

Article

Optimization of Sum-Rate for Downlink Transmission in Hybrid RIS-Assisted MISO Systems

Wei Pang  and Ying Zhang * 

College of Information Engineering, Shanghai Maritime University, Shanghai 201306, China;
202330310053@stu.shmtu.edu.cn

* Correspondence: yingzhang@shmtu.edu.cn

Abstract

Reconfigurable intelligent surfaces (RISs) hold promising technical prospects for 6G wireless communications to enhance system capacity, coverage and sum-rate. Unlike existing studies deploying only passive or active RISs, this paper adopts a novel hybrid RIS architecture that optimally allocates the number of active and passive elements. Under fixed quantities of both RIS element types in the fixed hybrid RIS, it simultaneously increases the number of base station antennas and served users, focusing on solving rate optimization for hybrid RIS-assisted MISO systems deployed in various scenarios. This paper establishes a fundamental model for hybrid RIS reflection signals. To better characterize the performance of the proposed hybrid RIS architecture, an optimization problem is formulated to maximize the sum-rate of the hybrid RIS-assisted multi-user, multiple-input, single-output (MU-MISO) system. An efficient algorithm is proposed combining fractional programming (FP), alternating optimization, and Lagrange duality transformation. Simulation results demonstrate that with hybrid RIS assistance, the system's sum-rate gain increases by 49.1% and 40%, respectively, compared to systems with only active RIS deployment. This achieves higher sum-rate gains at lower power consumption.

Keywords: reconfigurable intelligent surfaces; hybrid active-passive RIS; beamforming; reflection coefficient matrix optimization; rate optimization

1. Introduction

With the rapid advancement of modern wireless communication technologies, academia and industry have already initiated research and discussions on 5G Advanced and 6G. The objectives of 5G communication systems include massive machine-type communication (mMTC), ultra-reliable low-latency communication (URLLC) for critical services, and rate-centric enhanced mobile broadband (eMBB) [1,2]. Compared with these targets, 6G wireless communications impose more stringent performance requirements, including massive connectivity, higher transmission rates and bandwidth, and lower latency [3,4]. To address these challenges, reconfigurable intelligent surfaces (RISs) [5–8] have been proposed. RISs have multiple advantages, such as high array gain, low cost, low power consumption, ease of deployment, and improved spectral efficiency [8–10]. These advantages make RISs a promising technology for 6G networks by enhancing channel capacity and transmission rates, extending base station coverage, and improving energy efficiency [11–13]. In multi-user MISO systems, such as in urban or suburban areas, deploying an appropriate number of RIS elements can enhance system performance. This not only extends the BS's coverage area but also further increases the system's transmission rate. Furthermore, the



Academic Editors: Triantafyllos Kanakis and Charan Litchfield

Received: 15 January 2026

Revised: 11 February 2026

Accepted: 25 February 2026

Published: 3 March 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

RIS holds promising applications in numerous fields, including vehicle-to-everything (V2X) communication [14], drone-supported wireless networks [15], navigation [16], auxiliary relay communication [17] and covert secure communication [18,19], etc.

The existing RIS structures are primarily passive RIS and active RIS. However, both passive and active RIS systems possess distinct advantages and disadvantages. Specifically, when the number of deployed RIS elements N is limited or the transmission distance is relatively long, active RIS achieves higher amplification gain and SNR [20–23]. In contrast, when N is large, passive RIS offers higher beamforming gain, but introduces multiplicative fading effects, deployment challenges, and increased technical complexity. Therefore, under practical cost and hardware constraints, it is not feasible to achieve superior communication performance by deploying either active RIS or passive RIS alone.

To address the aforementioned issues, a novel RIS incorporating a hybrid active–passive configuration has been proposed. The hybrid RIS-assisted MISO system in [24] focuses on system capacity optimization in scenarios where the direct BS–user link is severely blocked or experiences deep fading, and its application scenarios are limited. The hybrid RIS structure in [25] is mainly designed for scenarios with a small number of deployed elements and focuses solely on energy efficiency optimization. Moreover, neither Ref. [24] nor Ref. [25] explicitly formulates a unified signal reflection model for hybrid RIS.

In this paper, motivated by the aforementioned limitations, we investigate a hybrid active–passive RIS-assisted multi-user MISO downlink system. Different from existing hybrid RIS studies, the proposed framework explicitly considers rate maximization under two distinct BS–user link conditions, namely with and without a direct transmission link. The number of served users and BS antennas is higher. Moreover, the thermal noise introduced by the active RIS elements is explicitly incorporated into the system model. This paper employs the hybrid RIS architecture proposed in [24], which optimally allocates the number of active and passive elements. By jointly optimizing the transmit beamforming and the hybrid RIS reflection coefficients, the proposed hybrid RIS architecture effectively balances amplification gain and beamforming gain, thereby achieving enhanced transmission rates under practical deployment and power constraints. Specifically, the main contributions of this paper are summarized as follows:

- A signal reflection model for hybrid RIS is proposed, which not only characterizes the amplification of the signal but also takes into account the non-negligible amplification noise introduced by the active elements.
- To assess the transmission rate enhancement achieved by hybrid RIS, it is deployed in a multi-user, multiple-input, single-output (MU-MISO) wireless system. Based on the proposed hybrid RIS signal model, this paper derives the user-received signal and formulates a rate maximization problem. To solve the formulated problem, this paper develops a joint beamforming and hybrid RIS reflection optimization scheme based on fractional programming (FP) [26], alternating optimization algorithm, and the Lagrange multiplier method [27].
- Unlike existing studies on hybrid RIS, this paper considers two distinct scenarios: severe blockage or fading of the direct BS–user link and the presence of a direct link. For both scenarios, this paper analyzes the rate gains achieved by hybrid RIS. The performance of hybrid RIS is validated through simulations and compared with passive and active RIS, demonstrating its effectiveness.

The subsequent sections of this paper will proceed in the following order: Section 2 introduces related work on active RIS, passive RIS and hybrid RIS. Section 3.1 introduces the architecture of hybrid RIS and constructs a hybrid RIS-assisted MU-MISO system. Sections 3.2.1 and 3.2.2 formulate a rate maximization problem for the system model and propose a joint optimization scheme for BS beamforming and hybrid RIS reflection matrix

to address this problem. Section 3.2.3 analyzes the complexity and convergence of the algorithm. Section 4 presents simulation results to validate the proposed hybrid RIS signal model and evaluate its performance in typical communication scenarios. Section 5 provides an overview of the simulation results and their implications. Finally, Section 6 concludes the study. The notation used throughout this paper is summarized in Table 1.

Table 1. Notations.

Symbol	Definition
$\mathbb{C}, \mathbb{R}, \mathbb{R}_+$	the set of complex numbers, the set of real numbers, and the set of positive real numbers
$(\cdot)^{-1}, (\cdot)^T, (\cdot)^*, (\cdot)^H$	the inverse, transpose, conjugate and conjugate-transpose operations of matrices
$\ \cdot\ $	the Euclidean norm of the argument
$\ \cdot\ _F$	the Frobenius norm of the argument
$\text{diag}(\cdot)$	the diagonalization operation of matrices
$\text{Re}\{\cdot\}$	the operation of taking the real part of the complex numbers
$\otimes$	the Kronecker product
$\ln(\cdot)$	natural logarithm
$\mathcal{CN}(\mu, \sigma^2)$	the complex multivariate Gaussian distribution (CSCG) with mean μ and variance σ^2
$\mathbf{I}_N$	the unit matrix with size $N \times N$
$\mathbf{0}_N$	the zero vector with size $N \times 1$

2. Related Work

This section will provide an overview of the various existing initiatives related to RIS. Sections 2.1 and 2.2 respectively describe the passive RIS and active RIS. Section 2.3 introduces the hybrid RIS.

2.1. Passive RIS

Passive RIS [3–8] is also called intelligent reflecting surface (IRS). As shown in Figure 1, in passive RIS, each component comprises two parts: a reflector and an impedance-adjustable circuit [8,28]. Without amplifiers, passive RIS can only reflect incident signals without amplification, thereby enhancing wireless propagation while introducing minimal additional noise [5,6]. By densely deploying such elements, the characteristics of reconfigurable wireless environments can be achieved [8,9]. In addition, passive RIS features low latency, supports full-duplex operation, and does not introduce self-interference [24]. Existing studies have shown that a passive RIS composed of N elements can effectively enhance the SINR at the signal reception point, with the SINR gain being proportional to N^2 [20,29]. This approach improves the SNR of the system receiver [8,19,24,30,31], effectively enhancing received signal quality. Moreover, since passive RIS does not include active RF components, its power consumption and thermal noise are negligible [8,11,12,30,31].

However, the performance gains reported in the literature are typically achieved under scenarios where the direct BS–user link is severely blocked or experiences strong fading [8,12,13,32,33]. When the direct link is relatively strong or the number of passive RIS elements N is limited, the achievable performance improvement becomes constrained [34]. This limitation mainly arises from the multiplicative fading effect introduced by passive RIS [21,34]. Relying solely on passive RIS to address multiplicative fading requires substantially more elements, which significantly increases implementation cost and system complexity [19–21].

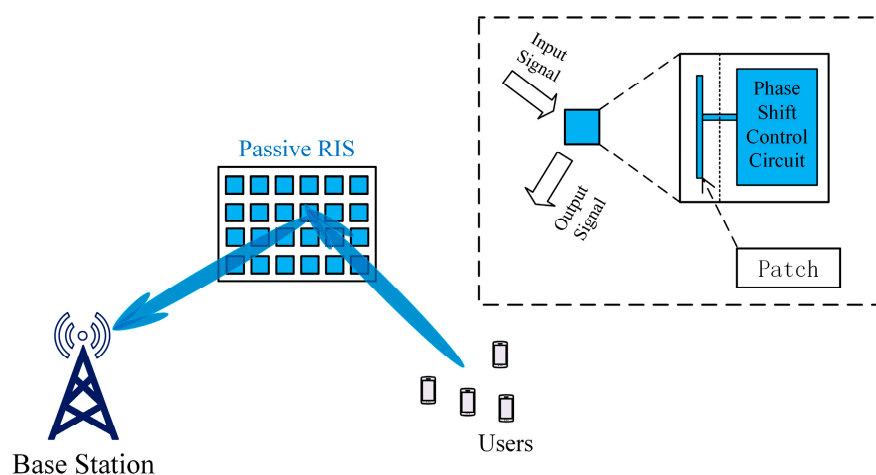


Figure 1. Passive RIS transmission method and hardware structure.

