Optimization for Reflection and Transmission Dual-Functional Active RIS-Assisted Systems

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Abstract—Reconfigurable intelligent surface (RIS) has been deemed as one of potential components of future wireless communication systems because it can adaptively manipulate the wireless propagation environment with low-cost passive devices. However, due to the severe double path loss, the traditional passive RIS can provide sufficient gain only when receivers are very close to the RIS. Moreover, passive RIS cannot provide signal coverage for the receivers at the back side of it. To address these drawbacks in practical implementation, we introduce a novel reflection and transmission dual-functional active RIS (DF-ARIS) architecture in this paper, which can simultaneously realize reflection and transmission functionalities with active signal amplification to significantly extend signal coverage and enhance the quality-of-service (QoS) of all users. The problem of joint transmit beamforming and dual-functional active RIS design is investigated in RIS-enhanced multiuser multiple-input single-output (MU-MISO) systems. Both sum-rate maximization and power minimization problems are considered. To address their non-convexity, we develop efficient iterative algorithms to decompose them into several separate design problems, which are efficiently solved by exploiting fractional programming (FP) and Riemannian-manifold optimization techniques. Simulation results demonstrate the superiority of the proposed dual-functional active RIS architecture and the effectiveness of our proposed algorithms over various benchmark schemes.

Index Terms—Reconfigurable intelligent surface, beamforming, fractional programming, Riemannian-manifold.

I. INTRODUCTION

RECONFIGURABLE intelligent surface (RIS) has been proposed as a promising technology for future wireless communication systems and extensively investigated in recent years [1], [2]. Specifically, an RIS is an array composed of massive passive elements. It can construct favorable wireless propagation environment between transmitters and receivers by adaptively adjusting the phase-shift of the reflected electromagnetic (EM) waves which impinge on the surface. By deploying RIS in wireless systems, the channel power gain can be effectively improved and the communication QoS can be enhanced without significant additional power consumptions.

Considering the low cost and low power consumption features, RIS has many promising applications in different wireless systems such as the multi-cell networks [3], multiple-input multiple-output (MIMO) communications [4], [5], unmanned aerial vehicle (UAV) networks [6], and non-orthogonal multiple access (NOMA) channel [7] for capacity optimization, secure transmission, symbol-level precoding design, energy/spectrum efficiency enhancement [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], etc. Besides, many technologies have been investigated for RIS-based communications, e.g., deep reinforcement learning (DRL) [13], [14] and compressive sensing [15]. An RIS architecture to achieve amplitude-and-phase-varying modulation was proposed in [16] and the free-space path loss models for RIS-assisted wireless communications were developed in [17] by studying the physics and EM nature of RIS. Furthermore, by embedding radio frequency (RF) chains and signal processing units in the surface, RIS can work as a transmitter or receiver [18], [19], which can realize a low-complexity and energy-efficient virtual MIMO system with only several RF chains.

However, due to double fading effect (i.e., the total path loss of the cascaded transmitter-RIS-receiver link is the product of the path losses of the transmitter-RIS link and RIS-receiver link, which is usually an order-of-magnitude larger than that of the direct link), RIS can only effectively improve communication performance if it is deployed close to users [20], [21], [22], [23]. Besides, recent studies showed that RIS can be easily outperformed by conventional full-duplex (FD) amplify-and-forward (AF) relays unless very large RIS is employed [24], [25]. However, massive reconfigurable elements will lead to high training overhead for channel estimation [26],

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[27] and high hardware complexity of the control link [28]. Therefore, the purely passive RIS might have limited application scenarios in practical wireless systems.

In order to overcome the double fading effect in passive RIS assisted systems, some proposals have been raised and attracted a lot of interest. In [29], the authors proposed a novel relay-aided RIS architecture consisting of two RISs connected via a FD relay. However, the designs of base station (BS) transmit beamforming and RIS coefficients have not been well investigated. A further question is that the first RIS in their proposed system only reflects the signals towards relay and cannot simultaneously serve users around it. In [30], the authors proposed a semi-active RIS architecture. However, the practical implementation of this semi-active RIS remains an open problem, as it needs expensive RF chains. Active RIS has been recently proposed [20], [21] to overcome the aforementioned practical issues of passive RIS by amplifying the reflected signal with low-cost hardware. Unlike the conventional AF relays that require power-hungry RF chains, the active RIS directly reflects signals in an FD manner with low-power reflection-type amplifiers.

However, the reflective property of the conventional RIS restricts the service coverage to only one side of the surface and users locating behind it cannot be effectively served. To resolve this limitation, the novel concept of simultaneously transmitting and reflecting RIS (STAR-RIS) was proposed in [31], [32], and [33]. In particular, the wireless signal impinging upon an element of a STAR-RIS is divided into two parts. One part is reflected to users in front of it, and the other is transmitted to users behind it. As a result, coverage is extended to $360^\circ$, which means that users at both sides of STAR-RIS can be served. Nevertheless, performance improvement of passive STAR-RIS is still limited due to severe signal attenuation.

Therefore, to overcome the double fading effect as well as enhance the coverage, in this paper we propose a novel reflection and transmission DF-ARIS architecture. Particularly, the DF-ARIS firstly amplifies the incident signals, divides them by power split circuits, and emits them with corresponding controllable phase shifters towards front and back to serve all users around. Different from conventional RIS which just redirects signals to receivers within the same half-space bounded by it, the coverage of the proposed DF-ARIS is extended to the entire space. Besides, unlike the existing STAR-RIS, the DF-ARIS architecture we proposed enables not only reflection and transmission functions, but also amplification function. Therefore, it can achieve the same performance as the traditional STAR-RIS with much fewer elements, which means that the overhead of channel estimation and the complexity of the control link can be greatly reduced. In addition, it should be noted that the DF-ARIS is completely different with the FD relays since no RF chains and complex signal processing modules are needed.

Based on the proposed DF-ARIS architecture, we consider the joint BS transmit beamforming and DF-ARIS coefficients design in MU-MISO system. The main contributions in this paper are summarized as follows:

- We propose a novel reflection and transmission DF-ARIS architecture, which can simultaneously realize active amplification and reflection/transmission functions to extend the coverage and improve the QoS of users at both sides of it. Based on this, we develop the specific reflected/transmitted signal model and element-wise power consumption model to ensure that the amplification electronics work in their linear region.
- We first focus on the sum-rate maximization problem, which attempts to maximize the achievable sum-rate of all users with given BS and DF-ARIS power consumption budgets. An efficient iterative algorithm is proposed to decompose the non-convex and multivariate problem into separate design problems, where the FP theory and Riemannian-manifold optimization are exploited.
- Then, considering the additional power consumption introduced by the DF-ARIS, we consider the power minimization problem, which aims to minimize the total power consumption of both BS and DF-ARIS while guaranteeing a certain QoS among users. An efficient iterative algorithm is proposed to optimize BS and DF-ARIS designs using the log-sum-exp approach and Riemannian-manifold algorithm after some transformations.
- Finally, we provide extensive simulation results to demonstrate the advancement of the proposed DF-ARIS architecture and the effectiveness of developed algorithms. In particular, we show that applying the DF-ARIS brings remarkable performance improvement in terms of achievable sum-rate and power-savings. Moreover, it can be noted that the current reflective-only active RIS and STAR-RIS designs are special cases of the proposed DF-ARIS. Hence, the developed algorithms are forward-looking and can provide a unified solution.

