

Resource Allocations for Active RIS Empowered Satellite-Terrestrial RSMA Networks

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Abstract: This paper studies an active reconfigurable intelligent surface (ARIS) empowered multiple-input single-output (MISO) downlink satellite-terrestrial network (STN) with a rate splitting multiple access (RSMA) scheme. The system comprises a satellite (SAT) equipped with multiple antennas, an ARIS with multiple reflecting elements, and multiple users adopting a power splitting architecture. Aiming to maximize the system spectral efficiency (SE), this paper focuses on the joint optimization of active beamforming of SAT, active phase shift matrix of ARIS, and power-splitting (PS) ratio of multiple terrestrial users. The formulated SE maximization problem is non-convex due to these coupled variables. To deal with it, we first propose an alternating optimization (AO) algorithm to jointly design active beamformers of SAT and ARIS, as well as PS ratio. Specifically, the AO framework decomposes the original problem into two subproblems. One subproblem optimizes the active beamformers of SAT and PS ratio while keeping the phase shifts of ARIS fixed, which can be efficiently solved by convex optimization techniques. The other subproblem optimizes the active phase shift matrix of ARIS with fixed SAT beamformers and PS ratio, which is tackled using semi-definite relaxation (SDR). Finally, numerical results are presented to verify the performance of the proposed algorithm.

Key words: spectral efficiency (SE); rate-splitting multiple access (RSMA); active reconfigurable intelligent surface (ARIS); satellite (SAT); alternating optimization (AO).

1 Introduction

With the exponential growth of wireless traffic demands and the escalating density of terminal devices,

conventional multiple access techniques face severe challenges in spectral efficiency (SE) bottlenecks and exacerbated multi-user interference. In this context,

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Manuscript received: 2025-8-31; revised: 2025-12-2; accepted: 2026-1-20

rate-splitting multiple access (RSMA) has emerged as a highly promising candidate for sixth generation (6G) network architectures^[1]. The core advantage of RSMA is to significantly improve system robustness in imperfect channel state information (CSI) scenarios through a hierarchical interference management mechanism^[2].

Existing studies demonstrated that in practical communication environments where transmitters cannot acquire perfect CSI, RSMA dynamically reconstructs multi-user interference, effectively reduces residual interference, and improves transmission reliability, thereby outperforming traditional techniques by substantial margins^[1–6]. The RSMA scheme involves message splitting at the transmitter, where user data is partitioned into a universally accessible common stream and multiple dedicated private streams. The common stream, superimposed with all users' private streams via superposition coding, is broadcast to all receivers. At the receiver, successive interference cancellation (SIC) is employed to first decode the common stream and subsequently eliminate its interference on the private streams. This design aims to reconstructs interference energy rather than passively suppressing it, markedly improving signal decoding success rates in multi-user scenarios^[2]. Moreover, RSMA dynamically optimizes the power allocation ratio between common and private streams based on real-time CSI and quality-of-service (QoS) requirements. In particular, in high-density user environments or under strong interference conditions, increasing the power allocated to the common stream enhances decoding ability of shared interference, reducing reliance on accurate channel estimation^[3]. Such flexibility enables RSMA to adapt to rapidly time-varying channels and heterogeneous user distributions. In Ref. [4], the authors demonstrated that RSMA serves as a more universal and powerful transmission framework in multi-antenna systems. By partially decoding interference, RSMA synergistically combines the advantages of non-orthogonal multiple access (NOMA) and space-division multiple access (SDMA)^[5], achieving superior SE and energy efficiency (EE) across diverse scenarios. As a unified framework that outperforms conventional multiple access schemes^[6], RSMA exhibited significant potential in addressing 6G network requirements, including ultra-high throughput, ultra-low latency, ultra-high reliability, and massive connectivity.

With its multidimensional performance advantages, the potential of RSMA in multi-user multiple-input single-output (MU-MISO) systems has become a focus of academic research^[7–13]. In Ref. [7], the authors investigated the sum-rate maximization problem using a successive convex approximation (SCA) algorithm and systematically compared RSMA with conventional schemes such as NOMA and SDMA in MU-MISO scenarios. These results revealed that under maximum transmit power constraints or dense user deployments, RSMA achieved significantly higher sum rates. Furthermore, Ref. [8] explored the synergistic optimization of SE and EE in RSMA systems, uncovering its inherent potential to balance performance metrics under varying network loads. Additionally, RSMA presented a unique value in enhancing EE^[9–11] and communication security^[12,13]. As demonstrated in Ref. [9], RSMA outperforms multi-user linear precoding (MU-LP) and NOMA in terms of spectral and EE. Meanwhile, the study in Ref. [10] showed that RSMA can achieve significant performance gains over conventional SDMA and NOMA schemes with much lower computational complexity. Furthermore, the work in Ref. [11] highlighted the effectiveness of RSMA in enhancing EE and ensuring secure information transfer in practical communication systems. RSMA is also a promising technique for enhancing secure spectrum sharing and physical layer security in wireless communications. In Ref. [12], the authors proposed a unified RSMA framework with joint precoding optimization to secure spectrum sharing in cognitive radio networks, improving private message security for primary and secondary users. Moreover, Ref. [13] presented the outage and secrecy outage performance results of RSMA systems with untrusted users, highlighting the impact of different decoding strategies on system performance.

On the other hand, reconfigurable intelligent surfaces (RISs) have garnered significant attention from academia and industry as an emerging wireless communication technology with the remarkable potential to enhance system performance. RIS comprises an array of programmable reflecting elements capable of dynamically manipulating the propagation direction and phase of incident electromagnetic waves. This enables the control over wireless signal propagation, offering advantages such as extended coverage, improved transmission

reliability, and superior SE and EE^[14–16]. With the operational mechanisms, RIS architectures are categorized into passive RIS (PRIS) and active RIS (ARIS): PRIS optimizes signal paths solely through phase shift adjustments, whereas ARIS incorporates low-noise amplifiers to jointly regulate signal phase and amplitude, effectively mitigating dual-path fading effects in cascaded channels^[17]. Unlike conventional radio frequency (RF) relays, RIS operates without decoding or regenerating received signals, relying upon programmable metamaterial units to redirect electromagnetic waves. This significantly reduces hardware costs and operational power consumption^[18].

In addition, the lightweight design of RIS can support the flexible deployment on the surface of urban infrastructure or indoor, providing a scalable solution for signal coverage enhancement in complex electromagnetic environments^[19–21]. RIS can achieve EE maximization through joint optimization of transmit beamforming and RIS phase shifts^[19]. Additionally, in Ref. [20] an RIS phase matrix optimization method was proposed for the downlink MISO system based on signal-to-noise ratio (SNR) maximization, demonstrating its capability to amplify signals in high-path-loss scenarios. Extending to multi-user multiple-input multiple-output (MU-MIMO) systems, Ref. [21] investigated the application of passive beamforming and information transmission techniques, revealing that RIS optimizes primary communication links via passive beamforming while modulating reflected signals to transmit additional information, thereby maximizing the sum rate of RIS-assisted multi-user MIMO channels. Current research has extensively explored RIS-aided transmission designs across diverse domains, including RSMA networks^[22], NOMA networks^[23], millimeter-wave networks^[24], satellite (SAT) communications^[25], unmanned aerial vehicle (UAV) communications^[26], and vehicle-to-everything (V2X) communications^[27], underscoring its broad applicability and research value.

However, PRIS suffers from the “multiplicative fading effect”, where the end-to-end path loss is equal to the product of the transmitter-RIS and RIS-receiver link losses rather than their linear summation. This results in substantially weaker reflected signals compared to direct links, severely limiting the potential of RIS capacity in the scenarios dominated by direct paths^[28]. To overcome this limitation, Ref. [28] introduced the ARIS architecture, which

integrates active amplification circuits into reflecting elements to jointly adjust signal phase and amplitude. ARIS transformed multiplicative fading into additive fading via active signal gain compensation, achieving significant capacity gains regardless of direct link strength^[29]. Furthermore, Ref. [30] proposed an ARIS phase shift design for multi-antenna NOMA systems, outperforming PRIS benchmarks in achievable rates. Additionally, Ref. [31] revealed that ARIS enhances secrecy rates in cognitive SAT-terrestrial integrated networks through dynamic interference suppression and beamforming optimization. These further demonstrated that ARIS can efficiently overcome “multiplicative fading effect” and effectively enhance signal coverage and quality. Despite the promising advantages of ARIS, its practical deployment faces several key challenges, including hardware complexity, increased power consumption, and the amplification of inherent noise due to the integration of active components like low-noise amplifiers across a large array. To address these issues, existing research primarily focuses on two fronts. First, at the hardware level, the authors in Ref. [29] explored to balance amplification gain with power consumption and cost. Secondly, at the signal processing level, the mainstream approach involves the joint optimization of the ARIS reflection matrix with the transmit beamforming at the base station or SAT^[31]. This joint optimization is crucial to coordinately manage the amplified signals and noise, thereby transforming the “multiplicative fading” into a beneficial “additive gain”.