2.2. Active RIS

To overcome the multiplicative fading effect and achieve higher system gain, active RIS has been proposed [20–22,35–37]. As shown in Figure 2, an active RIS employs active components and incorporates a reflective amplifier circuit, such as a current inverter converter [38] or certain integrated circuits [39], ultimately connected to a power source. Active RIS not only enables signal reflection in full-duplex mode but also amplifies signal amplitude. Compared with passive RIS, active RIS can significantly improve the received SNR [21]. Therefore, by introducing active RIS, the challenge of multiplicative fading can be overcome. Unlike passive RIS, active RIS introduces non-negligible thermal noise. Nevertheless, existing studies have demonstrated the effectiveness of active RIS in enhancing wireless link performance and improving signal quality in various system configurations [20,21,29,36,37]. Compared to the passive relay-type RIS equipped with RF components and relays, active RISs are quite different. Instead of receiving, processing, and retransmitting signals through RF chains, active RIS directly reflects incident signals with controllable phase shifts while amplifying their amplitude. Therefore, the active RIS transmits the signal with lower delay [21,40]. In addition, active RIS exhibits lower hardware costs and power loss [41].

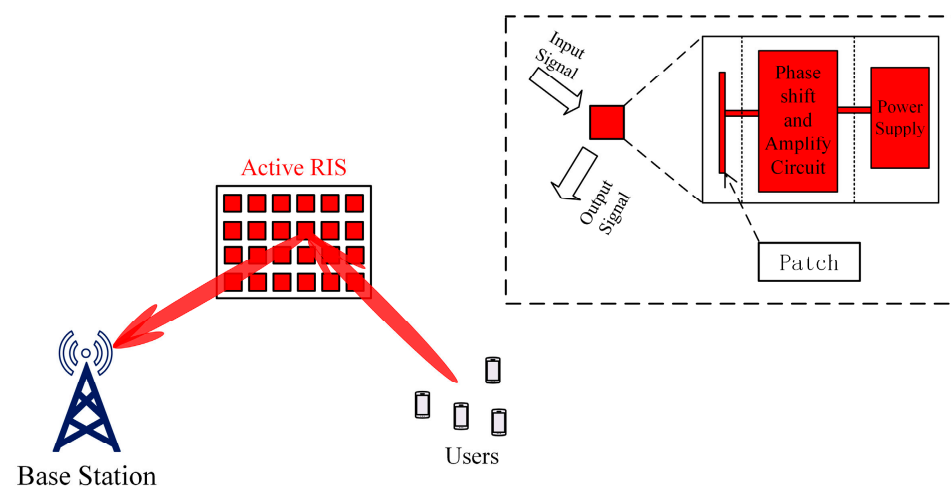


Figure 2. Active RIS transmission method and hardware architecture.

However, the more complex physical architecture of active RIS increases production and deployment costs compared to passive components. Moreover, the superior gain performance of active RIS requires additional power loss [22].

2.3. Hybrid RIS

To exploit the complementary advantages of passive and active RIS and overcome their inherent limitations, hybrid RIS architectures have been proposed [24,25,42]. In [24], ZHANG R et al. first proposed the hybrid RIS architecture. They evaluated the performance of the hybrid RIS under statistically known CSI and optimized the allocation problem for the two types of RIS elements in the hybrid RIS. Simultaneously, they formulated a capacity maximization problem for the hybrid RIS-assisted MISO system. In [25], Ioannis Krikidis et al. proposed and analyzed a hybrid RIS architecture, where multiple active RIS elements share a single amplifier while passive RIS elements remain unprocessed. They evaluated the performance of this novel hybrid RIS and formulated an optimization problem for maximizing energy efficiency (EE) in the hybrid RIS-assisted MISO system. This approach achieves significantly higher energy efficiency even with a small number of deployed elements N .

To provide a more intuitive overview of the research domains and respective strengths and weaknesses of various RIS systems, the Table 2 below has been compiled.

Table 2. Comparison of advantages and disadvantages of existing RIS.

Ref.	Classifications	Advantages	Disadvantages
[3–5,7,8], etc.	Passive RIS-assisted communication	Can slightly improve system capacity and transmission rate.	Suffers from multiplicative fading effect.
[20–22,35–37], etc.	Active RIS-assisted communication	Can overcome the multiplicative fading effect, providing significant system performance gain.	Suffers from severe power consumption.
[24]	Hybrid RIS-assisted MISO and capacity optimization	Further enhances system capacity under complex channel conditions; enables optimization of element number allocation.	Limited applicability in practical scenarios.
[25]	Novel hybrid RIS and energy efficiency optimization	Achieves higher energy efficiency.	Limited system and rate improvement due to fewer elements.

3. Materials and Methods

3.1. System Model

This section introduces the structure of hybrid RIS and the hybrid RIS-assisted MISO wireless system model. Note that in the following text, scalars are denoted by regular italic symbols, while vectors and matrices are represented using consistent boldface notation.

3.1.1. Hybrid RIS Architecture and Reflected Signal Model

Specifically, the hybrid RIS consists of two sub-surfaces co-planar to each other, with each sub-surface comprising a predetermined number of active and passive RIS elements, as shown in Figure 3. Unlike the architecture proposed in [25], each active element in the hybrid RIS is connected to an independent amplifier. To better characterize the transmission model of the hybrid RIS, a simplified wireless communication system assisted by the hybrid RIS is constructed. Assuming a significant distance between the BS and the user group, the hybrid RIS is deployed at an optimal location to transmit mutually independent data to a set of K users. Hybrid RIS can also operate in full-duplex mode.

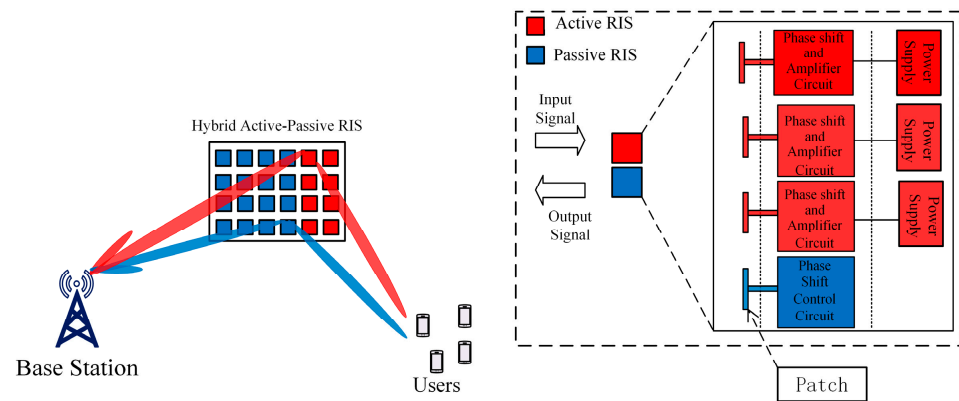


Figure 3. Hybrid active–passive RIS transmission method and hardware architecture.

The signal transmission models for passive and active RIS are provided by $\mathbf{y} = \Theta \mathbf{x}$ [10] and $\mathbf{y} = \Psi \mathbf{x} + \Psi \mathbf{v} + \mathbf{n}$ [21] respectively, where $\Theta \triangleq \text{diag}(\kappa_1 e^{j\theta_1}, \dots, \kappa_N e^{j\theta_N}) \in \mathbb{C}^{N \times N}$ signifies the reflection phase matrix of the passive RIS and $\Psi \triangleq \text{diag}\{a_1 e^{j\theta_1}, \dots, a_N e^{j\theta_N}\} \in \mathbb{C}^{N \times N}$ signifies the reflection coefficient matrix of the active RIS. When the passive RIS exhibits no loss for the incident signal, the reflection coefficient $\kappa = 1$, θ_N represents the reflection phase shift of the N element, $\theta_N \in (0, 2\pi]$. In active RIS, the amplification coefficient of the N element $a_N \in \mathbb{R}_+$ and $a_N > 1$, the reflection phase shift of the element $\theta_N \in (0, 2\pi]$.

Based on the above, the reflected signal of an N element hybrid RIS can be modeled as:

$$\mathbf{y} = \underbrace{\underbrace{\Psi \mathbf{x}}_{\text{Active RIS Reflected Signal}} + \underbrace{\Theta \mathbf{x}}_{\text{Passive RIS Reflected Signal}}}_{\text{Desired Signal}} + \underbrace{\Psi \mathbf{v}}_{\text{Dynamic Noise}} + \mathbf{n}, \quad (1)$$

where $\mathbf{x} \in \mathbb{C}$ denotes the incident signal, $\mathbf{y} \in \mathbb{C}$ denotes the signal received at user location k after reflection amplification by the hybrid RIS, $\Psi \mathbf{v}$ represents the dynamic noise introduced and amplified by the reflective amplifier [21] and $\mathbf{n}$ denotes the static noise generated by the patch and phase-shifting circuits [43]. However, $\mathbf{n}$ is negligible compared to $\mathbf{v}$ and is independent of Ψ ; thus, it can be disregarded [21,22].

3.1.2. Hybrid RIS-Assisted MISO Communication System Model

To evaluate the performance gains of the proposed in a wireless communication system, this section models the performance advantages of the hybrid RIS. We consider a hybrid RIS-assisted multi-user, multiple-input, single-output (MU-MISO) system and formulate a sum-rate maximization problem.

Specifically, a hybrid RIS-assisted downlink MU-MISO system is constructed as shown in Figure 4. The hybrid RIS is deployed at an optimal location, equipped with M ($M > 1$) antennas. This BS simultaneously serves single-antenna K users with the assistance of a hybrid RIS containing N ($N = N_{act} + N_{pas}$) elements, where N_{act} and N_{pas} denote the number of active RIS elements and passive RIS elements in the hybrid RIS, respectively. The BS transmits mutually independent symbols to each user. The model employs the Rician channel fading model.