The rest of this paper is organized as follows. The dual-functional active RIS architecture and system model are introduced in Section II. In Section III and Section IV, we develop optimization algorithms for sum-rate maximization problem and power minimization problem, respectively. To verify the superiority of the proposed DF-ARIS architecture, simulation results are presented in Section V. Finally, conclusions are drawn in Section VI.

Notations: The following notations are used throughout this paper. $a$ is a scalar, $a$ is a vector, and $A$ is a matrix. $A^*$, $A^T$, $A^H$, $A^{-1}$ denote the conjugate, transpose, Hermitian (conjugate transpose) and inversion of $A$, respectively. $\Re\{\cdot\}$ and $\cdot^*$ denote the real part and modulus of a complex number, respectively. $A = \text{diag}(a)$ is a diagonal matrix with the entries of $a$ on its main diagonal. Notation $n \sim \mathcal{CN}(0, \sigma^2)$ means that random variable $v$ is complex circularly symmetric Gaussian with zero mean and variance $\sigma^2$. $\mathbb{C}^{M \times N}$ denotes the set of all $M \times N$ complex-valued matrices. $a(m)$ denotes the $m$-th element of vector $a$ and $A(m,n)$ denotes the $(m,n)$-th element of matrix $A$.  

II. DUAL-FUNCTIONAL ACTIVE RIS ARCHITECTURE AND SYSTEM MODEL

A. Proposed Dual-Functional Active RIS

The architecture of the proposed DF-ARIS is shown in Fig. 1. Specifically, the signal impinging upon each element
is firstly magnified by an integrated amplifier, divided by power split circuits and fed to two controllable phase shifters, which can provide independent phase control. Then the signals are emitted from the front side and back side of the DF-ARIS and denoted as reflected signals and transmitted signals, respectively. Although the DF-ARIS is supported by a set of integrated active amplifiers which need additional power consumption to support the active load, it is noted that the power consumption of reflection-type amplifiers has been decreased to the microwatt level in recent years [34]. Besides, these integrated amplifiers significantly improve both the energy and hardware efficiency in contrast to the traditional antenna-array type relays built on power-hungry and expensive RF chain components. In practice, it can be realized by many existing active components, such as the tunnel diodes [34], the current-inverting converter [35], or even some integrated chips [36], which can amplify the incident signal without requiring significant energy consumption. Power split can be implemented by the power system’s interharmonic components [37]. In addition, it is assumed that the amplitude and phase-shift of each DF-ARIS element can be tuned independently since they are adjusted by separate components.

The proposed DF-ARIS provides enhanced degrees of freedom (DoFs) for signal propagation manipulation, which significantly increases the design flexibility in satisfying stringent communication requirements. One of the most promising applications is to extend the coverage range of wireless networks and improve the QoS of receivers, especially when the links between the BS and receivers are severely blocked by obstacles (e.g., trees along roads, buildings, and vehicles), as shown in Fig. 2. We should notice that the DF-ARIS may have deployment difficulties in reality, as it has a larger size than traditional relays and extra dimensions to design and control compared to passive RIS. However, owing to the significant advancement on the performance improvement, such deployment difficulties of DF-ARIS are acceptable and can be overcome relatively easily.

B. Signal Model

With the previous analysis, the reflected signal \( y_{t,m} \) at the \( m \)-th element of the DF-ARIS can be modeled as follows

\[
y_{t,m} = \phi_{t,m} \sqrt{\alpha_{m}} (x_{m} + v_{m}),
\]

where \( x_{m} \) is the incident signal, \( v_{m} \) is the introduced noise related to the input noise and thermal noise of the DF-ARIS [38], \( \sqrt{\alpha_{m}} \) denotes the amplification coefficient, \( \phi_{t,m} \subseteq [0,1] \) denotes the reflection coefficient of the \( m \)-th element. Similarly, the transmitted signal \( y_{t,m} \) at the \( m \)-th element can be modeled as

\[
y_{t,m} = \phi_{t,m} \sqrt{1 - \varsigma_{m}} \sqrt{\alpha_{m}} (x_{m} + v_{m}),
\]

where \( \sqrt{1 - \varsigma_{m}} \) denotes the transmission amplitude which needs to satisfy the energy conservation constraint and \( \phi_{t,m} = e^{j\theta_{t,m}} \) expresses the phase-shift likewise.

Then, the reflected signal vector \( y_{t} = [y_{t,1}, \ldots, y_{t,M}] \) of the DF-ARIS having \( M \) elements can be modeled as

\[
y_{t} = \Phi_{t} E_{t} A (x + v),
\]

where \( x \in \mathbb{C}^{M} \) is the incident signal vector, \( v \sim \mathcal{CN} (0, \sigma_{v}^2 I) \) denotes the introduced noise vector, \( A \triangleq \text{diag} (a) \) with \( a \triangleq [\sqrt{\alpha_{1}}, \ldots, \sqrt{\alpha_{M}}]^{T} \) is the amplification matrix, \( E_{t} \triangleq \text{diag}(\varsigma) \) with \( \varsigma \triangleq [\varsigma_{1}, \ldots, \varsigma_{M}]^{T} \) denotes the reflection amplitude coefficients matrix, \( \Phi_{t} \triangleq \text{diag}(\phi_{t}) \) and \( \phi_{t} \triangleq [\phi_{t,1}, \ldots, \phi_{t,M}]^{T} \) denote phase-shift matrix and vector, respectively. Similarly, the transmitted signal vector \( y_{t} \) can be expressed as

\[
y_{t} = \Phi_{t} E_{t} A (x + v),
\]

where \( E_{t} \triangleq \text{diag}(\varsigma) \) with \( \varsigma \triangleq [\sqrt{1 - \varsigma_{1}}, \ldots, \sqrt{1 - \varsigma_{M}}]^{T} \) indicates transmission amplitude coefficient matrix, \( \Phi_{t} \triangleq \text{diag}(\phi_{t}) \) and \( \phi_{t} \triangleq [\phi_{t,1}, \ldots, \phi_{t,M}]^{T} \) are defined in the same way to represent the phase-shift.