While the large-scale deployment of 6G Internet of Things (IoT) has significantly increased device connection density, it has exacerbated the dual challenges of spectrum scarcity and energy supply constraints. To tackle this synergetic issue, simultaneous wireless information and power transfer (SWIPT) technology has been proposed, which provides a cooperative transmission of information decoding (ID) and energy harvesting (EH) through shared wireless channels, offering a novel paradigm for joint spectrum-energy efficiency optimization^[32]. However, existing studies predominantly rely on simplified linear EH models, which fail to account for the nonlinear characteristics of radio frequency-to-direct current (RF-DC) power conversion, leading to mismatches between resource allocation strategies and actual hardware responses^[33]. It introduced a logistic function-based nonlinear EH model that

accurately captures saturation effects in energy conversion efficiency across wide input power ranges, establishing a more practical foundation for SWIPT system optimization. This model has been validated in diverse scenarios. Particularly, Ref. [34] investigated a full-duplex cooperative NOMA system with nonlinear EH, while Ref. [35] applied it to maximize the total throughput of wireless-powered NOMA networks. These studies demonstrated the substantial potential of nonlinear EH models for enhancing SWIPT system performance and resource allocation.

Recently, the potential integration of 6G techniques and SAT communications has become more attractive in academic community due to its advanced highlights such as wide coverage, long transmission distance, flexible networking, high reliability and mobility^[36]. Compared to terrestrial systems, SAT communications exhibited irreplaceable advantages in remote area coverage, emergency communications, and similar scenarios. In this context, integrating emerging technologies with SAT communications has gained momentum. In Ref. [37], the authors proposed an RIS-assisted SAT channel optimization framework, validating its effectiveness in improving channel capacity. Furthermore, Ref. [38] explored EE optimization mechanisms for the RSMA in multi-beam SAT multicast scenarios, highlighting its technical superiority in dense-user interference coordination. Despite the unique advantages of RSMA in interference management and ARIS in signal enhancement, their synergistic optimization in SAT communications remains understudied.

Inspired by the aforementioned research motivation, this work presents a MU-MISO SAT communication system with ARIS-empowered RSMA framework, incorporating a realistic nonlinear EH model to better align with hardware characteristics and improve EF efficiency. The main contributions of this work are summarized as follows:

- We establish a comprehensive MISO system model comprising SAT, ARIS, and multiple users, considering rician fading, shadowing effects, and nonlinear EH characteristics. To examine the performance of the system under consideration, we aim to maximize SE to jointly design SAT beamforming vectors, ARIS phase shift matrices, and user power-splitting (PS) ratios.
- To address the inherent non-convex optimization

problem, we propose an alternating optimization (AO) framework. This approach sequentially optimizes beamforming vectors at the SAT, PS ratios, and phase shifts at ARIS. By decomposing the problem into subproblems, each component is efficiently and accurately solved using convex optimization and semidefinite relaxation (SDR) techniques. In addition, we employ a penalty-based method to handle the rank-one constraint in the SDR problem and utilize AO to iteratively approximate the solution.

- Numerical results are demonstrated to verify that the proposed scheme achieves significantly higher SE compared to conventional multiple access techniques such as SDMA and NOMA. Moreover, ARIS-based designs outperform PRIS counterparts.

The remaining parts are organized as follows. The system architecture and mathematical formulation of the SE maximization problem are detailed in Section II. Building upon this foundation, Section III introduces an AO framework to rigorously derive the globally optimal solution to the formulated optimization problem. Subsequently, Section IV numerically assesses the effectiveness of the developed algorithm through comprehensive simulations. Finally, we conclude this paper in Section V.

Notations: Throughout the paper, a , $\mathbf{a}$, and $\mathbf{A}$ represent scalars, vectors, and matrices, respectively. We use $\mathbf{A}^*$, $\mathbf{A}^T$, $\mathbf{A}^H$, $\mathbf{A}^{-1}$ and $\text{Tr}(\mathbf{\Theta})$ to denote the conjugate, transpose, conjugate transpose, inverse and trace of matrix $\mathbf{A}$, respectively. $\text{diag}(\mathbf{A})$ denotes the main diagonal element of matrix $\mathbf{A}$. We use $\exp(\mathbf{A})$ and $\arg(\mathbf{A})$ to indicate the exponential function and the phase angle of matrix $\mathbf{A}$, respectively. $\mathbf{A} \succeq 0$ denotes $\mathbf{A}$ is a semi-positive definite matrix. Finally, $\Re\{\cdot\}$, $|\cdot|$ and $\|\cdot\|$ indicate the real part, the modulus, and euclidean norm representation of a complex number, respectively.

2 System Model

As indicated in Fig. 1, this paper investigates a MISO SAT communication system based on RSMA and ARIS. In particular, it consists of SAT equipped with N transmit antennas, ARIS with M reflective elements, and F single-antenna ground users, each adopting a PS architecture for ID and EH at the same time.

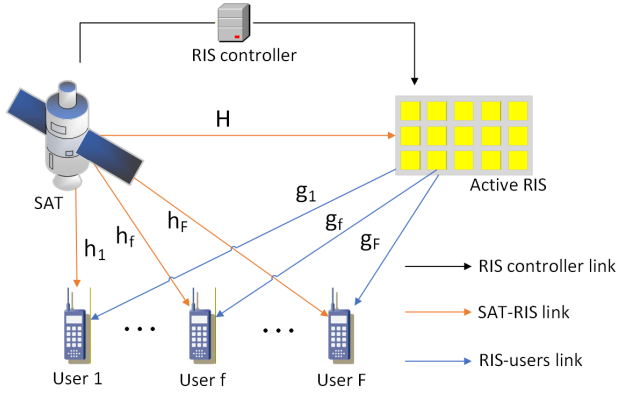


Fig. 1 An ARIS-assisted RSMA in SAT communications system.

2.1 Active RIS Model

Compared with the traditional PRIS, ARIS offer significant advantages. It can actively amplify reflected signals, effectively overcoming the “multiplicative fading effect” limitation in PRIS during communication^[28]. ARIS can achieve much higher capacity gain than PRIS under the same conditions, thus providing a more efficient solution for intelligent wireless channel control^[28].

The reflecting coefficient matrix of ARIS is denoted as $\Phi = \text{diag}(\varphi_1, \dots, \varphi_M) \in \mathbb{C}^{M \times M}$, where each $\varphi_m = \alpha_m e^{j\theta_m}$ with $\theta_m \in [0, 2\pi)$, and $\alpha_m \in [0, \alpha_{m,\max}]$ represents the phase shift and amplitude of the m -th reflection element, respectively^[39]. The parameter $\alpha_{m,\max}$ denotes the predefined maximum amplitude for the active load of the m -th reflecting element. Furthermore, SAT computes phase shift configurations through constrained optimization techniques, which are then transmitted to the RIS controller via a feedback channel. In addition, the channel vector from RIS to the f -th user is denoted as $\mathbf{g}_f \in \mathbb{C}^{M \times 1}$, the channel matrix from the SAT to the RIS is denoted as $\mathbf{H} \in \mathbb{C}^{M \times N}$, and the channel vector from the SAT to the f -th user is denoted as $\mathbf{h}_f \in \mathbb{C}^{N \times 1}$.

