_{G} is reduced, consequently, d_{r} decreases and d_{t} increases, i.e., the STAR-RIS is closer to the BS and $\mathrm{UE_r}$ and further to the $\mathrm{UE_t}$. Therefore, from Figure 5, it can be seen that when NOMA is considered, the performance of the proposed solution (PSO - STAR-RIS (NOMA)) is almost constant as the power allocation optimization can soften the distance effect. However, this is not completely true when OMA technique is considered, as it can be seen in Figure 5. In this case, the position of the STAR-RIS with relation to the $\mathrm{UE_r}$ and $\mathrm{UE_t}$ influences the system performance, e.g., when the STAR-RIS is close to the $\mathrm{UE_t}$ and far from to the $\mathrm{UE_r}$ ($d_{\mathrm{G}} = 80$, $d_{\mathrm{r}} = 60$, e $d_{\mathrm{t}} = 10$), $R_{\mathrm{T}} \sim 14.5$ bps/Hz and when the STAR-RIS is close to the $\mathrm{UE_r}$ and far from to the $\mathrm{UE_t}$ ($d_{\mathrm{G}} = 30$, $d_{\mathrm{r}} = 10$, e $d_{\mathrm{t}} = 60$), $R_{\mathrm{T}} \sim 13.2$ bps/Hz. This demonstrates that, when NOMA techniques are considered it is necessary to optimize the STAR-RIS position in order to maximize the system performance. In addition, for the lack of space, we have omitted the analysis for unfavorable propagation scenarios, however, the simulations also demonstrate that the STAR-RIS deployment is essential in scenarios where there is no LoS between the BS and users.

D. Training Overhead Analysis

To finish, as we propose to design the beamforming at the BS and the STAR-RIS without explicit CSI acquisition, it is necessary to consider the amount of feedback from the user, which is given by $N_{\mathrm{it}}L$ and adds some training overhead to the system. It is important that the amount of feedback is not larger

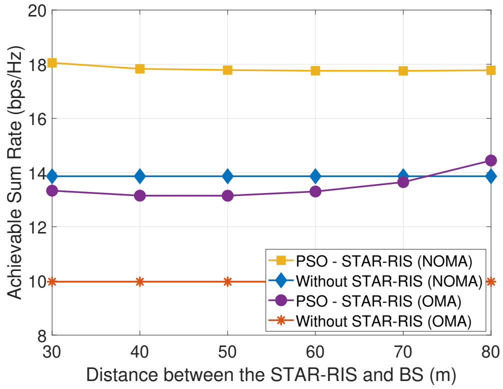


Figure 5: Achievable sum rate vs d_{G} considering *Favorable Propagation Scenario*.

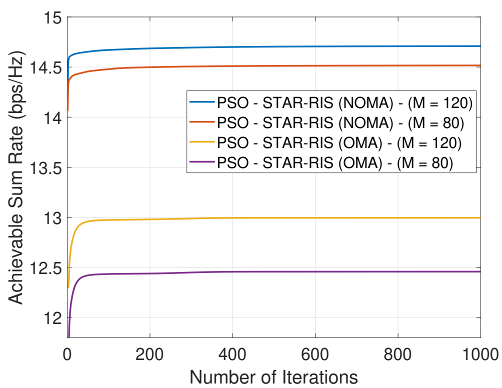


Figure 6: Convergence analysis of the proposed solution.

than the number of pilots that would be necessary to estimate the channel, *i.e.*, $N_{\text{it}}L < (2MN+2)$ [15]. Therefore, to prove the efficiency of the proposed method, Figure 6 illustrates the convergence of the proposed solution for $N = 10$ and $M \in \{120, 80\}$. From the results, it is possible to observe that the proposed solution achieves a reasonable performance with a smaller amount of feedback from the user ($N_{\text{it}}L$) than the number of pilots necessary to estimate the channel, more specifically, $N_{\text{it}}L = 800$ and $(2MN+2) = 1602$ for $M = 80$, and $N_{\text{it}}L = 1200$ and $(2MN+2) = 2402$ for $M = 120$, i.e., $N_{\text{it}}L \sim 0.5(2MN+2)$ for $M \in \{80, 120\}$.

VI. Conclusion

We proposed a method based on PSO to maximize the achievable sum rate by jointly optimizing the BS and STAR-RIS beamforming and the power allocation for all users, with a minimum rate constraint for each UE. The proposed solution achieves a reasonable performance without the need for explicit CSI estimation, reducing cost and energy consumption. As future works, we intend to investigate the impact of the STAR-RIS deployment considering different operation modes as well as explore statistical CSI knowledge to further reduce the training overhead.

Acknowledgments

This work has been partially funded by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior—Brazil (CAPES) and by RNP, with resources from MCTIC, Grant No. 01 245.010 604/2020-14, under the 6G Mobile Communications Systems project of the Radiocommunication Reference Center (Centro de Referência em Radiocomunicações — CRR) of the National Institute of Telecommunications (Instituto Nacional de Telecomunicações — Inatel), Brazil; by the Fundação de Amparo à Pesquisa do Estado de Minas Gerais (FAPEMIG) from Grant No. APQ-05305-23.

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