C. Power Consumption

The majority of existing literatures only investigates the total power consumption of the active RIS [20], [39]. However, the amplification circuit electronics have to work in their linear region within which the output power increases linearly with the input power. In this work, considering the limited power magnification capability due to the low cost of the amplifier, we also consider the element-wise power constraint, which reads as

\[
a_{m} (|x_{m}|^2 + \sigma_{v}^2) \leq p_{\text{max},m}, \quad \forall m,
\]

where \( p_{\text{max},m} \) is the maximum power supply for the \( m \)-th element. Moreover, with amplification matrix \( A \), the following total power constraint is also considered

\[
\|A x\|^2 + \sigma_{v}^2 \|A\|^2 \leq P_{t},
\]

where \( P_{t} \) is the total power budget at the DF-ARIS (\( P_{t} \leq \sum_{m=1}^{M} p_{\text{max},m} \) due to the thermal load of the circuit).
signals reflected from the S-r surface is denoted by $K$. Served by S-t. The set of all users in this system is denoted as $\mathcal{N}$ with the aid of DF-ARIS. As shown in Fig. 3, some users $N$ with single-antenna users $\mathcal{M}$ can receive the direct signal from the BS. Hence, the received signal at the $k$-th user in $\mathcal{K}_t$ can be modeled as

$$y_k = (h_{d,k}^H + h_{r,k}^H \Phi_r E_r A) \sum_{j=1}^{K} w_j s_j + h_{r,k}^H \Phi_r E_r A v + n_k, \quad k \in \mathcal{K}_t,$$

where $h_{d,k} \in \mathbb{C}^N$ and $h_{r,k} \in \mathbb{C}^M$ denote the channels from the BS to the $k$-th user and from the DF-ARIS to the $k$-th user, respectively, and $n_k \sim \mathcal{CN}(0, \sigma_n^2)$ denotes the noise at the $k$-th user. Thus, the corresponding signal-to-interference-plus-noise ratio (SINR) of the $k$-th user can be expressed as

$$\text{SINR}_k = \frac{\|\hat{h}_k^H w_k\|^2}{\sum_{j\neq k} \|h_j^H w_j\|^2 + \sigma_n^2 \|h_{r,k}^H \Phi_r E_r A\|^2 + \sigma_n^2}, \quad k \in \mathcal{K}_t,$$

where $\hat{h}_k^H \triangleq h_{d,k}^H + h_{r,k}^H \Phi_r E_r A G$ denotes the equivalent channel from the BS to the $k$-th user in $\mathcal{K}_t$ and (a) holds since $\Phi_r^H \Phi_r = I$.

Considering that there exists scattering and reflection from all directions, it is assumed that the users in $\mathcal{K}_t$ can receive the direct signal from the BS. Hence, the received signal at the $k$-th user in $\mathcal{K}_t$ can be modeled as

$$y_k = h_{d,k}^H \sum_{j=1}^{K} w_j s_j + h_{r,k}^H \Phi_r E_r A v + n_k, \quad k \in \mathcal{K}_t,$$

and the corresponding SINR can be given by

$$\text{SINR}_k = \frac{\|\hat{h}_k^H w_k\|^2}{\sum_{j\neq k} \|h_j^H w_j\|^2 + \sigma_n^2 \|h_{r,k}^H E_r A\|^2 + \sigma_n^2}, \quad k \in \mathcal{K}_t.$$
where $P_T$ is the power budget at the BS, $g_m^H$ denotes the equivalent channel from the BS to the $m$-th element of the DF-ARIS, i.e., the $m$-th row of the matrix $G$.

Obviously, solving problem (11) is extremely challenging since the objective function (11a) and the phase shift constraint (11f) are non-convex. Moreover, the optimization variables are coupled with each other in the expression of the sum rate. All these bring great difficulties to find the global optimal solution. As an alternative, we propose an efficient iterative algorithm to find the sub-optimal solution in this paper. Specifically, in the following, we attempt to convert the problem into several more tractable subproblems, and solve them iteratively by utilizing the FP and Riemannian-manifold methods.

### B. FP-Based Transformation of Objective Function

We first equivalently transform the original problem into a more tractable form based on FP theory. With the transformed objective function, BS transmit beamforming, DF-ARIS amplification matrix, phase-shift matrices and amplitude coefficient are designed iteratively.

The objective function in (11a) has a typical expression of sum-of-logarithmic function of SINR$_k$, which makes the optimization problem intractable. Motivated by the closed-form FP algorithm introduced in [48] and [49], we attempt to equivalently transform the original problem into a sum-of-ratios form by extracting the ratio term SINR$_k$ from the logarithmic function. Based on Lagrangian dual transform [49], the optimization problem (11) is equivalent to

$$
\max_{w_k, A, \Phi_r, \Phi_t, \varsigma} \ f(w_k, A, \Phi_r, \Phi_t, \varsigma) \\
\text{s.t.} \quad (11b) - (11f),
$$

where the objective function in (12a) is

$$
f(w_k, A, \Phi_r, \Phi_t, \varsigma) = \sum_{k=1}^{K} \log_2 (1 + \gamma_k) - \sum_{k=1}^{K} \gamma_k + \sum_{k \in K_r} \sum_{j=1}^{K} \frac{(1 + \gamma_k) |\bar{h}_j^H w_k|^2}{2 |\bar{h}_j^H w_k|^2 + \sigma_k^2 |h_j^H E_k A|^2 + \sigma_k^2} + \sum_{k \in K_t} \sum_{j=1}^{K} \frac{(1 + \gamma_k) |\bar{t}_j^H w_k|^2}{2 |\bar{t}_j^H w_k|^2 + \sigma_k^2 |t_j^H E_k A|^2 + \sigma_k^2},
$$

with $\gamma_k \triangleq [\gamma_1, \ldots, \gamma_K]^T$ being an auxiliary variable vector. Unfortunately, optimization problem (12) is still intractable due to the complicated form of the sum of $K$ fractional terms. Next, we apply quadratic transform [48] to further transform them into solvable formula by introducing another auxiliary variable vector $\tau \triangleq [\tau_1, \ldots, \tau_K]^T$. Then the optimization problem can be transformed into

$$
\max_{w_k, A, \Phi_r, \Phi_t, \varsigma, \gamma, \tau} h(\gamma) + g(w_k, A, \Phi_r, \Phi_t, \varsigma, \gamma, \tau) \\
\text{s.t.} \quad (11b) - (11f),
$$

where $h(\gamma) \triangleq \sum_{k=1}^{K} \log_2 (1 + \gamma_k) - \sum_{k=1}^{K} \gamma_k$ and $g(w_k, A, \Phi_r, \Phi_t, \varsigma, \gamma, \tau)$ is formulated as in (15), shown at the bottom of the page.

To deal with the above problem, we adopt the block coordinate ascent (BCA) methodology to iteratively update each block of variables while keeping others being fixed. The sub-problems of updating each block will be specified in details in the following.