2.2 Channel Model

The direct path is obstructed by physical barriers, the impact of scattering remains non-negligible. To proceed, the direct channel $\mathbf{g}_f$ can be modeled using Rayleigh fading as described below^[20].

$$\mathbf{g}_f = \sqrt{L_0 d_{RIS,f}^{-\tilde{\alpha}_{RIS,f}}} \left(\sqrt{\frac{K_1}{K_1 + 1}} \mathbf{g}_f^L + \sqrt{\frac{1}{K_1 + 1}} \mathbf{g}_f^{NL} \right), \quad (1)$$

where L_0 represents the path loss at the distance of 1 m, while $d_{RIS,f}$ represents the distance between the RIS and the f -th user, and $\tilde{\alpha}_{RIS,f}$ denotes the path loss exponent. The rician factor K_1 quantifies the dominance of the line-of-sight (LOS) component, expressed as $\mathbf{g}_f^L = \exp(-j \frac{2\pi d_{RIS,f}}{\lambda}) [1, \exp(-j \frac{2\pi d}{\lambda} \cos \theta_{r,f}), \dots, \exp(-j \frac{2\pi (M-1)d}{\lambda} \cos \theta_{r,f})]$, where λ is the carrier wavelength, d denotes the inter-user distance, and $\theta_{r,f}$ is the angle of departure. The non-line-of-sight (NLOS) component $\mathbf{g}_f^{NL}$ follows a Rayleigh fading distribution.

In practice, it is assumed that the SAT-to-ground portion of the channel experiences the widely adopted shadowed-rician fading^[40]. Hence, the channel coefficient between the SAT and user $\mathbf{h}_f$ and the channel between the SAT and RIS $\mathbf{H}$ can be modeled as

$$\mathbf{h}_f = \sqrt{b(\omega_f)} \tilde{\mathbf{h}}_f, \mathbf{H} = \sqrt{b(\omega_{RIS})} \tilde{\mathbf{H}}. \quad (2)$$

with

$$b(\omega) = \left(\frac{J_1(u)}{2u} + 36 \frac{J_3(u)}{u^3} \right)^2, u = 2.07123 \frac{\sin \omega}{\sin \omega_{3dB}}, \quad (3)$$

$$\tilde{\mathbf{h}}_f = A \exp(j\psi_f) + Z \exp(j\phi_f), \quad (4)$$

$$\tilde{\mathbf{H}} = A \exp(j\psi_{RIS}) + Z \exp(j\phi_{RIS}),$$

where $b(\omega)$ is the associated beamforming gain factor, determined by its position, while ω is the angle between the center of the beam and the corresponding receiver, and ω_{3dB} is the 3-dB angle. The functions $J_1(u)$ and $J_3(u)$ respectively indicate the first-kind Bessel functions of orders 1 and 3. The channel fading vector from SAT to the f -th user is denoted as $\tilde{\mathbf{h}}_f \in \mathbb{C}^{N \times 1}$, while the channel fading matrix from SAT to RIS is expressed as $\tilde{\mathbf{H}} \in \mathbb{C}^{N \times M}$, encompassing both scattering components and LOS contributions. $\psi \in [0, 2\pi)$ corresponds to the stationary random phase of the LOS component, whereas ϕ denotes its deterministic phase offset. The signal magnitudes for both scattered and LOS paths are represented by A and Z , respectively.

2.3 Signal Model

As shown in Fig. 2, we study the RSMA structure at SAT, where SAT employs a message combiner and linear precoding to partition each user's message M_f into two components: a common stream $M_{a,f}$ accessible for demodulation at every receiver node and a private stream $M_{q,f}$ designated for specific users. The common streams $\{M_{a,0}, \dots, M_{a,F}\}$ are aggregated into a unified common message M_a , which is modulated

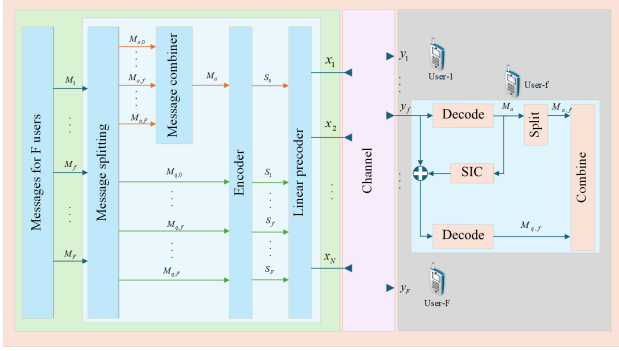


Fig. 2 Transceiver architecture of RSMA.

into a common broadcast waveform S_0 employing a universally accessible codebook among all receivers. Conversely, the private streams $\{M_{q,0}, \dots, M_{q,F}\}$ are independently encoded into user-specific signals $\{S_1, \dots, S_F\}$, exclusively decoded by their intended users. The composite transmit signal $\mathbf{S} = [S_0, S_1, \dots, S_F] \in \mathbb{C}^{(F+1) \times 1}$ is then precoded via a beamforming matrix $\mathbf{W} = [\mathbf{w}_a, \mathbf{w}_1, \dots, \mathbf{w}_F]^T \in \mathbb{C}^{N_s \times (L+1)}$, where $\mathbf{w}_a$ and $\mathbf{w}_f \in \mathbb{C}^{N \times 1}$ denote the precoded vectors for the common and the private signals, respectively. Therefore, the transmitted signal is represented as

$$\mathbf{x} = \mathbf{w}_a S_0 + \sum_{f=1}^F \mathbf{w}_f S_f. \quad (5)$$

Also, the observed signal at the f -th user is given by

$$y_f = (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{x} + \mathbf{g}_f^H \Phi \mathbf{n}_r + n_f, \quad (6)$$

where $\mathbf{n}_r \sim \mathcal{CN}(0, \sigma_r^2 \mathbf{I})$ represents the effective noise at RIS, and $n_f \sim \mathcal{CN}(0, \sigma_f^2)$ denotes the AWGN at the f -th user.

Under the PS protocol, the captured signal at every user is partitioned into two branches by a PS ratio $\varepsilon_f \in (0, 1)$, directed to the ID and EH modules, respectively. The signals received by the ID and EH modules are expressed as $y_f^{ID} = \sqrt{\varepsilon_f} y_f + v_f$ and $y_f^{EH} = \sqrt{1 - \varepsilon_f} y_f$, where $v_f \sim \mathcal{CN}(0, \delta_f^2)$ represents the additive circuit noise at the ID module. Initially, the ID module decodes the common signal S_a while treating all private signals as interference. Consequently, the signal-to-interference-plus-noise ratio (SINR) for decoding S_a at the f -th user is written as:

$$\xi_{a,f} = \frac{\varepsilon_f |(\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{w}_a|^2}{\varepsilon_f \left(\sum_{i=1}^F |(\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{w}_i|^2 + \|\mathbf{g}_f^H \Phi\|^2 \sigma_r^2 + \sigma_f^2 \right) + \delta_f^2}. \quad (7)$$

Upon successfully decoding the common stream S_a , the receiver employs a SIC process to remove S_a from

the received signal. Subsequently, the receiver proceeds to decode its private stream S_f , treating all the other private streams as interference. The SINR for decoding the private stream S_f at the f -th user's ID module is expressed as

$$\xi_f = \frac{\varepsilon_f |(\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{w}_f|^2}{\varepsilon_f \left(\sum_{i=1, i \neq f}^F |(\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{w}_i|^2 + \|\mathbf{g}_f^H \Phi\|^2 \sigma_r^2 + \sigma_f^2 \right) + \delta_f^2}. \quad (8)$$

The achievable rate corresponding to the common stream S_a and the private stream S_f at the f -th user are denoted as $V_{a,f} = \log_2(1 + \xi_{a,f})$ and $V_f = \log_2(1 + \xi_f)$, respectively. To guarantee correct recovery of S_a at every user, the common rate V_a must satisfy $V_a = \min\{V_{a,1}, \dots, V_{a,F}\}$. The maximum information rate supported by the network, defined as the sum of V_a and all private rates, is expressed as

$$\eta(\mathbf{W}, \Phi, \varepsilon_f) = V_a + \sum_{f=1}^F V_f, \text{ (bit/s/Hz)}. \quad (9)$$

In existing studies, the energy harvested at the f -th user conventionally derived by the linear model^[33], given by

$$E_f^{linear} = \eta_f E_f^{in}, \forall f, \quad (10)$$

where η_f denotes the constant energy conversion efficiency, with $\eta_f \in (0, 1]$ and $E_f^{in} = (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{W}^2 + \mathbf{g}_f^H \Phi^2 \sigma_r^2 + \sigma_f^2$. However, such linear approximations fail to capture the nonlinear saturation characteristics inherent in practical EH circuits. To address this limitation, we implement a more practical nonlinear EH model, as introduced in [33], diverging from the traditional linear model. This nonlinear EH model is represented by a logistic function, expressed as

$$E_f = \frac{\chi(E_f^{in}) - \Omega_f \Gamma_f}{1 - \Gamma_f}, \forall f, \quad (11)$$

where $\Gamma_f = \frac{1}{1 + e^{a_f b_f}}$ and $\chi(E_f^{in}) = \frac{\Omega_f}{1 + e^{-a_f (E_f^{in} - b_f)}}$. Ω_f represents the maximum harvestable power at the f -th user's EH module, while a_f and b_f are circuit-specific constants. In practical scenarios, for a given EH hardware circuit, these fixed parameters Ω_f , a_f and b_f can be determined using conventional curve regression analysis methods^[33]. Specifically, a_f dictates the transition steepness of the logistic function, controlling the sharpness of the switch from the linear region to the saturation region. b_f is intrinsically linked to the circuit's turn-on sensitivity, effectively

marking the input power level at which the EH circuit becomes operational and reaches half of maximum output power. Collectively, these parameters enable the model to replicate the key non-linear behavior of practical EH circuits, thereby providing a solid foundation for resource allocation.