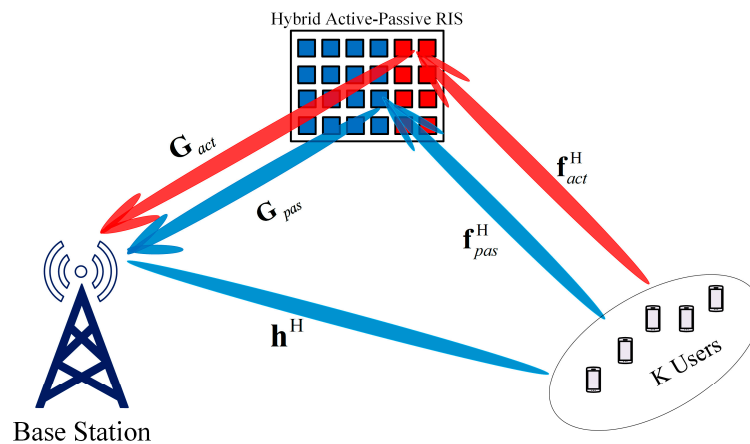


Figure 4. Downlink transmission in a hybrid RIS-assisted MU-MISO system.

The hybrid RIS reflection matrix is defined as a block-diagonal matrix $\Psi_H \triangleq \begin{bmatrix} \Psi & 0 \\ 0 & \Theta \end{bmatrix}$, where $\Psi = (a_1 e^{i\theta_{act}^1}, \dots, a_N e^{i\theta_{act}^N})$ and $\Theta = (e^{i\theta_{pas}^1}, \dots, e^{i\theta_{pas}^N})$ denote the reflection matrices of the active and passive RIS, respectively; $\mathbf{G}_{a,p} = [\mathbf{G}_{act}^T, \mathbf{G}_{pas}^T]^T \in \mathbb{C}^{N \times M}$, $\mathbf{f}^H = [\mathbf{f}_{act}^H \quad \mathbf{f}_{pas}^H]$, $\mathbf{s} \triangleq [s_1, \dots, s_K] \in \mathbb{C}^K$ represents the symbol vector transmitted from the base station to the user, and $\mathbf{b}_k$ denotes the beamforming vector generated by the base station for symbol s_k . Since each symbol is independent, $\mathbb{E}\{\mathbf{s}\mathbf{s}^H\} = \mathbf{I}_K$. Assuming the signal received at the user location is y_k , and $y_k \in \mathbb{C}$, according to (1), the signal y_k received at the user location k can be modeled as:

$$y_k = (\mathbf{h}^H + \mathbf{f}^H \Psi_H \mathbf{G}_{a,p}) \sum_{j=1}^K b_j s_j + \mathbf{f}_{act}^H \Psi \mathbf{n}_v + n_k$$

$$= \underbrace{\mathbf{h}^H \sum_{j=1}^K b_j s_j}_{\text{Direct Signal}} + \underbrace{\left(\underbrace{\mathbf{f}_{act}^H \Psi \mathbf{G}_{act}}_{\text{Active Reflected Signal}} + \underbrace{\mathbf{f}_{pas}^H \Theta \mathbf{G}_{pas}}_{\text{Passive Reflected Signal}} \right) \sum_{j=1}^K b_j s_j}_{\text{Reflected Signal}} + \underbrace{\mathbf{f}_{act}^H \Psi \mathbf{n}_v}_{\text{Noise introduced by Active RIS}} + n_k' \quad (2)$$

where, $\mathbf{h}^H$, $\mathbf{G}_{act}$, $\mathbf{G}_{pas}$, $\mathbf{f}_{pas}^H$ and $\mathbf{f}_{act}^H$ represent the channel vectors between the BS and user k , between the BS and active RIS, between the BS and passive RIS, between passive RIS and user k , and between active RIS and user k , respectively. $\mathbf{n}_v$ represents the dynamic noise introduced by the active RIS and model $\mathbf{n}_v$ as $\mathbf{n}_v \sim \mathcal{CN}(0_{N_{act}}, \sigma_v^2 \mathbf{I}_{N_{act}})$. n_k denotes the additive white Gaussian noise (AWGN) at user location k with zero mean and variance σ^2 . The dimensions of the variables are summarized in Table 3.

Table 3. Variable dimension.

Variable	Dimension
Ψ_H	$\mathbb{C}^{N \times N}$
Ψ	$\mathbb{C}^{N_{act} \times N_{act}}$
Θ	$\mathbb{C}^{N_{pas} \times N_{pas}}$
$\mathbf{G}_{a,p}$	$\mathbb{C}^{N \times M}$
$\mathbf{G}_{act}$	$\mathbb{C}^{N_{act} \times M}$
$\mathbf{G}_{pas}$	$\mathbb{C}^{N_{pas} \times M}$
$\mathbf{f}^H$	$\mathbb{C}^{1 \times N}$
$\mathbf{h}^H$	$\mathbb{C}^{1 \times M}$

Table 3. Cont.

Variable	Dimension
$\mathbf{f}_{pas}^H$	$\mathbb{C}^{1 \times N_{pas}}$
$\mathbf{f}_{act}^H$	$\mathbb{C}^{1 \times N_{act}}$
$\mathbf{s}$	$\mathbb{C}^K$
$\mathbf{b}_k$	$\mathbb{C}^{M \times 1}$

Based on the transmission model expressed in (2), the signal-to-interference-plus-noise ratio (SINR) at user location k is given by:

$$\gamma = \frac{\left| \left(\mathbf{h}^H + \mathbf{f}_{act}^H \mathbf{\Psi} \mathbf{G}_{act} + \mathbf{f}_{pas}^H \mathbf{\Theta} \mathbf{G}_{pas} \right) b_k \right|^2}{\sum_{j=1, j \neq k}^K \left| \left(\mathbf{h}^H + \mathbf{f}_{act}^H \mathbf{\Psi} \mathbf{G}_{act} \right) b_j \right|^2 + \left\| \mathbf{f}_{act}^H \mathbf{\Psi} \right\|^2 \sigma_v^2 + \sigma^2} \quad (3)$$

Let $\tilde{\mathbf{h}}^H \triangleq \mathbf{h}^H + \mathbf{f}_{act}^H \mathbf{\Psi} \mathbf{G}_{act} + \mathbf{f}_{pas}^H \mathbf{\Theta} \mathbf{G}_{pas}$, $\tilde{\mathbf{h}}_{act}^H \triangleq \mathbf{h}^H + \mathbf{f}_{act}^H \mathbf{\Psi} \mathbf{G}_{act}$ and $\tilde{\mathbf{h}}_{pas}^H \triangleq \mathbf{h}^H + \mathbf{f}_{pas}^H \mathbf{\Theta} \mathbf{G}_{pas}$ denote the equivalent channels from the BS to user k , from the BS to user k via the active RIS, and from the BS to user k via the passive RIS respectively, where $\tilde{\mathbf{h}}^H \in \mathbb{C}^{1 \times M}$, $\tilde{\mathbf{h}}_{act}^H \in \mathbb{C}^{1 \times M}$, and $\tilde{\mathbf{h}}_{pas}^H \in \mathbb{C}^{1 \times M}$. Then, the equivalent expression for SINR can be represented as:

$$\tilde{\gamma} = \frac{\left| \tilde{\mathbf{h}}^H \mathbf{b}_k \right|^2}{\sum_{j=1, j \neq k}^K \left| \tilde{\mathbf{h}}_{act}^H \mathbf{b}_j \right|^2 + \left\| \mathbf{f}_{act}^H \mathbf{\Psi} \right\|^2 \sigma_v^2 + \sigma^2} \quad (4)$$

The BS transmits power and the reflected power of the hybrid RIS can be expressed as:

$$P_{BS} = E \left\{ \left\| \sum_{j=1}^K \mathbf{b}_j \mathbf{s}_j \right\|^2 \right\} = \sum_{j=1}^K \left\| \mathbf{b}_j \right\|^2 \quad (5)$$

$$P_{A,P} = E \left\{ \left\| \mathbf{\Psi} \mathbf{G}_{act} \sum_{j=1}^K \mathbf{b}_j \mathbf{s}_j + \mathbf{\Psi} \mathbf{v} \right\|^2 \right\} = \sum_{j=1}^K \left\| \mathbf{\Psi} \mathbf{G}_{act} \mathbf{b}_j \right\|^2 + \left\| \mathbf{\Psi} \right\|_F^2 \sigma_v^2 \quad (6)$$

It is worth noting that when an active RIS amplifies signal amplitude, it also amplifies noise generated by its components. Therefore, the actual power loss of an active RIS should include both signal amplification and noise amplification components [21].

3.2. Methods

In Section 3.2.1, a sum-rate maximization problem is formulated for the downlink of a hybrid RIS-assisted MISO system. In Section 3.2.2, the problem is solved under P_{BS} and $P_{A,P}$ constraints via joint optimization of the hybrid RIS reflection amplification matrix and the transmit beamforming. In Section 3.2.3, the complexity and convergence of the algorithm are analyzed.

3.2.1. Problem Formulation

The information rates at user k are given by $R_k = \log_2(1 + \gamma)$ and $R_{sum} = \sum_{k=1}^K R_k$, respectively.

Therefore, under the constraints P_{BS} and $P_{A,P}$, the sum-rate maximization problem in a hybrid RIS-assisted wireless communication system can be expressed as:

$$P1 : \max_{\mathbf{b}, \mathbf{\Psi}, \mathbf{\Theta}} R_{\text{sum}}(\mathbf{b}, \mathbf{\Psi}, \mathbf{\Theta}) = \sum_{j=1}^K \log_2(1 + \tilde{\gamma}_j) \quad (7)$$

$$\text{s.t. } c_1 : \sum_{j=1}^K \|\mathbf{b}_j\|^2 \leq P_{BS}^{\max} \quad (8)$$

$$c_2 : \sum_{j=1}^K \|\mathbf{\Psi} \mathbf{G}_{act} \mathbf{b}_j\|^2 + \|\mathbf{\Psi}\|_{\text{F}}^2 \sigma_v^2 \leq P_{A,P}^{\max} \quad (9)$$

where $\mathbf{b} = [b_1^T, \dots, b_K^T]^T$ represents the overall beamforming vector formed by the BS transmitting signals to K users, where c_1 and c_2 are the constraints.

3.2.2. Joint Optimization of Beamforming and Hybrid RIS Reflection Matrix

Due to the non-convexity of problem (7) under the constraints in (8) and (9), coupled with the high coupling between variables, solving this problem using a joint optimization approach would result in high computational complexity. To effectively address this issue, this paper employs a solution based on fractional programming (FP), alternating optimization (AO), and the Lagrange multiplier method. Specifically, we first reformulate the problem $P1$ using fractional programming (FP) as proposed in [26] to achieve decoupling. Subsequently, we employ the alternating optimization method to optimize variables sequentially and find the optimal solution. For subsequent convenience, we refer to $\mathbf{b}$ as the BS beamforming vector. In the following, we refer to this method as the “FAL algorithm”.