### C. Update Auxiliary Variables

1) **Update $\gamma$:** When other variables are fixed, the objective function $f(w_k^*, A^*, \Phi_r^*, \Phi_t^*, \varsigma^*, \gamma)$ in (13) is a concave differentiable function with respect to $\gamma_k$. By setting $\frac{\partial f(w_k^*, A^*, \Phi_r^*, \Phi_t^*, \varsigma^*, \gamma)}{\partial \gamma_k}$ to zero, the optimal $\gamma_k^*$ can be found in a closed-form as

$$
\gamma_k^* = \left\{ \begin{array}{ll}
\frac{\sum_{j \in K_r} |\bar{h}_j^H w_k|^2}{\sum_{j \in K} |\bar{h}_j^H w_k|^2 + \sigma_k^2 |h_j^H E_k A|^2 + \sigma_k^2}, & k \in K_r, \\
\frac{\sum_{j \in K_t} |\bar{t}_j^H w_k|^2}{\sum_{j \in K} |\bar{t}_j^H w_k|^2 + \sigma_k^2 |t_j^H E_k A|^2 + \sigma_k^2}, & k \in K_t.
\end{array} \right.
$$

2) **Update $\tau$:** Similarly, $g(w_k^*, A^*, \Phi_r^*, \Phi_t^*, \varsigma^*, \gamma^*, \tau)$ in (15) is a concave differentiable function with respect to $\tau_k$. The optimal variable $\tau_k^*$ can be obtained by setting $\frac{\partial g(w_k^*, A^*, \Phi_r^*, \Phi_t^*, \varsigma^*, \gamma^*, \tau)}{\partial \tau_k}$ to zero and is expressed as

$$
\tau_k^* = \left\{ \begin{array}{ll}
\frac{\sqrt{1 + \gamma_k} |\bar{h}_k w_k|^2}{\sum_{j=1}^{K} |\bar{h}_j^H w_k|^2 + \sigma_k^2 |h_j^H E_k A|^2 + \sigma_k^2}, & k \in K_r, \\
\frac{\sqrt{1 + \gamma_k} |\bar{t}_k w_k|^2}{\sum_{j=1}^{K} |\bar{t}_j^H w_k|^2 + \sigma_k^2 |t_j^H E_k A|^2 + \sigma_k^2}, & k \in K_t.
\end{array} \right.
$$

### D. Update BS Transmit Beamforming $w_k$

With other variables being fixed, the update of BS transmit beamforming $w_k$ can be expressed by

$$
\max_{w_k} g(w_k, A^*, \Phi_r^*, \Phi_t^*, \varsigma^*, \gamma^*, \tau^*)
$$

with $g(w_k, A^*, \Phi_r^*, \Phi_t^*, \varsigma^*, \gamma^*, \tau^*)$

$$
= \sum_{k \in K_r} \left( 2 \sqrt{1 + \gamma_k} R \{ \tau_k^* |\bar{h}_k^H w_k|^2 \} - |\tau_k|^2 \left( \sum_{j=1}^{K} |\bar{h}_j^H w_j|^2 + \sigma_k^2 |h_j^H E_k A|^2 + \sigma_k^2 \right) \right) \\
+ \sum_{k \in K_t} \left( 2 \sqrt{1 + \gamma_k} R \{ \tau_k^* |\bar{t}_k^H w_k|^2 \} - |\tau_k|^2 \left( \sum_{j=1}^{K} |\bar{t}_j^H w_j|^2 + \sigma_k^2 |t_j^H E_k A|^2 + \sigma_k^2 \right) \right)
$$

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wherein $c$ and removing constants, the optimization of $\Phi$. Update Phase-Shift Matrices

$$\max_{\Phi} \left\{ \frac{1}{m} \sum_{k=1}^{m} \| A G w_k \|^2 + \sigma_\nu^2 \| A \|_F^2 \leq \bar{P}_R, \right. \tag{18c}$$

subject to

$$a_m \sum_{k=1}^{m} |g_m^H w_k|^2 + \sigma_v^2 \leq p_{\max,m}, \forall m, \tag{18d}$$

which is a convex problem whose optimal solution can be efficiently obtained by various existing algorithms or optimization tools, e.g., CVX [50].

**E. Update Amplification Matrix $A$**

Given other variables, the sub-problem with respect to the amplification matrix $A$ can be expressed as

$$\max_A g(w_k^*, A^*, \Phi^*, \Phi_t^*, \gamma^*, \tau^*) \tag{19a}$$

subject to

$$\sum_{k=1}^{K} \| A G w_k \|^2 \leq \bar{P}_R, \tag{19b}$$

$$a_m \leq c_m, \forall m, \tag{19c}$$

wherein $c_m \triangleq \frac{\sum_{k=1}^{m} p_{\max,m} \| g_m^H w_k \|^2 + \sigma_v^2}{\sum_{k=1}^{m} p_{\max,m} \| g_m^H w_k \|^2 + \sigma_v^2}$ represents the amplification maximum of the $m$-th element. This is also a convex problem whose optimal solution can be efficiently obtained by CVX.

**F. Update Phase-Shift Matrices $\Phi_r$, $\Phi_t$**

The sub-problem with respect to the phase-shift matrices $\Phi_r$ and $\Phi_t$ can be expressed as

$$\max_{\Phi_r, \Phi_t} g(w_k^*, A^*, \Phi_r^*, \Phi_t^*, \gamma^*, \tau^*) \tag{20a}$$

subject to

$$\max_{\Phi_r, \Phi_t} g(w_k^*, A^*, \Phi_r^*, \Phi_t^*, \gamma^*, \tau^*) \tag{20b}$$

Considering that the phase-shift matrices $\Phi_r$ and $\Phi_t$ are irrelevant, we turn to separately optimize either of them. By defining

$$r_{k,j} \triangleq \frac{h_{r,k}^H E_j A \{ G w_j \}^H}{\sqrt{1 + \gamma_k r_{k,j}^H}}, \; j \in \mathbb{K}, \; k \in \mathbb{K}_r, \tag{21}$$

$$B_r \triangleq \sum_{k \in \mathbb{K}_r} \sum_{j=1}^{K} |\tau_k|^2 r_{k,j}^H r_{k,j}^H, \tag{22}$$

$$c_t \triangleq \sum_{k \in \mathbb{K}_t} \sum_{j=1}^{K} (\sqrt{1 + \gamma_k r_{t,k}^H} - \sum_{j=1}^{K} |\tau_k|^2 r_{t,j}^H h_{d,k}^H w_j) \tag{23}$$

and removing constants, the optimization of $\phi_t$ is equivalent to solving the following problem

$$\min_{\phi_t} \sum_{k \in \mathbb{K}_t} |\tau_k|^2 \sum_{j=1}^{K} |h_{d,k}^H w_j + r_{t,k}^H \phi_t|^2$$