2.4 Problem Formulation

To evaluate the overall performance of the system under consideration, we aim to construct a SE maximization problem, with respect to the reflection coefficient matrix of RIS, beamforming of SAT, and PS ratio. This optimization problem is formulated as

$$\max_{\mathbf{W}, \Phi, \varepsilon_f} \eta(\mathbf{W}, \Phi, \varepsilon_f), \quad (12a)$$

$$s.t. \quad \|\mathbf{W}\|_F^2 \leq P_{s,\max}, \quad (12b)$$

$$\|\Phi \mathbf{H} \mathbf{W}\|_F^2 + \sigma_r^2 \|\Phi\|_F^2 \leq P_{r,\max}, \quad (12c)$$

$$|[\Phi]_m| \leq \alpha_{m,\max}, \forall m, \quad (12d)$$

$$V_a \geq V_{a,\min}, \quad (12e)$$

$$E_f \geq e_f, \forall f, \quad (12f)$$

$$0 < \varepsilon_f < 1, \forall f, \quad (12g)$$

where $P_{s,\max}$ and $P_{r,\max}$ represent the maximum transmission power available at SAT and the forward power at RIS, respectively. Furthermore, $[\Phi]_m$ represents the m -th element of the phase shift matrix Φ , with $[\Phi]_m = \varphi_m$. The parameter $V_{a,\min}$ corresponds to the predefined minimum rate for the common message, and e_f represents the minimum acceptable power for the f -th user. Constraints (12b) and (12c) impose the power limits on SAT and RIS, and set an upper bound on the maximum reflection power, respectively. Constraint (12e) ensures the minimum total rate for the f -th user, while constraint (12g) ensures valid PS ratios. However, due to the coupled nature of the variables $\mathbf{W}$, Φ and ε_f , Problem 12 is non-convex, which cannot be directly solved.

3 The Solution to Solve Problem (12)

To address 12, this section investigates an AO framework that systematically decouples the joint optimization problem into two tractable subproblems. In the first subproblem, we optimize the SAT beamforming vectors and user PS ratio while maintaining fixed the ARIS phase shifts, leveraging convex optimization methods for an efficient solution. The second subproblem focuses on optimizing the ARIS phase shift matrix with predetermined beamforming vectors and PS ratio, where we employ the SDR techniques coupled with a penalty-based

approach to ensure the rank-one constraint satisfaction. These subproblems alternately update the SAT beamforming vectors $\mathbf{W}$, ARIS phase shift matrix Φ , and PS ratio ε_f until convergence, achieving near-optimal SE performance.

To proceed, we first explore the lower bound approximation of $V_{a,f}$ and V_f . Specifically, during the t -th iteration, given the current feasible points $\mathbf{W}^{(t)}$, $\Phi^{(t)}$ and $\varepsilon_f^{(t)}$, Lemma 1 is presented to tractably approximate $V_{a,f}$ and V_f .

Lemma 1^[31]: For any feasible variables ν and λ , the following inequality holds

$$\log_2 \left(1 + \frac{|\nu|^2}{\lambda} \right) \geq \log_2 \left(1 + \frac{|\hat{\nu}|^2}{\hat{\lambda}} \right) - \frac{|\hat{\nu}|^2}{\hat{\lambda} \ln 2} + \frac{2\Re\{\hat{\nu}^* \hat{\nu}\}}{\hat{\lambda} \ln 2} - \frac{|\hat{\nu}|^2(\lambda + |\hat{\nu}|^2)}{\hat{\lambda}(\hat{\lambda} + |\hat{\nu}|^2) \ln 2}, \quad (13)$$

where $\{\hat{\nu}, \hat{\lambda}\}$ denote the fixed points.

Upon Lemma 1, the lower bound of $V_{a,f}$ is derived as

$$V_{a,f} \geq \log_2 \left(1 + \frac{|a_f^{(t)}|^2}{b_f^{(t)}} \right) - \frac{|a_f^{(t)}|^2}{b_f^{(t)} \ln 2} + \frac{2\Re\{(a_f^{(t)})^* a_f\}}{b_f^{(t)} \ln 2} - \frac{|a_f^{(t)}|^2 (b_f + |a_f|^2)}{b_f^{(t)} (b_f^{(t)} + |a_f^{(t)}|^2) \ln 2}, \quad (14)$$

where $a_f^{(t)} = (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi^{(t)} \mathbf{H}) \mathbf{w}_a^{(t)}$, $a_f = (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{w}_a$, $b_f^{(t)} = \sum_{i=1}^F |(\mathbf{h}_f^H + \mathbf{g}_f^H \Phi^{(t)} \mathbf{H}) \mathbf{w}_i^{(t)}|^2 + \mathbf{g}_f^H \Phi^{(t)2} \sigma_r^2 + \sigma_f^2 + \frac{\delta_f^2}{\varepsilon_f^{(t)}}$, $b_f = \sum_{i=1}^F |(\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{w}_i|^2 + \mathbf{g}_f^H \Phi^2 \sigma_r^2 + \sigma_f^2 + \frac{\delta_f^2}{\varepsilon_f}$.

Similarly, the lower bound of V_f is derived as

$$V_f \geq \log_2 \left(1 + \frac{|c_f^{(t)}|^2}{b_f^{(t)} - |c_f^{(t)}|^2} \right) - \frac{|c_f^{(t)}|^2}{(b_f^{(t)} - |c_f^{(t)}|^2) \ln 2} + \frac{2\Re\{(c_f^{(t)})^* c_f\}}{(b_f^{(t)} - |c_f^{(t)}|^2) \ln 2} - \frac{|c_f^{(t)}|^2 b_f}{b_f^{(t)} (b_f^{(t)} - |c_f^{(t)}|^2) \ln 2}, \quad (15)$$

where $c_f^{(t)} = (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi^{(t)} \mathbf{H}) \mathbf{w}_f^{(t)}$, and $c_f = (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{w}_f$.

We substitute approximated reformulations (14) and (15) into (12a) to reformulate problem (12) as

$$\begin{aligned} \max_{\mathbf{W}, \Phi, \varepsilon_f} V_a + \sum_{f=1}^F \left\{ \frac{2\Re\left\{\left(c_f^{(t)}\right)^* (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{w}_f\right\}}{\left(b_f^{(t)} - |c_f^{(t)}|^2\right) \ln 2} + \log_2 \left(1 + \frac{|c_f^{(t)}|^2}{b_f^{(t)} - |c_f^{(t)}|^2}\right) - \frac{|c_f^{(t)}|^2}{\left(b_f^{(t)} - |c_f^{(t)}|^2\right) \ln 2} \left(1 + \frac{\sigma_f^2}{b_f^{(t)}}\right) - \frac{|c_f^{(t)}|^2 \left(\sum_{i=1}^F |(\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{w}_i|^2 + \mathbf{g}_f^H \Phi^2 \sigma_r^2 + \frac{\delta_f^2}{\varepsilon_f}\right)}{b_f^{(t)} \left(b_f^{(t)} - |c_f^{(t)}|^2\right) \ln 2} \right\} \end{aligned} \quad (16a)$$

$$\begin{aligned} \text{s.t. } V_a \leq & \frac{2\Re\left\{\left(a_f^{(t)}\right)^* (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{w}_0\right\}}{b_f^{(t)} \ln 2} \\ & + \log_2 \left(1 + \frac{|a_f^{(t)}|^2}{b_f^{(t)}}\right) - \frac{|a_f^{(t)}|^2}{b_f^{(t)} \ln 2} \left(1 + \frac{\sigma_f^2}{b_f^{(t)} + |a_f^{(t)}|^2}\right) \\ & - \frac{|a_f^{(t)}|^2 \left(\|(\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{W}\|^2 + \|\mathbf{h}_f^H \Phi\|^2 \sigma_r^2 + \frac{\delta_f^2}{\varepsilon_f}\right)}{b_f^{(t)} \left(b_f^{(t)} + |a_f^{(t)}|^2\right) \ln 2} \end{aligned} \quad (16b)$$

$$(12b - (12g)) \quad (16c)$$

To further make (16) tractable, constraint (12f) is equivalent to

$$E_f^{in} \geq b_f - \frac{1}{a_f} \ln \left(\frac{M_f}{M_f \Gamma_f + (1 - \Gamma_f) e_f} - 1 \right). \quad (17)$$