By introducing three auxiliary variables β , χ , and τ , where $\beta \triangleq [\beta_1, \dots, \beta_K] \in \mathbb{R}_+^K$, $\chi \triangleq [\chi_1, \dots, \chi_K] \in \mathbb{C}^K$, and $\tau \triangleq [\tau_1, \dots, \tau_K] \in \mathbb{C}^K$, and applying the fractional programming (FP) approach proposed in [26], the problem $P1$ can be equivalently expressed as

$$P2 : \max_{\substack{\mathbf{b}, \mathbf{\Psi}, \mathbf{\Theta} \\ \beta, \chi, \tau}} R_{\text{sum}}(\mathbf{b}, \mathbf{\Psi}, \mathbf{\Theta}, \beta, \chi, \tau) = \sum_{j=1}^K \ln(1 + \beta_j) - \sum_{j=1}^K \beta_j + \sum_{j=1}^K f(\mathbf{b}, \mathbf{\Psi}, \mathbf{\Theta}, \beta_j, \chi_j, \tau_j) \quad (10)$$

$$\text{s.t. } c_1 : \sum_{j=1}^K \|\mathbf{b}_j\|^2 \leq P_{BS}^{\max} \quad (11)$$

$$c_2 : \sum_{j=1}^K \|\mathbf{\Psi} \mathbf{G}_{act} \mathbf{b}_j\|^2 + \|\mathbf{\Psi}\|_{\text{F}}^2 \sigma_v^2 \leq P_{A,P}^{\max} \quad (12)$$

where the complete form of $f(\mathbf{b}, \mathbf{\Psi}, \mathbf{\Theta}, \beta_j, \chi_j, \tau_j)$ can be expressed as follows:

$$f(\mathbf{b}, \mathbf{\Psi}, \mathbf{\Theta}, \beta_j, \chi_j, \tau_j) = 2\sqrt{1 + \beta_j \bar{\Pi} - \bar{\Xi} \times \bar{Z}} \quad (13)$$

$$\bar{\Pi} = \text{Re}\{\chi_j^* \tilde{\mathbf{h}}_{act,j}^H \mathbf{b}_j\} + \text{Re}\{\tau_j^* \tilde{\mathbf{h}}_{pas,j}^H \mathbf{b}_j\} \quad (14)$$

$$\bar{\Xi} = |\chi_j|^2 + |\tau_j|^2 + 2\text{Re}\{\chi_j^* \tilde{\mathbf{h}}_{act,j}^H \mathbf{b}_j\} \text{Re}\{\tau_j^* \tilde{\mathbf{h}}_{pas,j}^H \mathbf{b}_j\} \quad (15)$$

$$\bar{Z} = \sum_{j=1}^K \left| \tilde{\mathbf{h}}_{act}^H \mathbf{b}_j \right|^2 + \left\| \tilde{\mathbf{h}}_{act}^H \mathbf{\Psi} \right\|^2 \sigma_v^2 + \sigma^2 \quad (16)$$

Equation (7) is decoupled to yield its equivalent form (10). The BS beamforming vector $\mathbf{b}$, the passive RIS reflection phase matrix $\mathbf{\Theta}$, the active RIS reflection coefficient matrix $\mathbf{\Psi}$,

and auxiliary variables β , χ , and τ can all be obtained through iterative methods to find their optimal solutions at each iteration. By alternately optimizing these variables, a locally optimal solution for Equation (10) can be obtained, thereby achieving convergence R_{sum} .

1. Fixed variable $\mathbf{b}$, Ψ , Θ , χ , τ , optimization variable β . After fixing the BS beamforming vector $\mathbf{b}$, the passive RIS reflection phase matrix Θ , the active RIS reflection coefficient matrix Ψ , and the auxiliary variable χ , τ , the optimal solution β^{opt} can be obtained by solving for $\frac{\partial R_{sum}}{\partial \beta} = 0$. The resulting β^{opt} can be expressed:

$$\beta^{opt} = \frac{\zeta^2 + \zeta\sqrt{\zeta^2 + 4}}{2}, \quad (17)$$

where $\zeta = \text{Re}\{\beta^* \tilde{\mathbf{h}}^H \mathbf{b} + \tau^* \tilde{\mathbf{h}}^H \mathbf{b}\}$.

2. Fixed variables $\mathbf{b}$, Ψ , Θ , β , τ and optimization variable χ . After fixing the BS beamforming vector $\mathbf{b}$, the reflection phase matrix Θ of the passive RIS, the reflection coefficient matrix Ψ of the active RIS, and auxiliary variables β , τ , the optimal solution χ^{opt} of χ can be obtained by solving $\frac{\partial R_{sum}}{\partial \chi} = 0$. The obtained χ^{opt} can be expressed:

$$\chi^{opt} = \frac{\sqrt{1 + \beta} \tilde{\mathbf{h}}^H \mathbf{b}}{\sum_{j=1}^K |\tilde{\mathbf{h}}_{act}^H \mathbf{b}_j|^2 + \|\tilde{\mathbf{f}}_{act}^H \Psi\|^2 \sigma_v^2 + \sigma^2} - \tilde{\mathbf{h}}_{act}^H \mathbf{b} \cdot \text{Re}\{\tau^* \tilde{\mathbf{h}}_{pas}^H \mathbf{b}\} \quad (18)$$

3. Fixed variables $\mathbf{b}$, Ψ , Θ , β , χ and optimization variable τ . After fixing the BS beamforming vector $\mathbf{b}$, the reflection phase matrix Θ of the passive RIS, the reflection coefficient matrix Ψ of the active RIS, and auxiliary variables β , χ , the optimal solution τ^{opt} of τ can be obtained by solving $\frac{\partial R_{sum}}{\partial \tau} = 0$. The obtained τ^{opt} can be expressed:

$$\tau^{opt} = \frac{\sqrt{1 + \beta} \tilde{\mathbf{h}}^H \mathbf{b}}{\sum_{j=1}^K |\tilde{\mathbf{h}}_{act}^H \mathbf{b}_j|^2 + \|\tilde{\mathbf{f}}_{act}^H \Psi\|^2 \sigma_v^2 + \sigma^2} - \tilde{\mathbf{h}}_{pas}^H \mathbf{b} \cdot \text{Re}\{\chi^* \tilde{\mathbf{h}}_{act}^H \mathbf{b}\} \quad (19)$$

4. Fixed variables Ψ , Θ , β , χ , τ , optimize the base station beamforming vector $\mathbf{b}$. After fixing the reflection phase matrix Θ of the passive RIS, the reflection coefficient matrix Ψ of the active RIS, and auxiliary variables β , χ , τ , the optimal solution $\mathbf{b}^{opt}$ for the BS beamforming vector $\mathbf{b}$ can be obtained. At this point, the problem (7) can be equivalently formulated as [21]:

$$P3 : \max_{\mathbf{b}} \text{Re}\{2\mathbf{t}^H \mathbf{b}\} - \mathbf{b}^H \mathbf{W} \mathbf{b} \quad (20)$$

$$\text{s.t. } c_1 : \|\mathbf{b}\|^2 \leq P_{BS}^{\max} \quad (21)$$

$$c_2 : \mathbf{b}^H \mathbf{N} \mathbf{b} \leq P_L^{\max} \quad (22)$$

where $\mathbf{t} = [t_1^T, \dots, t_N^T]^T$, $\mathbf{t}_k^H = \sqrt{1 + \beta}(\chi^* + \tau^*) \tilde{\mathbf{h}}^H$, $P_L = P_{A,P}^{\max} - \|\Psi\|_F^2 \sigma_v^2$, $\mathbf{N} = \mathbf{I}_K \otimes [\mathbf{G}_{a,p}^H (\Psi^H \Psi + \Theta^H \Theta) \mathbf{G}_{a,p}]$, $\mathbf{W} = \mathbf{I}_K \otimes \sum_{j=1}^K (|\chi_j|^2 + |\tau_j|^2) \tilde{\mathbf{h}}_j \tilde{\mathbf{h}}_j^H$.

The problem represented by factor (20) conforms to the typical quadratic constrained quadratic programming (QCQP) form, constituting a standard quadratic constrained quadratic programming problem. This problem (20) can be solved using the Lagrange dual multiplier method, yielding the following optimal solution:

$$\mathbf{b}^{opt} = (\mathbf{W} + \lambda \mathbf{I}_{MK} + \mu \mathbf{N})^{-1} \mathbf{t} \quad (23)$$

where λ and μ are the optimal multipliers obtained through a two-dimensional grid search selected to solve the problem [27]. The selection of λ and μ must satisfy the constraints c_1 and c_2 in the problem (20).