$$- \sum_{k \in \mathbb{K}_t} 2 \sqrt{1 + \gamma_k} \Re \{ \tau_k r_{t,k}^H \phi_t \}$$

$$= \phi_t^H B_r \phi_t - 2 \Re \{ \phi_t^H c_t \} \tag{24a}$$

subject to

$$|\phi_{r,m}| = 1, \; \forall m, \tag{24b}$$

where $\bar{a} \triangleq \sum_{k \in \mathbb{K}_t} \sum_{j=1}^{K} |\tau_k|^2 w_j^H h_{d,k}^H h_{d,k}^H w_j$ is a constant independent of $\phi_t$. It can be observed that, although the objective function in (24a) is continuous and convex, problem (24) is still difficult to solve due to the constant-modulus constraint (24b). There are two popular methods for handling this type of constraint: non-convex relaxation and alternating minimization. However, the non-convex relaxation method always suffers a performance loss and the alternating minimization method usually has slow convergence as the number of variables increases. To solve this problem effectively, we adopt the Riemannian-manifold method with very fast convergence [51].

The search space can be regarded as the product of $M$ complex circles, which can be given by

$$C^M \triangleq \{ x \in \mathbb{C}^M : |x(m)| = 1, m = 1, 2, \cdots, M \}, \tag{25}$$

where $x(m)$ is the $m$-th element of vector $x$. The main idea of the Riemannian-manifold algorithm is to derive a gradient descent algorithm based on the manifold space defined in (25), which is similar to the concept of the gradient descent technique developed for the conventional optimization over the Euclidean space. The most common search direction for a minimization problem is to move towards the direction opposite to its Euclidean gradient, which is given by

$$g^{(t)} = -\nabla f(\phi^{(t)}) = -2 B_r \phi^{(t)} + 2 c_t, \tag{26}$$

where $\phi^{(t)}$ is the iteration point in the $t$-th update. Since we optimize over the Riemannian manifold space, we have to find the Riemannian gradient, which can be calculated as follows

$$g^{(t)}_R \triangleq g^{(t)} - R \left( g^{(t)} \odot \phi^{(t)} \right) \odot \phi^{(t)}, \tag{27}$$

where $\odot$ represents the Hadamard product. Then, we update the current point

$$\phi^{(t+1)} = \phi^{(t)} + \beta g^{(t)}_R, \tag{28}$$

where $\beta$ is a constant step-size. In general, the obtained $\phi^{(t)}$ is not in the search space, i.e. $\phi^{(t)} \in C^M$. Hence, it has to be mapped into the search space by using the retraction operator as follows

$$\phi^{(t+1)} \triangleq \phi^{(t)} \odot \frac{1}{\left| \phi^{(t)} \right|}. \tag{29}$$

Now $\phi^{(t+1)}$ belongs to $C^M$, which satisfies the unit-modulus constraint. Details of the Riemannian-manifold algorithm are presented in Algorithm 1 and the computational complexity is approximated by $O(M^2)$ [51].

We can solve $\phi_t$ by repeating the same procedure. Specifically, by defining

$$r_{k,j} \triangleq \frac{h_{r,k}^H E_j A \{ G w_j \}^H}{\sqrt{1 + \gamma_k r_{k,j}^H}}, \; j \in \mathbb{K}, \; k \in \mathbb{K}_t, \tag{30}$$

$$B_t \triangleq \sum_{k \in \mathbb{K}_t} \sum_{j=1}^{K} |\tau_k|^2 r_{k,j}^H r_{k,j}^H, \tag{31}$$

$$c_t \triangleq \sum_{k \in \mathbb{K}_t} \sum_{j=1}^{K} (\sqrt{1 + \gamma_k} r_{t,k}^H h_{d,k}^H h_{d,k}^H w_j) \tag{32}$$

and removing constants, the optimization of $\phi_r$ is equivalent to solving the following problem

$$\min_{\phi_r} \sum_{k \in \mathbb{K}_r} |\tau_k|^2 \sum_{j=1}^{K} |h_{d,k}^H w_j + r_{t,k}^H \phi_t|^2$$

$$- \sum_{k \in \mathbb{K}_r} 2 \sqrt{1 + \gamma_k} \Re \{ \tau_k r_{t,k}^H \phi_t \}$$

$$= \phi_r^H B_r \phi_r - 2 \Re \{ \phi_r^H c_t \} \tag{24a}$$

subject to

$$|\phi_{t,m}| = 1, \; \forall m, \tag{24b}$$

where $\bar{a} \triangleq \sum_{k \in \mathbb{K}_r} \sum_{j=1}^{K} |\tau_k|^2 w_j^H h_{d,k}^H h_{d,k}^H w_j$ is a constant independent of $\phi_r$. It can be observed that, although the
Algorithm 1 Riemannian-Manifold-Based Phase-Shift Design

Input: $f(\phi_t^{(1)}), \phi_t^{(1)}, T_{\text{max}}, \delta_t$.
Output: $\phi_t^{(t+1)}$
1: Initialize $t = 1, \delta = \infty$.
2: While $t \leq T_{\text{max}}$ and $\delta \geq \delta_t$ do
3: Calculate the search direction $g^{(t)}$ by (26).
4: Calculate the Riemannian gradient $g_{\mathbb{R}}^{(t)}$ by (27).
5: Update the current point $\tilde{\phi}^{(t)}$ by (28).
6: Update $\phi_t^{(t+1)}$ using the retraction operator by (29).
7: $\delta = \frac{f(\phi_t^{(t+1)}) - f(\phi_t^{(t)})}{f(\phi_t^{(t+1)})}$.
8: $t = t + 1$.
9: End while.

and removing constants, the corresponding optimization problem of $\phi_t$ can be formulated as
\[
\min_{\phi_t} \sum_{k \in K_t} |\tau_k|^2 \sum_{j=1}^K |h_{d,k}^H w_j + r_{k,j}^H \phi_t|^2
- \sum_{k \in K_t} 2 \sqrt{1 + \gamma_k} \Re \{\tau_k r_{k,j}^H \phi_t\}
= \phi_t^H B_t \phi_t - 2 \Re \{\phi_t^H c_t\} + \hat{b} \triangleq f(\phi_t) \quad \text{(33a)}
\]
s.t. $|\phi_{t,m}| = 1, \forall m$, \quad \text{(33b)}

where $\hat{b} \triangleq \sum_{k \in K_t} \sum_{j=1}^K |\tau_k|^2 w_j^H h_{d,k}^H w_j$ is a constant independent of $\phi_t$. The optimal solution can be obtained following the identical argument as above. The search direction can be given by
\[
g^{(t)} = -\nabla f(\phi_t^{(t)}) = -2B_t \phi_t^{(t)} + 2c_t. \quad \text{(34)}
\]

Then, the Riemannian-manifold-based algorithm in Algorithm 1 can be applied to obtain phase-shift $\phi_t$. Since the phase-shift vectors $\phi_t$ and $\phi_{t+1}$ are separate, they can be optimized in parallel to reduce computational time.