Subsequently, we transform (17) into the following constraint

$$\|(\mathbf{h}_f^H + \mathbf{g}_f^H \Phi \mathbf{H}) \mathbf{W}\|^2 + \sigma_r^2 \|\mathbf{g}_f^H \Phi\|^2 + \sigma_f^2 \geq \frac{\tau_f}{1 - \varepsilon_f}. \quad (18)$$

where $\tau_f = b_f - \frac{1}{a_f} \ln \left(\frac{\Omega_f}{M_f \Gamma_f + (1 - \Gamma_f) e_f} - 1 \right)$.

In practice, the SE of RSMA networks can be effectively optimized by solving problem (16). However, problem (16) is non-convex with respect to the joint optimization variables $\mathbf{W}$, Φ and ε_f . Nevertheless, the problem can be decomposed into two subproblems with reduced coupling complexity. To deal with this issue, we adopt an AO algorithm to derive near-optimal solutions in an alternating fashion.

3.1 Given Φ , optimize $\mathbf{W}$ and ε_f

This subsection aims to address problem (16) with respect to $\mathbf{W}$ and ε_f for given Φ , which is further

written as

$$\max_{\mathbf{W}, \varepsilon_f} V_a + \sum_{f=1}^F \left\{ 2\Re\{\mathbf{q}_f^H \mathbf{w}_f\} - \mathbf{w}_f^H \mathbf{Q} \mathbf{w}_f + q_f - \frac{\tilde{q}_f}{\varepsilon_f} \right\}, \quad (19a)$$

$$\text{s.t. } V_a \leq -\text{Tr}(\mathbf{P}_f \mathbf{W} \mathbf{W}^H) + 2\Re\{\mathbf{p}_f^H \mathbf{w}_a\} + p_f - \frac{\tilde{p}_f}{\varepsilon_f}, \forall f, \quad (19b)$$

$$\text{Tr}(\mathbf{R}_f \mathbf{W} \mathbf{W}^H) + \sigma_r^2 \|\mathbf{g}_f^H \Phi\|^2 + \sigma_f^2 \geq \frac{\tau_f}{1 - \varepsilon_f}, \quad (19c)$$

$$(12b)(12c)(12e)(12g), \quad (19d)$$

where $\{\mathbf{q}_f^H, \mathbf{Q}, q_f, \tilde{q}_f, \mathbf{P}_f, \mathbf{p}_f^H, p_f, \tilde{p}_f, \mathbf{R}_f\}$ are given by (20) in the top of the next page, respectively.

Given a fixed phase shift matrix Φ , the objective function of problem (19) becomes convex w.r.t. $\mathbf{W}$ and ε_f . The objective function $V_a + \sum_{f=1}^F \left\{ 2\Re\{\mathbf{q}_f^H \mathbf{w}_f\} - \mathbf{w}_f^H \mathbf{Q} \mathbf{w}_f + q_f - \frac{\tilde{q}_f}{\varepsilon_f} \right\}$ retains concavity, because each term in it is concave. Consequently, the optimal beamforming vectors $\mathbf{W}$ and power splitting ratio ε_f can be efficiently solved using the CVX toolbox^[41].

3.2 Given $\mathbf{W}$ and ε_f , optimize Φ

Fixing $\mathbf{W}$ and ε_f , this subsection focuses on optimizing the phase shift matrix Φ by solving problem (16). The transformed formula is shown as

$$\begin{aligned} \max_{\Phi} V_a + \sum_{f=1}^F \left\{ 2\Re\{T_f(\mu_{f,f} + \varphi^H v_{f,f})\} + t_f \right. \\ \left. - U_f \left(\sum_{i=1}^F |(\mu_{f,i} + \varphi^H v_{f,i})|^2 + \varphi^H \mathbf{D}_f \varphi \sigma_r^2 \right) \right\}, \end{aligned} \quad (21a)$$

$$\begin{aligned} \text{s.t. } V_a \leq 2\Re\{\mathbf{S}_f(\mu_{f,0} + \varphi^H v_{f,0})\} + u_f \\ - P_f \left(\sum_{i=0}^F |(\mu_{f,i} + \varphi^H v_{f,i})|^2 + \varphi^H \mathbf{D}_f \varphi \sigma_r^2 \right), \end{aligned} \quad (21b)$$

$$\sum_{i=0}^F \varphi^H \mathbf{J}_i \varphi + \sigma_r^2 \varphi^H \varphi \leq P_{r,\max}, \quad (21c)$$

$$\sum_{i=0}^F |(\mu_{f,i} + \varphi^H v_{f,i})|^2 \varphi^H \mathbf{D}_f \varphi \sigma_r^2 + \sigma_f^2 \geq \frac{\tau_f}{1 - \varepsilon_f}, \quad (21d)$$

$$(12e), |[\varphi]_m| \leq \alpha_{m,\max}, \forall m, \quad (21e)$$

First, let us define the phase shift vector as $\varphi = [\varphi_1, \dots, \varphi_M]^H$, and denote variable substitutions $\mu_{f,i} = \mathbf{h}_f^H \mathbf{w}_i$, $v_{f,i} = \text{diag}(\mathbf{g}_f^H \mathbf{H} \mathbf{w}_i)$, $\mathbf{J}_i = \text{diag}(\mathbf{H} \mathbf{w}_i)$, $\mathbf{D}_f = \text{diag}(\mathbf{g}_f^H) \text{diag}(\mathbf{g}_f)$, problem (16)

$$\mathbf{Q} = \sum_{f=1}^F \frac{|c_f^{(t)}|^2 (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi^{(t)} \mathbf{H})^H (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi^{(t)} \mathbf{H})}{b_f^{(t)} (b_f^{(t)} - |c_f^{(t)}|^2) \ln 2}, \quad \mathbf{q}_f^H = \frac{(c_f^{(t)})^* (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi^{(t)} \mathbf{H})}{(b_f^{(t)} - |c_f^{(t)}|^2) \ln 2}, \quad (20a)$$

$$q_f = \log_2 \left(1 + \frac{|c_f^{(t)}|^2}{b_f^{(t)} - |c_f^{(t)}|^2} \right) - \frac{|c_f^{(t)}|^2}{(b_f^{(t)} - |c_f^{(t)}|^2) \ln 2} - \frac{|c_f^{(t)}|^2 (\sigma_r^2 \|\mathbf{g}_f^H \Phi\|^2 + \sigma_f^2)}{b_f^{(t)} (b_f^{(t)} - |c_f^{(t)}|^2) \ln 2}, \quad (20b)$$

$$\tilde{q}_f = \frac{|c_f^{(t)}|^2 \delta_f^2}{b_f^{(t)} (b_f^{(t)} - |c_f^{(t)}|^2) \ln 2}, \quad \mathbf{R}_f = (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi^{(t)} \mathbf{H})^H (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi^{(t)} \mathbf{H}), \quad (20c)$$

$$\mathbf{P}_f = \frac{|a_f^{(t)}|^2 (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi^{(t)} \mathbf{H})^H (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi^{(t)} \mathbf{H})}{b_f^{(t)} (b_f^{(t)} + |a_f^{(t)}|^2) \ln 2}, \quad \mathbf{p}_f^H = \frac{(a_f^{(t)})^* (\mathbf{h}_f^H + \mathbf{g}_f^H \Phi^{(t)} \mathbf{H})}{b_f^{(t)} \ln 2}, \quad (20d)$$

$$p_f = \log_2 \left(1 + \frac{|a_f^{(t)}|^2}{b_f^{(t)}} \right) - \frac{|a_f^{(t)}|^2}{b_f^{(t)} \ln 2} - \frac{|a_f^{(t)}|^2 (\|\mathbf{g}_f^H \Phi^{(t)}\|^2 \sigma_r^2 + \sigma_f^2)}{b_f^{(t)} (b_f^{(t)} + |a_f^{(t)}|^2) \ln 2}, \quad \tilde{p}_f = \frac{|a_f^{(t)}|^2 \delta_f^2}{b_f^{(t)} (b_f^{(t)} + |a_f^{(t)}|^2) \ln 2}. \quad (20e)$$

is further reformulated with respect to Φ for given $\mathbf{W}$ and ϵ_f . And $\{T_f, U_f, t_f, \mathbf{S}_f, u_f, P_f\}$ are given by (23) in the top of the next page, respectively.