5. Fixed variables $\mathbf{b}$, Θ , β , χ , τ , optimize the reflection coefficient matrix Ψ of the active RIS. After fixing the BS beamforming vector $\mathbf{b}$, the reflection phase matrix Θ of the passive RIS, and auxiliary variables β , χ , τ , the optimal reflection amplification matrix Ψ^{opt} of the active RIS is obtained through iterative optimization. In this section, to facilitate problem-solving, we first redefine the reflection coefficient matrix Ψ of the active RIS. Let $\Phi \triangleq [a_1 e^{j\theta_{act}^1}, \dots, a_N e^{j\theta_{act}^N}]^H$, then $\Psi \triangleq \text{diag}(\Phi^H)$. Therefore, the equivalent channel $\tilde{\mathbf{h}}_{act}^H$ of the active RIS can be rewritten as:

$$\tilde{\mathbf{h}}_{act}^H = \mathbf{h}^H + \Phi^H \text{diag}(\mathbf{f}_{act}^H) \mathbf{G}_{act} \quad (24)$$

The equivalent channel of an active RIS can be expressed [21]:

$$\mathbf{c}^\dagger = \sum_{j=1}^K \sqrt{1 + \beta_j} \text{diag}(\chi_j^* \mathbf{f}_{pas,j}^H) \mathbf{G}_{pas} \mathbf{b}_j - \sum_{j=1}^K |\chi_j|^2 \text{diag}(\mathbf{f}_{act,j}^H) \mathbf{G}_{act} \left(\sum_{j=1}^K \mathbf{b}_j \mathbf{b}_j^H \mathbf{h}_j \right) \quad (25)$$

$$\mathbf{o}^\dagger = \sum_{j=1}^K |\chi_j|^2 \text{diag}(\mathbf{f}_{act,j}^H) \text{diag}(\mathbf{f}_{act,j}) \sigma_v^2 + \sum_{j=1}^K |\chi_j|^2 \sum_{j=1}^K \text{diag}(\mathbf{f}_{act}^H) \mathbf{G}_{act} \mathbf{b}_j \mathbf{b}_j^H \text{diag}(\mathbf{f}_{act}) \quad (26)$$

$$\mathbf{u}^\dagger = \sum_{j=1}^K \text{diag}(\mathbf{G}_{act} \mathbf{b}_j) (\text{diag}(\mathbf{G}_{act} \mathbf{b}_j))^H + \sigma_v^2 \mathbf{I}_N \quad (27)$$

After fixing the variables $\mathbf{b}$, Θ , β , χ , τ , the problem (7) can be equivalently expressed [21]:

$$P4 : \max_{\Phi} \text{Re} \left\{ 2 \Phi^H \mathbf{c}^\dagger \right\} - \Phi^H \mathbf{o}^\dagger \Phi \quad (28)$$

$$\text{s.t. } c_1 : \Phi^H \mathbf{u}^\dagger \Phi \leq P_{A,P}^{\max} \quad (29)$$

The problem described in Equation (28) also conforms to the standard quadratic constrained quadratic programming (QCQP) form. Therefore, the problem (28) is solved using the Lagrange dual multiplier method, and its optimal solution Ψ^{opt} can be expressed as follows:

$$\Psi^{opt} = \left(\mathbf{o}^\dagger + \lambda \mathbf{u}^\dagger \right)^{-1} \mathbf{c}^\dagger \quad (30)$$

where λ is the optimal multiplier obtained through a two-dimensional grid search that satisfies the constraint conditions. In this work, we adopt a total power constraint for the active elements of the hybrid RIS, which reflects a practical scenario where the active elements share a common power budget provided by a centralized power supply.

6. Fixed variables $\mathbf{b}$, Ψ , β , χ , τ , optimize the reflection phase matrix Θ of the passive RIS. Unlike the optimization of active elements, the focus of element optimization in passive RIS lies in the phase of reflection beamforming. After fixing the base station beamforming vector $\mathbf{b}$, the reflection coefficient matrix Ψ of the active RIS, and auxiliary variables β , χ , τ , the optimal reflection phase matrix Θ^{opt} of the passive RIS is obtained through iterative optimization.

Redefine the variable Θ . Let $\varphi \triangleq [e^{j\theta_{pas}^1}, \dots, e^{j\theta_{pas}^N}]^H$, then $\Theta \triangleq \text{diag}(\varphi^H)$. Thus, the equivalent channel $\tilde{\mathbf{h}}_{pas}^H$ of the original passive RIS can be rewritten as follows:

$$\tilde{\mathbf{h}}_{pas}^H = \mathbf{h}^H + \varphi^H \text{diag}(\mathbf{f}_{pas}^H) \mathbf{G}_{pas} \quad (31)$$

$$\mathbf{C}^\dagger = \sum_{j=1}^K \sqrt{1 + \beta_j} \text{diag}(\boldsymbol{\tau}_j^* \mathbf{f}_{pas,j}^H) \mathbf{G}_{pas} \mathbf{b}_j - \sum_{j=1}^K |\tau_j|^2 \text{diag}(\mathbf{f}_{pas,j}^H) \mathbf{G}_{pas} \left(\sum_{j=1}^K \mathbf{b}_j \mathbf{b}_j^H \mathbf{h}_j \right) \quad (32)$$

$$\mathbf{O}^\dagger = \sum_{j=1}^K |\tau_j|^2 \sum_{j=1}^K \text{diag}(\mathbf{f}_{pas}^H) \mathbf{G}_{pas} \mathbf{b}_j \mathbf{b}_j^H \text{diag}(\mathbf{f}_{pas}) \quad (33)$$

$$\mathbf{U}^\dagger = \sum_{j=1}^K \text{diag}(\mathbf{G}_{pas} \mathbf{b}_j) (\text{diag}(\mathbf{G}_{pas} \mathbf{b}_j))^H \quad (34)$$

After fixing the variables $\mathbf{b}$, $\boldsymbol{\Psi}$, β , $\boldsymbol{\chi}$, $\boldsymbol{\tau}$, the problem (7) can be equivalently expressed as [8]:

$$P5 : \max_{\boldsymbol{\varphi}, \theta_{pas}} \text{Re} \left\{ 2 \boldsymbol{\varphi}^H \mathbf{C}^\dagger \right\} - \boldsymbol{\varphi}^H \mathbf{O}^\dagger \boldsymbol{\varphi} \quad (35)$$

$$s.t. \quad c_1 : \boldsymbol{\varphi}^H \mathbf{U}^\dagger \boldsymbol{\varphi} \leq P_L^{\max} \quad (36)$$

$$c_2 : 0 < \theta \leq 2\pi \quad (37)$$

Equivalent problem (35) also conforms to the typical quadratic constrained quadratic programming (QCQP) form, and thus can be solved using the Lagrange dual multiplier method. Its optimal solution can be expressed as follows:

$$\boldsymbol{\Theta}^{opt} = \left(\mathbf{O}^\dagger + \lambda \mathbf{U}^\dagger \right)^{-1} \mathbf{C}^\dagger, \quad (38)$$

where λ is the optimal multiplier obtained through a two-dimensional grid search that satisfies the constraint conditions.

Algorithm 1 summarizes the FAL algorithm for solving problem (10). The BS beamforming vector and the hybrid RIS reflection matrices are randomly initialized with feasible values. Each subproblem is approximately solved under the associated constraints.

Algorithm 1 FAL optimization scheme for beamforming and reflection matrix of hybrid RIS

Input: Channels $\mathbf{G}_{a,p}$, $\mathbf{h}^H$, $\mathbf{f}_{act}^H$, $\mathbf{f}_{pas}^H$.

Output: Optimized BS beamforming $\mathbf{b}^{opt}$; optimized active RIS matrix $\boldsymbol{\Psi}^{opt}$; optimized passive RIS matrix $\boldsymbol{\Theta}^{opt}$ and optimized sum-rate R_{sum} .

1: Randomly initialize variables $\mathbf{b}$, $\boldsymbol{\Psi}$ and $\boldsymbol{\Theta}$ with feasible values

2: **while** $|R_{\text{sum}}^t - R_{\text{sum}}^{t-1}| / R_{\text{sum}}^{t-1} > \varepsilon$ **do**

3: Use variables $\mathbf{b}$ and $\mathbf{h}^H$ to update variable β by (17)

4: Use variables $\boldsymbol{\Psi}$, $\mathbf{b}$, $\mathbf{G}_{a,p}$, and $\mathbf{h}^H$ to update $\boldsymbol{\chi}$ by (18)

5: Use variables $\boldsymbol{\Psi}$, $\mathbf{b}$, $\mathbf{G}_{a,p}$, and $\mathbf{h}^H$ to update $\boldsymbol{\tau}$ by (19)

6: Use variables $\boldsymbol{\Psi}$, $\boldsymbol{\Theta}$, $\mathbf{G}_{a,p}$, and $\mathbf{h}^H$, to update $\mathbf{b}$ by solving (23) under the BS power constraint

7: Use variables $\boldsymbol{\chi}$, $\boldsymbol{\tau}$, β , $\mathbf{b}$, $\mathbf{G}_{a,p}$, and $\mathbf{h}^H$ to update $\boldsymbol{\Psi}$ by solving (30) under the hybrid RIS power constraint

8: Use variables $\boldsymbol{\chi}$, $\boldsymbol{\tau}$, β , $\mathbf{b}$, $\mathbf{G}_{a,p}$, and $\mathbf{h}^H$ to update $\boldsymbol{\Theta}$ by solving (38)

9: After updating the variable β , $\boldsymbol{\chi}$, $\boldsymbol{\tau}$, $\mathbf{b}$, $\boldsymbol{\Psi}$, and $\boldsymbol{\Theta}$, update R_{sum} by (10)

10: **end while**

11: **return** optimized $\mathbf{b}^{opt}$, $\boldsymbol{\Psi}^{opt}$, $\boldsymbol{\Theta}^{opt}$ and R_{sum}

The proposed algorithm follows an alternating optimization framework in which each variable block is updated while keeping the others fixed. Each update step does not decrease the objective value under the given constraints. Since the objective function is upper-bounded by the transmit power and hybrid RIS power constraints, the objective sequence is bounded and non-decreasing, which guarantees convergence of the objective value. The algorithm terminates when the relative improvement of the objective value

between two consecutive iterations is smaller than a predefined tolerance ε or when the maximum number of iterations is reached. The maximum number of iterations is 500.

3.2.3. Complexity Analysis and Convergence

The complexity of the algorithm is primarily determined by the updates to six variables: β , χ , τ , $\mathbf{b}$, Ψ , and Θ . The specific complexity of each variable is shown in Table 4.

Table 4. Complexity analysis of variables.

Variables	Complexity
β	$\mathcal{O}(KM)$
χ, τ	$\mathcal{O}(K^2M + KN)$
$\mathbf{b}$	$\mathcal{O}(\log_2(1/\varepsilon)\sqrt{MK+2}(1+MK)M^3K^3)$
Ψ	$\mathcal{O}(\log_2(1/\varepsilon)\sqrt{N+2}(1+2N)N^3)$
Θ	$\mathcal{O}(\log_2(1/\varepsilon)\sqrt{N+2}(1+2N)N^3)$

Therefore, the complexity of algorithm FAL is $\mathcal{O}(\log_2(1/\varepsilon)I'_o(M^{4.5}K^{4.5} + N^{4.5}))$. Here, I'_o represents the number of iterations required for the algorithm to end.

It is worth noting that the overall computational complexity is mainly dominated by the updates of the variables $\mathbf{b}$, Ψ , and Θ , which are solved via convex optimization techniques. In contrast, the updates of auxiliary variables such as β , χ , and τ admit low-complexity solutions and thus incur significantly lower computational complexity compared with the dominant subproblems.