G. Update Amplitude Coefficient

Obtaining other variables, the problem of updating amplitude coefficient $\varsigma$ can be expressed as
\[
\max_{\varsigma} \quad g(w_t^*, A^*, \Phi_t^*, \Phi_t^*, \varsigma, \gamma^*, \tau^*) \\
\text{s.t.} \quad \varsigma_m \in [0, 1], \forall m. \quad \text{(35a)}
\]
\[
\text{By defining} \\
\begin{align*}
Q_t & \triangleq \sum_{k \in K_t} \sum_{j=1}^K |\tau_k|^2 u_{k,j}^H u_{k,j}^H \\
& + \sum_{k \in K_t} |\tau_k|^2 \sigma_2^2 \text{diag}(h_{r,k}^H) A A^H \text{diag}(h_{r,k}^H)^H, \\
Q_{t,m} & \triangleq \sum_{k \in K_t} |\tau_k|^2 u_{k,j}^H u_{k,j}^H \\
& + \sum_{k \in K_t} |\tau_k|^2 \sigma_2^2 \text{diag}(h_{r,k}^H) A A^H \text{diag}(h_{r,k}^H)^H, \\
b_t & \triangleq \sum_{k \in K_t} (\sqrt{1 + \gamma_k} \tau_k u_{k,j} - \sum_{j=1}^K |\tau_k|^2 u_{k,j}^H w_j), \\
b_{t,m} & \triangleq \sum_{k \in K_t} (\sqrt{1 + \gamma_k} \tau_k u_{k,j} - \sum_{j=1}^K |\tau_k|^2 u_{k,j}^H w_j), \\
\end{align*}
\]

problem (35) can be rearranged as
\[
\min_{\varsigma} \varsigma^H Q_t \varsigma - 2R \{\varsigma^H b_t\} + \tilde{\varsigma}^H Q_t \tilde{\varsigma} - 2R \{\tilde{\varsigma}^H b_t\} \quad \text{(41a)}
\]
s.t. $\varsigma_m \in [0, 1], \forall m$. \quad \text{(41b)}

To effectively solve this problem, we propose to iteratively design each element of vector $\varsigma$ until convergence. To facilitate this calculation, we first split the objective function (41a) as
\[
\varsigma^H Q_t \varsigma - 2R \{\varsigma^H b_t\} + \tilde{\varsigma}^H Q_t \tilde{\varsigma} - 2R \{\tilde{\varsigma}^H b_t\}
= \sum_{m=1}^M \sum_{n=1}^M Q_t(m,n) \varsigma_m \varsigma_n - 2R \{\sum_{m=1}^M \varsigma_m b_t(m)\}
+ \sum_{m=1}^M \sum_{n=1}^M Q_t(m,n) \sqrt{1 - \varsigma_m^2} \sqrt{1 - \varsigma_n^2}
- 2R \{\sum_{m=1}^M \sqrt{1 - \varsigma_m^2} b_t(m)\}, \quad \text{(42)}
\]

where $b_t(m), b_t(n)$ are the $m$-th element of $b_t, b_t$, respectively. Since $Q_t = Q_t^H$ and $Q_t = Q_t^H$, the objective function with respect to the element $\varsigma_m$ is given by
\[
2R\{\sum_{n \neq m} Q_t(m,n) \varsigma_n - b_t(m)\} + Q_t(m,m) (1 - \varsigma^2_m)
+ 2R\{\sum_{n \neq m} Q_t(m,n) \sqrt{1 - \varsigma_m^2} \varsigma_n - b_t(m)\} \sqrt{1 - \varsigma^2_m}
+ Q_t(m,m) (1 - \varsigma^2_m). \quad \text{(43)}
\]

Hence, the sub-problem with respect to $\varsigma_m$ while fixing other elements can be formulated as
\[
\min_{\varsigma_m} \varsigma_m^2 + r_m \varsigma_m + q_t(m,1 - \varsigma^2_m) + t_m \sqrt{1 - \varsigma^2_m} \quad \text{(44a)}
\]
s.t. $\varsigma_m \in [0, 1], \forall m.$ \quad \text{(44b)}

where we define
\[
q_{t,m} \triangleq Q_t(m,m), \quad \text{(45)}
q_t \triangleq Q_t(m,m), \quad \text{(46)}
\]
\[
r_m \triangleq 2R\{\sum_{n \neq m} Q_t(m,n) \varsigma_n - b_t(m)\}, \quad \text{(47)}
\]
\[
t_m \triangleq 2R\{\sum_{n \neq m} Q_t(m,n) \sqrt{1 - \varsigma^2_m} - b_t(m)\}. \quad \text{(48)}
\]

It can be noted that the objective function in problem (44) is an ellipse. Hence, there is at most one stationary point between 0 and 1. By judging the derivative value at 0 and 1, the optimal solution can easily be obtained. Specifically, the derivative $g_m$ and its value at 0 and 1 can be derived by
\[
g_m = 2(q_{t,m} - q_t) \varsigma_m + r_m - t_m \sqrt{1 - \varsigma^2_m}. \quad \text{(49)}
\]
Algorithm 2: Amplitude Coefficient Design

Input: \( Q_t, Q_r, b_t, b_r \).

Output: \( \varsigma^* \).

1. Initialize \( \varsigma \).
2. while no convergence do
3. for \( m = 1 : M \) do
4. Calculate \( g_m(0), g_m(1 - \triangle) \).
5. if \( g_m(0) \geq 0 \) & \( g_m(1 - \triangle) \geq 0 \) \( c_m^* = 0 \).
6. if \( g_m(0) < 0 \) & \( g_m(1 - \triangle) < 0 \) \( c_m^* = 1 \).
7. if \( g_m(0) < 0 \) & \( g_m(1 - \triangle) > 0 \) \( c_m^* \) can be obtained by \( \frac{dg_m}{ds_m} = 0 \).
8. if \( g_m(0) > 0 \) & \( g_m(1 - \triangle) < 0 \) \( c_m^* = \arg \min \{g_m(0), g_m(1 - \triangle)\} \).
9. end for
10. end while

\[
g_m(0) = r_m, \quad g_m(1 - \triangle) = 2(q_{t,m} - q_{r,m})(1 - \triangle) + r_m - \frac{t_m(1 - \triangle)}{\sqrt{1 - (1 - \triangle)^2}},
\]

where \( \triangle \to 0 \) is an introduced small number in order to approach the derivative at 1. There are four possible scenarios:

1. \( g_m(0) \geq 0 \) and \( g_m(1 - \triangle) \geq 0 \). The objective function in (44) is monotonically increasing and the optimal value is 0.
2. \( g_m(0) < 0 \) and \( g_m(1 - \triangle) < 0 \). The objective function in (44) is monotonically decreasing and the optimal value is 1.
3. \( g_m(0) < 0 \) and \( g_m(1 - \triangle) > 0 \). The objective function in (44) is first decreasing and then increasing, and the optimal value can be obtained by \( \frac{dg_m}{ds_m} = 0 \).
4. \( g_m(0) > 0 \) and \( g_m(1 - \triangle) < 0 \). The objective function in (44) is first increasing and then decreasing, and the optimal value is the point at which the objective function is allowed to take its minimum value.