Problem (21) is still non-convex due to its quadratic inequality and equality constraints. To tackle this issue, we adopt the SDR to transform (21) into a convex formulation. Specifically, we define auxiliary matrices $\tilde{\varphi}^H = [\varphi^H \ 1]$, $\tilde{\mathbf{T}}_{f,i} = [v_{f,i} v_{f,i}^H, v_{f,i} \mu_{f,i}^H; v_{f,i}^H \mu_{f,i}, \mu_{f,i} \mu_{f,i}^H]$, $\tilde{\mathbf{T}}_{f,f} = [0, v_{f,f}; 0, \mu_{f,f}]$. Moreover, we formulate $\Theta = \tilde{\varphi} \tilde{\varphi}^H$, which must satisfy $\Theta \geq 0$ and $\text{rank}(\Theta) = 1$. By relaxing the rank-one non-convex constraint, problem (21) is reformulated as

$$\max_{\Theta} V_a + \sum_{f=1}^F \left\{ 2\Re\{T_f \text{Tr}(\tilde{\mathbf{T}}_{f,f} \Theta)\} + t_f \right. \quad (22a)$$

$$\left. - U_f \left(\sum_{i=1}^F \text{Tr}(\tilde{\mathbf{T}}_{f,i} \Theta) + \sigma_r^2 \text{Tr}(\tilde{\mathbf{D}}_f \Theta) \right) \right\}, \quad (22a)$$

$$\text{s.t. } V_a \leq 2\Re\{\mathbf{S}_f(\text{Tr}(\tilde{\mathbf{T}}_{f,0} \Theta))\} + u_f$$

$$- P_f \left(\sum_{i=0}^F \text{Tr}(\tilde{\mathbf{T}}_{f,i} \Theta) + \sigma_r^2 \text{Tr}(\tilde{\mathbf{D}}_f \Theta) \right), \quad (22b)$$

$$\sum_{i=0}^F \text{Tr}(\tilde{\mathbf{J}}_i \Theta) + \sigma_r^2 (\text{Tr}(\Theta) - 1) \leq P_{r,\max}, \quad (22c)$$

$$\sum_{i=0}^F \text{Tr}(\tilde{\mathbf{T}}_{f,i} \Theta) + \sigma_r^2 \text{Tr}(\tilde{\mathbf{D}}_f \Theta) + \sigma_f^2 \geq \frac{\tau_f}{1 - \epsilon_f}, \quad (22d)$$

$$(12e), \Theta \geq 0, \Theta(m, m) \leq \alpha_{m,\max}, \quad (22e)$$

where $\tilde{\mathbf{J}}_i$ and $\tilde{\mathbf{D}}_f$ are matrices extended with additional zero rows and zero columns. The resulting problem (22)

is an SDP problem that can be solved by using CVX^[41].

By solving (22) with the SDR, the relaxed solution Θ does not necessarily satisfy the rank-one constraint, we thus propose a penalty-based strategy to approximate the near-optimal RIS phase configuration. Since Θ is constrained as a positive semidefinite matrix, it inherently satisfies $\text{Tr}(\Theta) \geq \lambda_{\max}(\Theta)$, where $\lambda_{\max}(\mathbf{X}) - \lambda_{\max}(\mathbf{Y}) \geq \nu$ denotes the maximum eigenvalue of Θ . Equality $\text{Tr}(\Theta) = \lambda_{\max}(\Theta)$ holds if and only if $\text{rank}(\Theta) = 1$. To enforce this property, we reformulate problem (22) by incorporating a penalty term $\alpha(\text{Tr}(\Theta) - \lambda_{\max}(\Theta))$.

$$\min_{\Theta} \alpha(\text{Tr}(\Theta) - \lambda_{\max}(\Theta)) - V_a - \sum_{f=1}^F \left\{ 2\Re\{T_f \text{Tr}(\tilde{\mathbf{T}}_{f,f} \Theta)\} \right. \quad (24a)$$

$$\left. + t_f - U_f \left(\sum_{i=1}^F \text{Tr}(\tilde{\mathbf{T}}_{f,i} \Theta) + \sigma_r^2 \text{Tr}(\tilde{\mathbf{D}}_f \Theta) \right) \right\}, \quad (24a)$$

$$\text{s.t. } (23b - 23e). \quad (24b)$$

where $\alpha \geq 0$ denotes the penalty factor, which must be sufficiently large to enforce $\text{Tr}(\Theta) = \lambda_{\max}(\Theta)$. However, since $\lambda_{\max}(\Theta)$ is a convex function, we reformulate problem (24) via an iterative approximation approach. Hence, the following lemma is required to facilitate this approximation.

Lemma 2^[42]: For any two positive semidefinite matrices $\mathbf{X}$ and $\mathbf{Y}$, the subsequent inequality holds

$$\lambda_{\max}(\mathbf{X}) - \lambda_{\max}(\mathbf{Y}) \geq \nu_{\max, \mathbf{Y}}^H (\mathbf{X} - \mathbf{Y}) \nu_{\max, \mathbf{Y}}, \quad (25)$$

where $\nu_{\max, \mathbf{Y}}$ represents the unit eigenvector corresponding to the maximum eigenvalue $\lambda_{\max}(\mathbf{X})$.

$$T_f = \frac{(c_f^{(t)})^*}{\left(b_f^{(t)} - |c_f^{(t)}|^2\right) \ln 2}, \quad U_f = \frac{|c_f^{(t)}|^2}{b_f^{(t)} \left(b_f^{(t)} - |c_f^{(t)}|^2\right) \ln 2}, \quad (23a)$$

$$t_f = \log_2 \left(1 + \frac{|c_f^{(t)}|^2}{b_f^{(t)} - |c_f^{(t)}|^2} \right) - \frac{|c_f^{(t)}|^2}{\left(b_f^{(t)} - |c_f^{(t)}|^2\right) \ln 2} \left(1 + \frac{\sigma_f^2}{b_f^{(t)}} + \frac{\delta_f^2}{\varepsilon_f^{(t)} b_f^{(t)}} \right), \quad (23b)$$

$$S_f = \frac{(a_f^{(t)})^*}{b_f^{(t)} \ln 2}, \quad P_f = \frac{|a_f^{(t)}|^2}{b_f^{(t)} \left(b_f^{(t)} + |a_f^{(t)}|^2\right) \ln 2}, \quad (23c)$$

$$u_f = \log_2 \left(1 + \frac{|a_f^{(t)}|^2}{b_f^{(t)}} \right) - \frac{|a_f^{(t)}|^2}{b_f^{(t)} \ln 2} \left(1 + \frac{\sigma_f^2}{b_f^{(t)} + |a_f^{(t)}|^2} + \frac{\delta_f^2}{\varepsilon_f^{(t)} \left(b_f^{(t)} + |a_f^{(t)}|^2\right)} \right). \quad (23d)$$

Upon Lemma 2, given a feasible $\Theta^{(j)}$ at the j -th iteration, $\lambda_{\max}(\Theta)$ can be approximated as

$$\lambda_{\max}(\Theta) \geq \lambda_{\max}(\Theta^{(j)}) + \nu_{\max, \Theta}^{(j)H} (\Theta - \Theta^{(j)}) \nu_{\max, \Theta}^{(j)}. \quad (26)$$

At the j -th iteration, the convex subproblem is reformulated as

$$\begin{aligned} \min_{\Theta} & \alpha (\text{Tr}(\Theta) - \lambda_{\max}(\Theta^{(j)}) - \nu_{\max, \Theta}^{(j)H} (\Theta - \Theta^{(j)}) \nu_{\max, \Theta}^{(j)}) \\ & - V_a - \sum_{f=1}^F \left\{ 2\Re\{T_f \text{Tr}(\tilde{\mathbf{T}}_{f,f} \Theta)\} \right. \\ & \left. + t_f - U_f \left(\sum_{i=1}^F \text{Tr}(\tilde{\mathbf{T}}_{f,i} \Theta) + \sigma_r^2 \text{Tr}(\tilde{\mathbf{T}}_k \Theta) \right) \right\}, \end{aligned} \quad (27a)$$

$$\text{s.t.} (23b - 23e). \quad (27b)$$

The convexity of (27) allows efficient solutions via the CVX toolbox^[41]. The overall penalty-based algorithm is outlined in Algorithm 1.