Compared with conventional passive/active RIS-assisted MISO systems [21,34], the proposed hybrid RIS framework introduces additional optimization variables associated with the active elements. However, this additional complexity does not lead to an exponential increase in computational burden. Moreover, the proposed algorithm follows a standard alternating optimization structure, whose per-iteration complexity is comparable to existing active RIS or hybrid RIS optimization schemes reported in the literature.

4. Results

This section will conduct experimental verification of the system model, introduce simulation parameters, and validate the feasibility and effectiveness of the proposed hybrid RIS-assisted wireless system through simulation results. All power-related parameters are specified in “dBm” for reporting convenience, while all numerical evaluations, including SINR and achievable rate computations, are performed using the corresponding linear scale (Watts) values.

In the system model, this paper considers a two-dimensional Cartesian coordinate system, placing the BS and hybrid RIS at positions (0 m, 0 m) and (240 m, 220 m), respectively. The experiment examines a hybrid RIS-assisted MU-MISO system operating at 5 GHz, employing a Rician fading channel model [35] for enhanced realism. The channel can be expressed as follows:

$$\mathbf{G} = \sqrt{PF} \left(\sqrt{\frac{K_F}{K_F + 1}} \mathbf{G}_{LoS} + \sqrt{\frac{1}{K_F + 1}} \mathbf{G}_{NLoS} \right), \quad (39)$$

$$\mathbf{h} = \sqrt{PF} \left(\sqrt{\frac{K_F}{K_F + 1}} \mathbf{h}_{LoS} + \sqrt{\frac{1}{K_F + 1}} \mathbf{h}_{NLoS} \right), \quad (40)$$

where K_F denotes the Rician fading factor. $\mathbf{G}_{LoS}$ and $\mathbf{G}_{NLoS}$ represent the deterministic LoS and Rayleigh fading components, respectively. Similarly, $\mathbf{h}_{LoS}$ and $\mathbf{h}_{NLoS}$ also represent the deterministic LoS and Rayleigh fading components, respectively. To better align with the

model proposed in this paper, we set $K_F = 2.2$. $\sqrt{PF}$ represents the path loss corresponding to the channel. The value of $\sqrt{PF}$ is referenced from two different path loss models compliant with the 3GPP standard [21]:

$$PF_1 = 37.3 + 22.0 \log d, \quad (41)$$

$$PF_2 = 41.2 + 28.7 \log d, \quad (42)$$

where d denotes the Euclidean distance between two communication devices. The experiments consider two practical channel scenarios that differ in the quality of the direct BS–user link. Scenario 1 corresponds to a weak direct link caused by severe obstruction, representative of dense urban environments. Scenario 2 corresponds to an unobstructed and strong direct link, representative of suburban or open areas. The performance of the hybrid RIS is evaluated and compared under these two scenarios. The two scenarios are shown in Figure 5. The fading loss model PF_1 applies to scenarios where the direct link between the BS and users is strong, as well as the links between the BS and the hybrid RIS and between the hybrid RIS and users. The fading loss model PF_2 applies to scenarios where the direct link between the BS and users is weak.

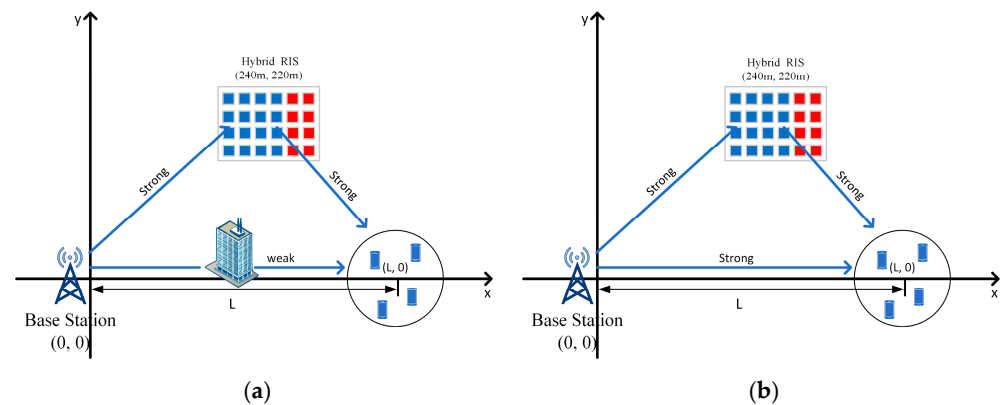


Figure 5. Simulation scenarios under two different channel conditions. (a): A weak direct link between the BS and the user. (b): A strong direct link between the BS and the user.

Set the number of users in the experiment $K = 6$, number of BS antennas $M = 8$, $\sigma_v^2 = -110$ dbm, power of Additive Gaussian White Noise (AWGN) received at the user's $\sigma^2 = -100$ dbm. The total power consumption of the system is P_{MAX} then $P_{MAX} = P_{BS}^{\max} + P_{A,P}^{\max}$ ($P_{BS}^{\max}$ and $P_{A,P}^{\max}$ represent the maximum transmit power of the BS and the maximum reflect power of the hybrid RIS, respectively). Let $P_{MAX} = 12$ dbm; to ensure fairness in energy distribution, the BS allocates energy as follows: $P_{BS}^{\max} = 0.9 \times P_{MAX}$, and the maximum reflected power of the hybrid RIS is $P_{A,P}^{\max} = 0.1 \times P_{MAX}$.

To evaluate the effectiveness of the proposed hybrid RIS architecture, we compare it with the following four approaches: active RIS-assisted MISO under ideal conditions without self-interference [21]; passive RIS-assisted MISO; passive RIS with random phase shifts and BS beamforming optimized using the minimum mean square error (MMSE) scheme; and not deploying the RIS at all. In the simulation results, for easy distinction, the proposed method is denoted as “FAL-Hybrid RIS” in the figure.

4.1. Coverage Performance of Hybrid RIS

Assume the user group is randomly distributed within a circular area centered at point L ($L > 240$) on the horizontal axis of the coordinate system, with a radius of 10 m and located at a distance L m from the origin. For fair comparison, the total number of hybrid RIS deployments in the experiment is kept consistent with the combined total of

standalone active or passive RIS deployments. In this section, the number of passive or active RIS elements deployed alone is denoted as $N = 500$. Therefore, in the hybrid RIS architecture, the total deployment count is $N = 500$, with active and passive RIS deployed in an optimal ratio [24]. When $K_F = 2.2$, the optimal deployment quantities for active and passive RIS are approximately $N_{act} = 350$ and $N_{pas} = 150$, respectively.

Based on the above system configuration, experiments produced the graphs shown in Figure 6a,b. These illustrate the relationship between transmission rate and distance L from the BS to the user.

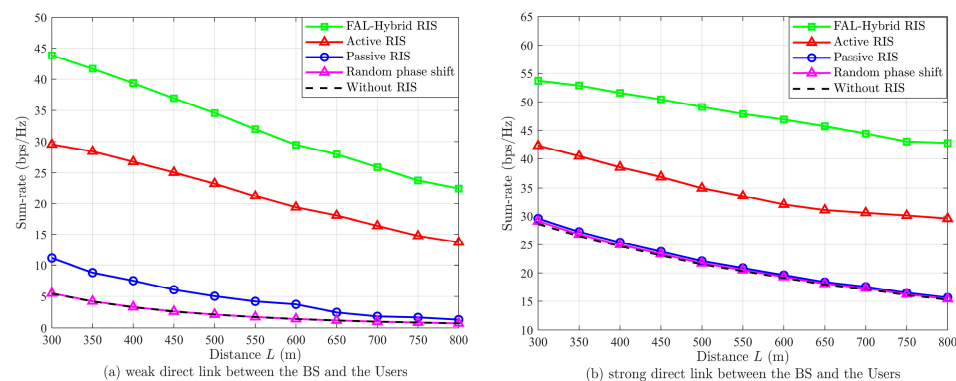


Figure 6. Simulation results for sum-rate versus coverage distance L in a hybrid RIS-assisted MU-MISO system. (a): A weak direct link between the BS and the user. (b): A strong direct link between the BS and the user.

As shown in Figure 6a, when the direct link between the BS and the user is weak, the sum-rate improvement is greater with hybrid RIS assistance. In the strong direct link scenario shown in Figure 6b, deploying hybrid RIS still enables the system to achieve significant power and rate gains compared to deploying either passive RIS or active RIS alone. Furthermore, as L increases, the system exhibits lower attenuation and higher stability.

Taking point $L = 500$ m as an example, when the link between the BS and the user is a weak direct link, the system rates for passive RIS deployment, active RIS deployment and hybrid RIS deployment are 5 bps/Hz, 23.2 bps/Hz, and 34.6 bps/Hz, respectively. When a direct link exists between the BS and users, the system's aggregate rates are 22 bps/Hz, 35 bps/Hz, and 49 bps/Hz, respectively. Therefore, at point $L = 500$ m, for weak direct links, passive RIS provides a 150% aggregate rate gain over no RIS deployment, while active RIS offers a 1060% gain. For strong direct links, passive RIS delivers a 4.76% gain and active RIS achieves a 66.67% gain. In contrast, hybrid RIS achieves 1630% and 133.33% aggregate rate gains under these two conditions. Deploying hybrid RIS improves efficiency by 49.1% and 40% compared to deploying only active RISs, demonstrating significantly better performance than the two aforementioned schemes.

4.2. Effect of System Total Power Consumption on Sum-Rate

To more intuitively demonstrate the performance comparison of hybrid RIS versus active RIS and passive RIS in coverage range, we conduct experimental tests assuming the center of user distribution is located at point $L = 500$ m on the horizontal axis. The user distribution range is expanded by increasing the distribution radius from 10 m to 30 m. At the same time, the number of components deployed for both active RIS and passive RIS is $N = 500$. In the hybrid RIS, $N_{act} = 350$ and $N_{pas} = 150$. While maintaining the aforementioned baseline settings, increase the system's total power consumption P_{Max} and observe the relationship between system performance and rate versus total power consumption P_{Max} .