The whole transmission and reflection amplitude coefficient optimization is summarized in Algorithm 2. Since the algorithm is linear, the overall complexity is about \( O(I_M M) \), where \( I_M \) denotes the number of iterations.

Now, the complete procedure of finding auxiliary vectors \( \gamma^* \) and \( \tau^* \). BS transmit beamforming \( w_k^* \), RIS amplification matrix \( A^* \), phase-shift matrices \( \Phi_f^*, \Phi_t^* \), and amplitude coefficient \( \varsigma^* \) is straightforward. The initial point of amplification matrix \( A \) is obtained by setting \( A = \sqrt{a_{\text{max}}}I_M \) with \( a_{\text{max}} = \frac{P_T}{\sum_{k=1}^{K} ||Gw_k||^2 + \sigma^2_M} \). The powers of reflected signal and transmitted signal are fixed at the same value, i.e., \( s_m = 1/\sqrt{2} \), \( \forall m \). We just simply give random values of phase-shift vectors \( \phi_f \) and \( \phi_t \). The typical MMSE beamforming as the initial value of the BS transmit beamforming \( w_k \) is given by \( w_k = (\sum_{k=1}^{K} \bar{h}_k^H \bar{h}_k + \sigma_k^2 I_k)^{-1} \bar{h}_k, k \in \mathcal{K}_t \), with \( \bar{h}_k = \frac{h_k^H - \sigma_k^2 \bar{h}_k E_k A}{\sigma_k^2 + \sigma_k^2} \) and \( \bar{h}_k = (\sum_{k=1}^{K} \bar{h}_k^H \bar{h}_k + \sigma_k^2 I_k)^{-1} \bar{h}_k, k \in \mathcal{K}_r \) with \( \bar{h}_k = \frac{h_k^H - \sigma_k^2 \bar{h}_k E_k A}{\sigma_k^2 + \sigma_k^2} \). Then the BS beamforming is further normalized to satisfy the transmit power budget by \( w_k = \frac{\sqrt{P_T} \bar{h}_k}{\sqrt{\sum_{k=1}^{K} ||w_k||^2}}, \forall k \).

With appropriate initialization, we iteratively update \( \gamma, \tau, w_k, A, \Phi_f, \Phi_t \), and \( \varsigma \) until convergence. For clarity, the proposed FP-based BS transmit beamforming and DF-ARIS design algorithm is summarized in Algorithm 3.

Algorithm 3: Joint BS Beamforming and DF-ARIS Design for the Sum-Rate Maximization Problem

Input: \( h_{d,k}^H, h_{t,k}^H, G, \sigma^2_r, \sigma^2_v, P_T, P_{\text{RF}}, P_{\text{max}, m}, T_{\text{max}}, \delta_{\text{th}} \).

Output: \( w_k^*, A^*, \Phi_f^*, \Phi_t^*, \varsigma^* \).

1. Initialize \( w_k, A, \Phi_f, \Phi_t, \varsigma_t, \tau_t, \delta_t, t = 1, \delta = \infty, R_{\text{temp}} = 0 \).
2. while \( t \leq T_{\text{max}} \) and \( \delta \geq \delta_{\text{th}} \) do
3. \( R_{\text{pre}} = R_{\text{temp}} \).
4. Update \( \gamma^*_k, \forall k \) by (16).
5. Update \( \tau^*_k, \forall k \) by (17).
6. Update BS beamforming \( w_k^* \), \( \forall k \) by (18).
7. Update amplification matrix \( A^* \) by (19).
8. Update phase-shift matrices \( \Phi_f^*, \Phi_t^* \) using Algorithm 1.
9. Update amplitude coefficient \( \varsigma^* \) using Algorithm 2.
10. Calculate sum rate \( \sum_{k=1}^{K} \log_{2} (1 + \text{SINR}_k) \).
11. \( \delta = R_{\text{temp}} - R_{\text{pre}} \).
12. \( t = t + 1 \).
13. end while

H. Complexity Analysis

In this subsection, we provide a brief computational complexity analysis for the proposed joint BS transmit beamforming and DF-ARIS design for the sum-rate maximization problem, i.e., Algorithm 3.

The overall computational complexity of the proposed algorithm is mainly caused by the update of variables. In each iteration, obtaining the optimal solution of \( \gamma \) and \( \tau \) requires approximately \( O(K^2 M^2) \) and \( O(K(K + 1)M^2) \) operations, respectively; updating BS transmit beamforming \( w_k \) requires approximately \( O((KN)^3(M + 2)1.5) \) operations; updating RIS amplification matrix \( A \) has a complexity of approximately \( O(M^3(M + 1)^{1.5}) \). Therefore, the total computational complexity of Algorithm 3 can be approximated by \( O \left( I_R \left( M^{4.5} + (KN)^3 M^{1.5} + K^2 M^2 + M^2 + I_M M \right) \right) \), wherein \( I_R \) represents the required number of iterations for the convergence.

IV. POWER MINIMIZATION PROBLEM

A. Problem Formulation

In this section, we aim to minimize the total power consumption of the BS and the DF-ARIS subject to the SINR constraint of each user. With the previous analysis, the power minimization problem can be formulated as

\[
\min_{w_k, A, \Phi_f, \Phi_t, \varsigma} \alpha \sum_{k=1}^{K} ||w_k||^2 + (1 - \alpha) \sum_{k=1}^{K} ||A Gw_k||^2 \quad \text{(52a)}
\]

s.t. \( \text{SINR}_k \geq \gamma_k, \quad k \in \mathcal{K} \), \quad \text{(52b)}
where \( \alpha \in (0, 1) \) acts as the weighting factor and \( \gamma_k > 0 \) is the minimum SINR requirement of the user \( k \). Although the objective function of problem (52) is convex, it is still challenging to solve since the constant-modulus constraint (52e) is non-convex. Moreover, the design of the phase-shift matrices \( \Phi_r, \Phi_t \) and amplitude coefficient \( \varsigma \) becomes a feasibility-check problem. As a result, it is very difficult to find a global optimal solution. Instead, we attempt to find a sub-optimal solution to it.