Algorithm 1 The Penalty-Function-Based Method for Approximating the Solution to the Problem (22).

- 1: **Input:** Penalty factor α_2 , tolerance value δ , and initial optimal solution Θ for problem (22).
- 2: **If** $\text{rank}(\Theta) = 1$, then proceed to step 10; **else**, continue to step 3.
- 3: Initialize iteration counter $j = 0$.
- 4: Iteration $\Theta^{(j)} = \Theta^{(*)}$.
- 5: **while** $\text{Tr}(\Theta) - \lambda_{\max}(\Theta) > \delta$ **do**
- 6: Compute $\Theta^{(*)}$ by solving problem (27) via CVX solver.
- 7: Update $\Theta^{(j+1)} = \Theta^{(*)}$ and $j = j + 1$ for subsequent iterations.
- 8: **end while**
- 9: **Output:** converged optimal solution $\Theta^{(j)}$ (i.e., $\Theta^{(*)}$).

3.3 Convergence of AO

Let us denote $f(\mathbf{W}, \Phi, \varepsilon_f)$ and $f^{(t)}(\mathbf{W}, \Phi, \varepsilon_f)$ as the objective values of problem (12) and its approximation

in (16) at the t -th iteration, respectively. For any feasible $\mathbf{W}, \Phi$ and ε_f , the following relationship holds

$$\begin{aligned} f(\mathbf{W}, \Phi, \varepsilon_f) & \geq f^{(t)}(\mathbf{W}, \Phi, \varepsilon_f), \\ f(\mathbf{W}^{(t)}, \Phi^{(t)}, \varepsilon_f^{(t)}) & = f^{(t)}(\mathbf{W}^{(t)}, \Phi^{(t)}, \varepsilon_f^{(t)}), \end{aligned} \quad (28)$$

when $\{\mathbf{W}, \Phi, \varepsilon_f\} \leftarrow \{\mathbf{W}^{(t)}, \Phi^{(t)}, \varepsilon_f^{(t)}\}$. Leveraging the convexity properties of problems (19) and (22), we derive

$$\begin{aligned} f(\mathbf{W}^{(t+1)}, \Phi^{(t+1)}, \varepsilon_f^{(t+1)}) & \geq f^{(t)}(\mathbf{W}^{(t+1)}, \Phi^{(t+1)}, \varepsilon_f^{(t+1)}) \\ & > f^{(t)}(\mathbf{W}^{(t)}, \Phi^{(t)}, \varepsilon_f^{(t)}) = f(\mathbf{W}^{(t)}, \Phi^{(t)}, \varepsilon_f^{(t)}), \end{aligned} \quad (29)$$

where the second inequality stems from the fact that both $\{\mathbf{W}^{(t+1)}, \Phi^{(t+1)}, \varepsilon_f^{(t+1)}\}$ and $\{\mathbf{W}^{(t)}, \Phi^{(t)}, \varepsilon_f^{(t)}\}$ are optimal and feasible for problem (12). This implies that $\{\mathbf{W}^{(t+1)}, \Phi^{(t+1)}, \varepsilon_f^{(t+1)}\}$ is an improvement over $\{\mathbf{W}^{(t)}, \Phi^{(t)}, \varepsilon_f^{(t)}\}$. Furthermore, the sequence $\{\mathbf{W}^{(t)}, \Phi^{(t)}, \varepsilon_f^{(t)}\}$ is bounded by constraints (12c)-(12g). By invoking Proposition 2 in Ref. [43], there exists a convergent subsequence $\{\mathbf{W}^{(t_\tau)}, \Phi^{(t_\tau)}, \varepsilon_f^{(t_\tau)}\}$ with limit points $\{\mathbf{W}^*, \Phi^*, \varepsilon_f^*\}$, such that

$$\lim_{\tau \rightarrow +\infty} [f(\mathbf{W}^{(t_\tau)}, \Phi^{(t_\tau)}, \varepsilon_f^{(t_\tau)}) - f(\mathbf{W}^*, \Phi^*, \varepsilon_f^*)] = 0. \quad (30)$$

For any t , there exists τ such that $t_\tau \leq t \leq t_{\tau+1}$, yielding

$$\begin{aligned} 0 & = \lim_{\tau \rightarrow +\infty} [f(\mathbf{W}^{(t_\tau)}, \Phi^{(t_\tau)}, \varepsilon_f^{(t_\tau)}) - f(\mathbf{W}^*, \Phi^*, \varepsilon_f^*)] \leq \\ & \lim_{t \rightarrow +\infty} [f(\mathbf{W}^{(t)}, \Phi^{(t)}, \varepsilon_f^{(t)}) - f(\mathbf{W}^*, \Phi^*, \varepsilon_f^*)] \leq \\ & \lim_{\tau \rightarrow +\infty} [f(\mathbf{W}^{(t_{\tau+1})}, \Phi^{(t_{\tau+1})}, \varepsilon_f^{(t_{\tau+1})}) - f(\mathbf{W}^*, \Phi^*, \varepsilon_f^*)] = 0. \end{aligned} \quad (31)$$

which implies that $\lim_{t \rightarrow +\infty} f(\mathbf{W}^{(t)}, \Phi^{(t)}, \varepsilon_f^{(t)}) = f(\mathbf{W}^*, \Phi^*, \varepsilon_f^*)$. Thus, the convergence of the

proposed algorithm is proved. Upon the above convergence guarantee, we propose Algorithm 2 to implement the complete alternating optimization process.

Algorithm 2 The Overall AO Algorithm to Solve Problem (16).

```

1: Input: Initial feasible points  $\mathbf{W}^{(0)}, \Phi^{(0)}, \varepsilon_f^{(0)}$ , tolerance  $\epsilon > 0$ , maximum iterations  $T_{\max}$ .
2: Initialize iteration index  $t = 0$ .
3: repeat
4:   Fix  $\Phi^{(t)}$  and solve subproblem (19) via CVX to obtain  $\mathbf{W}^{(t+1)}$  and  $\varepsilon_f^{(t+1)}$ .
5:   Fix  $\mathbf{W}^{(t+1)}$  and  $\varepsilon_f^{(t+1)}$ , solve subproblem (22) using Algorithm 1 to obtain  $\Phi^{(t+1)}$ .
6:   Compute updated objective value  $\eta^{(t+1)} = \eta(\mathbf{W}^{(t+1)}, \Phi^{(t+1)}, \varepsilon_f^{(t+1)})$ .
7:   Set  $t = t + 1$ .
8: until  $|\eta^{(t+1)} - \eta^{(t)}| \leq \epsilon$  or  $t > T_{\max}$ .
9: Return  $\mathbf{W}^* = \mathbf{W}^{(t)}, \Phi^* = \Phi^{(t)}$  and  $\varepsilon_f^* = \varepsilon_f^{(t)}$ .
10: Output:  $\mathbf{W}^*, \Phi^*$  and  $\varepsilon_f^*$ .

```

3.4 Complexity Analysis

The complexity of solving (19) is $O_1 = n_{\text{AO1}}(2(F+1) + F + 1) + n_{\text{AO1}}^2(2(F+1) + F + 1) + n_{\text{AO1}}(2(F+1)(N+1)^2) + n_{\text{AO1}}^3 = n_{\text{AO1}}[(F+1)(2(N+1)^2 + 3n_{\text{AO1}} + 3) + n_{\text{AO1}}^2]$, where $n_{\text{AO1}} = (F+1)N + F = \mathcal{O}(F+1)N$ represents the number of variables that needs to be optimized. Then we count the number of iterations $I_{\text{AO1}} = \sqrt{2(F+1) + F + 1 + 2 \times 2(F+1)} = \sqrt{7(F+1)}$. Thus the total complexity of solving (19) is $I_{\text{AO1}}O_1$.