As observed in Figure 7, passive RIS achieves only limited sum-rate gains under two different scenarios. While active RIS achieves higher gains, the sum-rate of gains obtained by deploying hybrid RIS is comparatively higher than those of active RIS. As shown in Figure 7a under the weak direct link scenario, hybrid RIS achieves higher sum-rate gains at the same total power loss. Similarly, in the strong direct link scenario depicted in Figure 7b, at total power loss $P_{\text{Max}} \leq 25$ dbm, deploying hybrid RIS achieves a higher rate gain of 4–14 bps/Hz than deploying active RIS at the same power loss. This occurs because allocating more energy to active RIS enables more active elements to be activated in amplification mode, achieving higher performance gains through optimization.

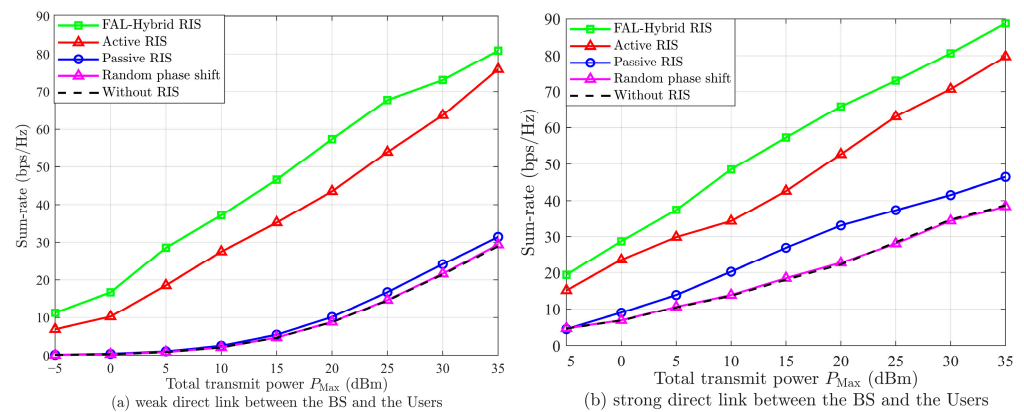


Figure 7. Simulation results for sum-rate and total power consumption P_{Max} for hybrid RIS-assisted MU-MISO systems. (a): A weak direct link between the BS and the user. (b): A strong direct link between the BS and the user.

4.3. Impact of the Number N of Mixed RIS Deployments on Sum-Rate

Maintaining the same system power settings and allocation strategy as in Figure 6, and assuming users are randomly distributed within a circular area centered at point $L = 500$ m on the horizontal axis with a radius of 30 m, this experiment fixes the total system power loss P_{Max} . The number of deployed elements for each type of RIS is increased, with active RIS or passive RIS deployed in increments of 100 each time. For hybrid RIS, the number of active/the allocation of active and passive elements in hybrid RIS follows the optimal quantity distribution outlined in [24]. When the total deployment budget is 200, 300, 400, 500, or 600, the allocated quantities of active and passive RIS ($N_{\text{act}}, N_{\text{pas}}$) are (50, 150), (75, 225), and (100, 300). When the total deployment quantity is $500 \leq N \leq 1000$, the optimal deployment quantities for N_{act} is $N_{\text{act}} = 350$, $N_{\text{pas}} = N - N_{\text{pas}}$, respectively.

Figure 8 illustrates the relationship between the sum-rate and the number of deployed RIS N elements. It is evident that passive RIS, active RIS, and hybrid RIS all yield significant sum-rate gains as the number of elements increase. The system achieves higher sum-rate gains with hybrid RIS assistance than with active RIS alone. In Figure 8a, under weak direct link conditions, when the number of deployed elements N varies from 200 to 1000, the system achieves a sum-rate gain increase of 9 bps/Hz to 17 bps/Hz compared to no RIS deployment when assisted by active RIS. When assisted by hybrid RIS, the gain increase ranges from 12 bps/Hz to 22 bps/Hz. In Figure 8b with direct links, the system achieves a gain increase of 11 bps/Hz to 19 bps/Hz when assisted by active RIS, while hybrid RIS assistance yields a gain increase of 13 bps/Hz to 25 bps/Hz.

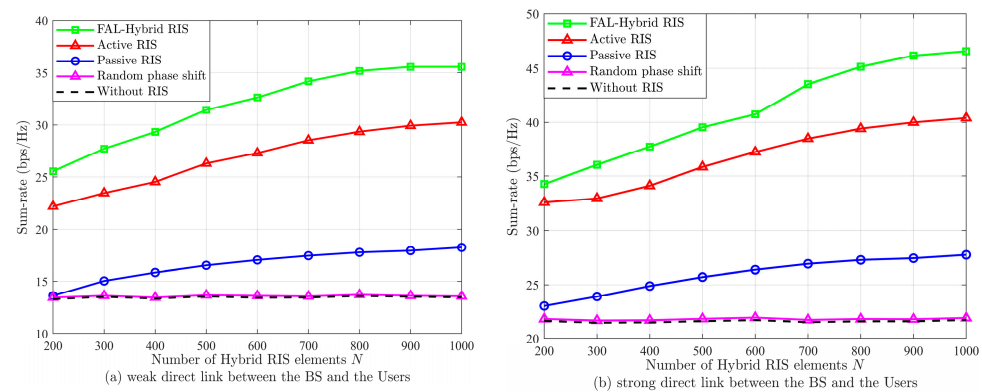


Figure 8. Simulation results of the sum-rate and the number N of hybrid RIS elements in a hybrid RIS-assisted MU-MISO system. (a): A weak direct link between the BS and the user. (b): A strong direct link between the BS and the user.

5. Discussion

In this section, we shall discuss the simulation results for a typical communication system employing hybrid RIS-assisted MU-MISO.

The results in Section 4.1 demonstrate that, under the two scenarios illustrated in Figure 6, the hybrid RIS-assisted MISO system consistently provides enhanced signal coverage. Moreover, when the distance between the BS and users increased, it exhibited lower attenuation levels, thereby enabling the system to achieve higher sum-rate performance. These results indicate that the hybrid RIS is more effective than active RIS in extending the BS transmission range.

The results in Section 4.2 show that, under the two scenarios illustrated in Figure 7, the hybrid RIS-assisted MISO system consistently achieves higher sum-rate performance for the same level of power loss. Consequently, the hybrid RIS enables communication systems to achieve higher transmission rates at lower system power consumption, thereby reducing both power expenditure and cost implications.

The results in Section 4.3 show that, under the two scenarios illustrated in Figure 8, the hybrid RIS-assisted MISO system achieves superior sum-rate performance by optimally allocating the ratio of active and passive elements under a fixed total number of RIS elements. This approach not only achieves lower deployment costs compared to deploying active RIS alone, but also compensates for the insufficient gain observed when deploying passive RIS exclusively.

In summary, the hybrid RIS demonstrates greater performance than active RIS and passive RIS. It enables systems to achieve higher transmission ranges and rates alongside lower power consumption during medium-scale or large-scale deployments. It effectively combines the strengths of active and passive RIS and alleviates the multiplicative fading effect.

6. Conclusions

This paper proposes a hybrid RIS structure that fixes the number of active/passive elements based on the optimal allocation of active/passive components in active-passive RIS. A fundamental signal model for the hybrid RIS is established. Based on this model, the hybrid RIS is employed to assist a MU-MISO communication system, evaluating its capability to enhance communication system transmission rates. Unlike existing research, this study simultaneously considers two scenarios: direct links between the BS and users experiencing blockage or severe fading, and unobstructed direct links. This approach enriches the application scenarios by increasing both the number of BS antennas and the number of served users. Subsequently, an optimization problem for maximizing the sum-rate was

formulated under instantaneous CSI. This problem aimed to maximize the sum-rate of the hybrid RIS-assisted MU-MISO system. It was solved using fractional programming (FP) decoupling, alternating optimization (AO) variables, and the Lagrange multiplier method, yielding the optimal BS beamforming vectors and the reflection coefficient matrix of the hybrid RIS. Simulation results demonstrate that, under both scenarios, the hybrid RIS achieves superior rate gains at lower total power loss P_{Max} .

Author Contributions: Conceptualization, Y.Z.; methodology, Y.Z. and W.P.; validation, W.P. and Y.Z.; resources, Y.Z.; data curation, W.P.; writing—original draft preparation and revision, W.P.; writing—review, Y.Z.; funding acquisition, Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by the National Natural Science Foundation of China under Grant 61673259, in part by the Natural Science Foundation of Shanghai under Grant 25ZR1401159, in part by the Shanghai Municipal Science and Technology Commission's 2025 Key Technology R&D Program "New Generation Information Technology" Project under Grant 25511103902, and in part by the Shanghai Key Laboratory of Intelligent Information Processing of Fudan University under Grant No. IIPL-2025-RD5-01.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Wu, Q.; Li, G.Y.; Chen, W.; Ng, D.W.K.; Schober, R. An Overview of Sustainable Green 5G Networks. *IEEE Wirel. Commun.* **2017**, *24*, 72–80. [\[CrossRef\]](#)
2. Zhang, S.; Wu, Q.; Xu, S.; Li, G.Y. Fundamental Green Tradeoffs: Progresses, Challenges, and Impacts on 5G Networks. *IEEE Commun. Surv. Tutor.* **2017**, *19*, 33–56. [\[CrossRef\]](#)
3. Saad, W.; Bennis, M.; Chen, M. A Vision of 6G Wireless Systems: Applications, Trends, Technologies, and Open Research Problems. *IEEE Netw.* **2020**, *34*, 134–142. [\[CrossRef\]](#)
4. Giordani, M.; Polese, M.; Mezzavilla, M.; Rangan, S.; Zorzi, M. Toward 6G Networks: Use Cases and Technologies. *IEEE Commun. Mag.* **2020**, *58*, 55–61. [\[CrossRef\]](#)
5. Zhang, L.; Chen, X.Q.; Liu, S.; Zhang, Q.; Zhao, J.; Dai, J.Y.; Bai, G.D.; Wan, X.; Cheng, Q.; Castaldi, G.; et al. Space-time-coding digital metasurfaces. *Nat. Commun.* **2018**, *9*, 4334. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Venkatesh, S.; Lu, X.; Saeidi, H.; Sengupta, K. A high-speed programmable and scalable terahertz holographic metasurface based on tiled CMOS chips. *Nat. Electron.* **2020**, *3*, 785–793. [\[CrossRef\]](#)
7. Wu, Q.; Zhang, R. Towards Smart and Reconfigurable Environment: Intelligent Reflecting Surface Aided Wireless Network. *IEEE Commun. Mag.* **2020**, *58*, 106–112. [\[CrossRef\]](#)
8. Wu, Q.; Zhang, S.; Zheng, B.; You, C.; Zhang, R. Intelligent Reflecting Surface-Aided Wireless Communications: A Tutorial. *IEEE Trans. Commun.* **2021**, *69*, 3313–3351. [\[CrossRef\]](#)
9. Liu, Y.; Liu, X.; Mu, X.; Hou, T.; Xu, J.; Di Renzo, M.; Al-Dhahir, N. Reconfigurable Intelligent Surfaces: Principles and Opportunities. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 1546–1577. [\[CrossRef\]](#)
10. Basar, E.; Di Renzo, M.; De Rosny, J.; Debbah, M.; Alouini, M.-S.; Zhang, R. Wireless Communications Through Reconfigurable Intelligent Surfaces. *IEEE Access* **2019**, *7*, 116753–116773. [\[CrossRef\]](#)
11. Huang, C.; Mo, R.; Yuen, C. Reconfigurable Intelligent Surface Assisted Multiuser MISO Systems Exploiting Deep Reinforcement Learning. *IEEE J. Sel. Areas Commun.* **2020**, *38*, 1839–1850. [\[CrossRef\]](#)
12. Wang, P.; Fang, J.; Yuan, X.; Chen, Z.; Li, H. Intelligent Reflecting Surface-Assisted Millimeter Wave Communications: Joint Active and Passive Precoding Design. *IEEE Trans. Veh. Technol.* **2020**, *69*, 14960–14973. [\[CrossRef\]](#)
13. Huang, C.; Zappone, A.; Alexandropoulos, G.C.; Debbah, M.; Yuen, C. Reconfigurable Intelligent Surfaces for Energy Efficiency in Wireless Communication. *IEEE Trans. Wirel. Commun.* **2019**, *18*, 4157–4170. [\[CrossRef\]](#)
14. Wang, P.; Li, D.; Zhang, Y.; Chen, X. Real-time multi-IRS partitioning for sum-rate optimization in a UAV-IRS-aided vehicular communication system. *Digit. Signal Process.* **2025**, *160*, 105047. [\[CrossRef\]](#)
15. Li, S.; Duo, B.; Yuan, X.; Liang, Y.-C.; Di Renzo, M. Reconfigurable Intelligent Surface Assisted UAV Communication: Joint Trajectory Design and Passive Beamforming. *IEEE Wirel. Commun. Lett.* **2020**, *9*, 716–720. [\[CrossRef\]](#)