Similarly, the all complexity of solving (22) is $I_{\text{AO2}}O_2$, where the complexity of updating Θ in (22) is $O_1 = n_{\text{AO2}}(3(F+1) + M^3 + M + 1) + n_{\text{AO2}}^2(3(F+1) + M^2 + M + 1) + n_{\text{AO2}}^3 = n_{\text{AO2}}((M^3 + M + 3F + 4) + n_{\text{AO2}}(M^2 + M + 3F + 4) + n_{\text{AO2}}^2)$, $n_{\text{AO2}} = \mathcal{O}(M+1)^2$ is the variables number, $I_{\text{AO2}} = \sqrt{3(F+1) + M + M + 1} = \sqrt{3F + 2M + 4}$ represents the iteration number to meet the convergence of the proposed algorithm.

4 Simulation Results

This section presents numerical results to examine the proposed algorithm and highlight the scheme under investigation in comparison to the benchmark schemes. Specifically, we denote $F = 4$ users who are randomly distributed within a circular area with a radius of 1 meter, centered at coordinates (1.5m, 2m, 1.5m). The

other configurations are provided in Table I unless otherwise stated.

Table 1 The parameter settings.

Parameter	Value
RIS Location	(0m, 0m, 10m)
SAT Antenna Count (N)	8
ARIS Element Count (M)	40
SAT Power Budget (P_s)	10 dBm
ARIS Power Budget (P_r)	35 dBm
EH Requirement (e_f)	-50 dBm
Parameters of EH circuit ($\Omega_f = \Omega$)	0.2 mW
Parameters of EH circuit ($a_f = a$)	6400
Parameters of EH circuit ($b_f = b$)	0.003 mW
SAT Noise Power (σ_f^2)	-60 dBm
ID Module Circuit Noise (δ_f^2)	-60 dBm
ARIS Self-Interference Power (σ_r^2)	-60 dBm
Common Rate Constraint (V_a)	2 bits/s/Hz
ARIS Maximum Amplitude ($\alpha_{m,\max}$)	10
SAT Channel Fading Factor (b_i)	0.063

To validate the effectiveness and convergence of the proposed algorithm rigorously, the convergence behavior is demonstrated as a key performance metric in Fig. 3, which illustrates the relationship between the iteration index and the SE for varying numbers of reflecting elements M . The results present the SE improvement for all M values, with convergence achieved after approximately 7-th iteration. Furthermore, to evaluate the robustness of the algorithm, multiple sets of random initial values were tested. All experiments converged to consistent performance levels, indicating that the proposed AO algorithm is insensitive to the initial values.

The proposed ARIS-assisted RSMA framework (labeled “Proposed scheme”) is benchmarked against four baseline methods: 1) SDMA scheme: ARIS-assisted SDMA. 2) NOMA scheme: ARIS-assisted NOMA. 3) Passive scheme: Passive RIS-assisted RSMA. 4) NORIS scheme: Conventional system without RIS. The remaining parts of this section will compare the aforementioned schemes to highlight the proposed algorithm.

Fig. 4 demonstrates that the SE monotonically increases with the number of transmit antennas N across all evaluated schemes. The proposed ARIS-assisted RSMA framework consistently achieves the highest SE, outperforming both PRIS and non-RIS benchmarks. This superiority stems from ARIS’s dual control over signal phase and amplitude, which

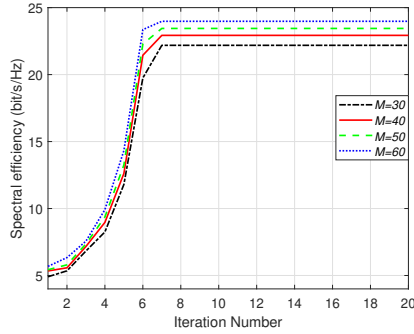


Fig. 3 Convergence of the proposed algorithm.

enables precise beamforming for directional signal enhancement and interference suppression. In contrast, PRIS exhibits constrained beam steering performance due to the absence of signal amplification and independent amplitude control at each element, despite retaining dynamic phase adjustment capabilities. RIS-aided systems universally surpass conventional non-RIS configurations by mitigating SAT-to-user channel fading and intelligently reshaping electromagnetic propagation environments. The performance gains highlight the critical role of active beamforming optimization and RIS-aided channel conditioning to improve the SE performance.

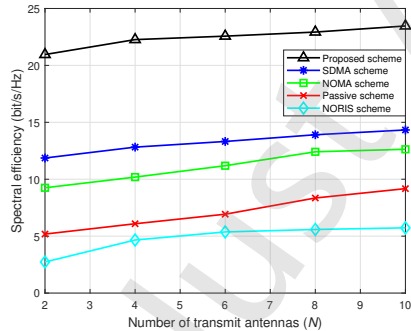


Fig. 4 SE versus number of antennas of the SAT (N).

To examine the impact of the SAT transmission power on the overall system performance, we analyzed the SE variations at different power levels P_s in Fig. 5, which demonstrates that the SE all the schemes has an monotonically increasing behaviour with respect to the transmission power. The proposed ARIS-assisted RSMA scheme consistently outperforms other baselines, this is due to the fact that with the ARIS's enhanced signal amplification, the integration of ARIS and RSMA can effectively boost the SE to mitigate double fading effect. Compared to the scheme without RIS, all RIS-integrated schemes achieve markedly

higher SE performance. This enhancement dynamically adjust the wireless propagation environment, effectively compensating for channel fading between the SAT and users and boosting signal strength. The RSMA scheme outperforms the SDMA and NOMA schemes by strategically partitioning the power and spatial domains, optimizing the splitting ratio and power allocation to mitigate multi-user interference. Additionally, RSMA dynamically adjusts signal power and coding based on users' channel conditions to enhance the SE.

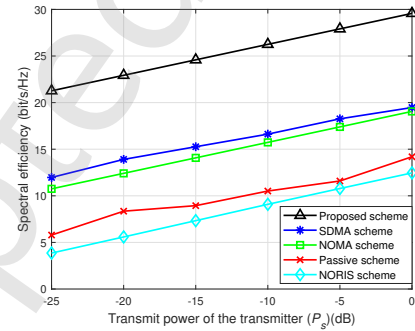


Fig. 5 SE versus transmit power of the SAT (P_s).

Fig. 6 illustrates the relationship between the SE performance and the number of M . This result demonstrates that with increasing number of RIS elements, the SE of the proposed scheme exhibits an increasing trend. The additional reflecting elements provide greater degrees of freedom (DoF) to optimize the signal direction and strength, thereby enhancing the overall system performance. The proposed ARIS-RSMA scheme outperforms all baseline schemes across different numbers of reflecting elements. This can be explained by the fact that ARIS's ability to actively adjust both signal phase and amplitude, enabling high-precision beamforming. In addition, RIS offers a cost-effective solution for practical system deployment.

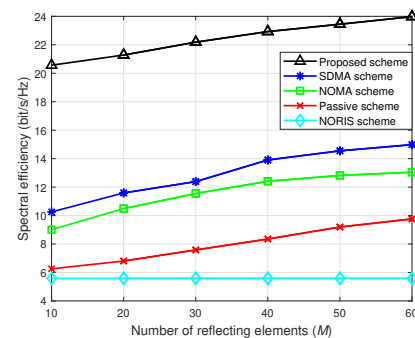


Fig. 6 SE versus number of RIS reflecting elements (M).

5 Conclusion

This paper investigated a MU-MISO SAT communication system by integrating RSMA and ARIS, aiming to maximize the system SE. The joint optimization of PS ratios, phase shift matrices, and beamforming vectors presents a non-convex problem. To tackle this challenge, the AO framework has been proposed, decomposing the problem into subproblems that can be efficiently addressed by the SDR and penalty-based algorithm. Numerical results demonstrated that the proposed scheme achieves a significant improvement in SE in comparison to the conventional multiple access techniques. ARIS-based designs have shown superiority over PRIS counterparts. While this work has focused on a single SAT system, the proposed framework lays a foundation for future extensions to multi-SAT cooperative networks. Such extensions would open new research avenues in addressing challenges like inter-SAT interference management and distributed ARIS coordination, potentially unlocking further gains in system capacity and coverage.

Acknowledgment

This work was supported by the National Natural Science Foundation of China (No. 62571495 and 62571182), the State key Laboratory of Networking and Switching Technology (Beijing University of Posts and Telecommunications) (No. SKLNST-2025-1-07), the Zhejiang Provincial Natural Science Foundation of China under Grant (No. ZCLMS26F0101), and the Ningbo Natural Science Foundation under Grant (No. 2024J233).

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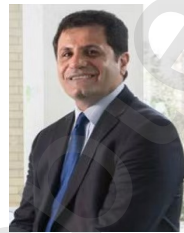
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