16. Zhao, Q.; Gong, W.; Hou, T.; Sun, X.; Li, A.; Bodanese, E. Integrated-Navigation-and-Communication (INAC): A Reconfigurable Intelligent Surface (RIS)-aided Approach. In Proceedings of the 2023 IEEE 97th Vehicular Technology Conference (VTC2023-Spring), Florence, Italy, 20–23 June 2023; pp. 1–6.
17. Yi, P.; Cheng, W.; Wang, J.; Zhang, W. RIS-Assisted Seamless Connectivity in Wireless Multi-Hop Relay Networks. *IEEE Trans. Mob. Comput.* **2025**, *24*, 8600–8611. [\[CrossRef\]](#)
18. Song, D.; Yang, Z.; Pan, G.; Wang, S.; An, J. RIS-Assisted Covert Transmission in Satellite–Terrestrial Communication Systems. *IEEE Internet Things J.* **2023**, *10*, 19415–19426. [\[CrossRef\]](#)
19. Huang, S.; Zhang, Y. Secrecy Rate Optimization for Multi-User Secure Communication Assisted by Intelligent Reflecting Surfaces (IRS) Under Imperfect CSI Conditions. *Trans. Emerg. Telecommun. Technol.* **2025**, *36*, e70117. [\[CrossRef\]](#)
20. Kang, Z.; You, C.; Zhang, R. Active-IRS-Aided Wireless Communication: Fundamentals, Designs and Open Issues. *IEEE Wirel. Commun.* **2024**, *31*, 368–374. [\[CrossRef\]](#)
21. Zhang, Z.; Dai, L.; Chen, X.; Liu, C.; Yang, F.; Schober, R.; Poor, H.V. Active RIS vs. Passive RIS: Which Will Prevail in 6G? *IEEE Trans. Commun.* **2023**, *71*, 1707–1725. [\[CrossRef\]](#)
22. Zhi, K.; Pan, C.; Ren, H.; Chai, K.K.; Elkashlan, M. Active RIS Versus Passive RIS: Which is Superior With the Same Power Budget? *IEEE Commun. Lett.* **2022**, *26*, 1150–1154. [\[CrossRef\]](#)
23. You, C.; Zhang, R. Wireless Communication Aided by Intelligent Reflecting Surface: Active or Passive? *IEEE Wirel. Commun. Lett.* **2021**, *10*, 2659–2663. [\[CrossRef\]](#)
24. Kang, Z.; You, C.; Zhang, R. Active-Passive IRS Aided Wireless Communication: New Hybrid Architecture and Elements Allocation Optimization. *IEEE Trans. Wirel. Commun.* **2024**, *23*, 3450–3464. [\[CrossRef\]](#)
25. Ntougias, K.; Chatzinotas, S.; Krikidis, I. Hybrid RIS With Sub-Connected Active Partitions: Performance Analysis and Transmission Design. *IEEE Trans. Wirel. Commun.* **2025**, *24*, 6705–6721. [\[CrossRef\]](#)
26. Shen, K.; Yu, W. Fractional Programming for Communication Systems—Part I: Power Control and Beamforming. *IEEE Trans. Signal Process.* **2018**, *66*, 2616–2630. [\[CrossRef\]](#)
27. Boyd, S.; Parikh, N.; Chu, E.; Peleato, B.; Eckstein, J. Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers. *Found. Trends Inf. Retr.* **2011**, *3*, 1–122.
28. Yang, H.; Yang, F.; Cao, X.; Xu, S.; Gao, J.; Chen, X.; Li, M.; Li, T. A 1600-Element Dual-Frequency Electronically Reconfigurable Reflectarray at X/Ku-Band. *IEEE Trans. Antennas Propag.* **2017**, *65*, 3024–3032. [\[CrossRef\]](#)
29. Long, R.; Liang, Y.-C.; Pei, Y.; Larsson, E.G. Active Reconfigurable Intelligent Surface-Aided Wireless Communications. *IEEE Trans. Wirel. Commun.* **2021**, *20*, 4962–4975. [\[CrossRef\]](#)
30. Yu, X.; Xu, D.; Sun, Y.; Ng, D.W.K.; Schober, R. Robust and Secure Wireless Communications via Intelligent Reflecting Surfaces. *IEEE J. Sel. Areas Commun.* **2020**, *38*, 2637–2652. [\[CrossRef\]](#)
31. Yang, H.; Xiong, Z.; Zhao, J.; Niyato, D.; Xiao, L.; Wu, Q. Deep Reinforcement Learning-Based Intelligent Reflecting Surface for Secure Wireless Communications. *IEEE Trans. Wirel. Commun.* **2021**, *20*, 375–388. [\[CrossRef\]](#)
32. Zhang, Z.; Dai, L. A Joint Precoding Framework for Wideband Reconfigurable Intelligent Surface-Aided Cell-Free Network. *IEEE Trans. Signal Process.* **2021**, *69*, 4085–4101. [\[CrossRef\]](#)
33. Hou, T.; Liu, Y.; Song, Z.; Sun, X.; Chen, Y. MIMO-NOMA Networks Relying on Reconfigurable Intelligent Surface: A Signal Cancellation-Based Design. *IEEE Trans. Commun.* **2020**, *68*, 6932–6944. [\[CrossRef\]](#)
34. Najafi, M.; Jamali, V.; Schober, R.; Poor, H.V. Physics-Based Modeling and Scalable Optimization of Large Intelligent Reflecting Surfaces. *IEEE Trans. Commun.* **2021**, *69*, 2673–2691. [\[CrossRef\]](#)
35. Guo, H.; Liang, Y.-C.; Chen, J.; Larsson, E.G. Weighted Sum-Rate Maximization for Reconfigurable Intelligent Surface Aided Wireless Networks. *IEEE Trans. Wirel. Commun.* **2020**, *19*, 3064–3076. [\[CrossRef\]](#)
36. Liu, K.; Zhang, Z.; Dai, L.; Xu, S.; Yang, F. Active Reconfigurable Intelligent Surface: Fully-Connected or Sub-Connected? *IEEE Commun. Lett.* **2022**, *26*, 167–171. [\[CrossRef\]](#)
37. Wu, Q.; Zhang, R. Intelligent Reflecting Surface Enhanced Wireless Network via Joint Active and Passive Beamforming. *IEEE Trans. Wirel. Commun.* **2019**, *18*, 5394–5409. [\[CrossRef\]](#)
38. Lončar, J.; Grbic, A.; Hrabar, S. Ultrathin active polarization-selective metasurface at X-band frequencies. *Phys. Rev. B* **2019**, *100*, 075131. [\[CrossRef\]](#)
39. Kishor, K.K.; Hum, S.V. An Amplifying Reconfigurable Reflectarray Antenna. *IEEE Trans. Antennas Propag.* **2012**, *60*, 197–205. [\[CrossRef\]](#)
40. Ntontin, K.; Song, J.; Renzo, M.D. Multi-Antenna Relaying and Reconfigurable Intelligent Surfaces: End-to-End SNR and Achievable Rate. *arXiv* **2019**. [\[CrossRef\]](#)
41. Tasci, R.A.; Kilinc, F.; Basar, E.; Alexandropoulos, G.C. A New RIS Architecture With a Single Power Amplifier: Energy Efficiency and Error Performance Analysis. *IEEE Access* **2022**, *10*, 44804–44815. [\[CrossRef\]](#)

42. Chen, S.; Gu, J.; Duan, W.; Ho, P.-H. Hybrid RIS-Assisted Communications: Optimal Allocation Under a Total Power Constraint. *IEEE Internet Things J.* **2025**, *12*, 2283–2286. [[CrossRef](#)]
43. Bousquet, J.-F.; Magierowski, S.; Messier, G.G. A 4-GHz Active Scatterer in 130-nm CMOS for Phase Sweep Amplify-and-Forward. *IEEE Trans. Circuits Syst. I Regul. Pap.* **2012**, *59*, 529–540. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.