Prior to solving it, we present a sufficient condition for its feasibility. When the equivalent channel \((G_Hh_t + H_d)\) is full rank where \( H_d = [h_{d,1}, \cdots, h_{d,K}] \in \mathbb{C}^{N \times K} \) and \( H_r = [h_{r,1}, \cdots, h_{r,K}] \in \mathbb{C}^{M \times K} \), problem (52) is feasible for any finite user SINR requirement \( \gamma_k \). The specific proof is shown in Proposition 1 in [22]. Note that this full rank assumption is widely adopted in the literature [5], [12], [22]. In fact, the channel coefficient matrix always satisfies full rank, when it independently follows some identical continuous distribution, e.g. Rayleigh or Rician. We also assume that the channels are full rank in this paper.

**B. Update BS Transmit Beamforming \( w_k \)**

When other variables are fixed, the overall channel vectors are determined. The sub-problem for optimizing BS beamforming \( w_k \) is given by

\[
\begin{align*}
\min_{w_k} & \quad \alpha \sum_{k=1}^{K} \|w_k\|^2 + (1 - \alpha) \sum_{k=1}^{K} \|Agw_k\|^2 \\
\text{s.t.} & \quad \text{SINR}_k \geq \gamma_k, \quad k \in \mathcal{K}, \\
& \quad a_m \left( \sum_{k=1}^{K} |g_m^Hw_k|^2 + \sigma_r^2 \right) \leq p_{\max, m}, \quad \forall m,
\end{align*}
\]

(53a)

which is a convex problem and can be solved by standard convex tools, e.g., CVX.

**C. Update Amplification Matrix \( A \)**

Given other variables, the optimization problem of amplification matrix \( A \) can be expressed by

\[
\begin{align*}
\min_{A} & \quad (1 - \alpha) \sum_{k=1}^{K} \|Agw_k\|^2 \\
\text{s.t.} & \quad \text{SINR}_k \geq \gamma_k, \quad k \in \mathcal{K}, \\
& \quad a_m \leq c_m, \quad \forall m,
\end{align*}
\]

(54a)

where \( c_m = \frac{p_{\max, m}}{\sum_{k=1}^{K}|g_m^Hw_k|^2 + \sigma_r^2} \) also represents the amplification maximum of the \( m \)-th element. This is again a convex problem and can be efficiently solved.

**D. Transform Objective Function and Update Phase-Shift Matrices \( \Phi_r, \Phi_t \)**

After obtaining the BS transmit beamforming \( w_k \) and the DF-ARIS amplification matrix \( A \), the objective of the original optimization problem (52) has been determined. This means that, with given \( w_k \) and \( A \), the design of phase-shift matrices \( \Phi_r, \Phi_t \) and amplitude coefficient \( \varsigma \) becomes a feasibility-check problem and could not directly affect the power minimization objective of (52a). Therefore, we attempt to formulate another proper objective function that can facilitate the reduction of the total power consumption for next iteration and guarantee its feasibility.

We note that the conditionally optimal \( w_k \) and \( A \) of the power minimization problem (52) usually make constraint (52b) almost equal, i.e., the QoS requirement is satisfied almost with equality. In order to further reduce the total power consumption in the next iteration, we propose to use the QoS balancing as the objective function, which can introduce an improved QoS and provide more freedom for power minimization. To this end, when optimizing phase-shift vector \( \phi_r \), the QoS balancing problem can be formulated as

\[
\begin{align*}
\max \min_{\phi_r, k \in \mathcal{K}_r} & \quad \frac{\text{SINR}_k}{\gamma_k} \\
\text{s.t.} & \quad |\phi_{r,m}| = 1, \quad \forall m.
\end{align*}
\]

(55a)

Unfortunately, problem (55) is very challenging to handle due to the following reasons: i) the objective function (55a) is max-min function and non-differentiable which hamper the algorithm development, ii) the fractional terms in objective function (55a) are non-convex, iii) the unit-modulus constraint for phase-shift (55b) is also non-convex. In order to tackle these difficulties, the max-min function is equivalently transformed into min-max form to apply the log-sum-exp approach and Riemannian-manifold algorithm. Then, we reformulate the fractional term into a form with decoupled numerator and denominator by applying Dinkelbach’s transform [52]. Therefore, by introducing a new auxiliary variable \( \varsigma_r \), the transformed problem can be expressed as

\[
\begin{align*}
\min \max_{\phi_r, \varsigma_r} & \quad \left\{ f_k - \varsigma_r g_k \right\} \\
\text{s.t.} & \quad |\phi_{r,m}| = 1, \quad \forall m,
\end{align*}
\]

(56a)

where \( f_k \) and \( g_k \) are auxiliary functions which are presented as

\[
\begin{align*}
f_k & \triangleq \gamma_k \left( \sum_{j \neq k} \left( |h_{d,k}^H + h_{r,k}^H \Phi_r E_r AG w_j|^2 + \sigma_r^2 \right), \quad k \in \mathcal{K}_r, \\
g_k & \triangleq \left( |h_{d,k}^H + h_{r,k}^H \Phi_r E_r AG w_k|^2, \quad k \in \mathcal{K}_r.
\end{align*}
\]

(57)

(58)

The optimal \( \varsigma^*_r \) can be expressed in a closed-form as [52]

\[
\varsigma^*_r = \max \left\{ \frac{f_k}{g_k} \right\}, \quad \forall k \in \mathcal{K}_r.
\]

(59)

However, problem (56) is still non-differentiable. Then we smooth the max function by the well-known log-sum-exp approximation and obtain

\[
\begin{align*}
\min_{\phi_r, \varsigma_r} & \quad \varepsilon \log \sum_{k \in \mathcal{K}_r} \exp \left\{ \frac{f_k - \varsigma_r g_k}{\varepsilon} \right\} \\
\text{s.t.} & \quad |\phi_{r,m}| = 1, \quad \forall m,
\end{align*}
\]

(60a)

(60b)
where $\varepsilon$ is a relatively small positive number to maintain the approximation. While the objective of (60) is smooth and differentiable, the non-convex constraint (60b) still makes the problem difficult to solve. Therefore, we use Riemannian-manifold algorithm presented in Section III to solve it. Its Euclidean gradient can be derived by

$$
\nabla f = \sum_{k \in K_s} \exp \left\{ \frac{f_k - \varepsilon g_k}{\varepsilon} \right\} (a_k - \varepsilon w_k), \quad k \in K_s,
$$

(61)

where we define

$$
a_k \triangleq 2\gamma_k \sum_{j \neq k} (r_{k,j} r_{H,k,j}^H \phi_t + r_{k,j} h_{dk,j}^H w_j), \quad k \in K_s,
$$

(62)

$$
b_k \triangleq 2(r_{k,k} r_{H,k,k}^H \phi_t + r_{k,k} h_{dk,k}^H w_k), \quad k \in K_s.
$$

(63)

Then, the Riemannian-manifold-based phase-shift design presented in Algorithm 1 can be applied.

Similarly, as we discussed above, the optimization problem of $\phi_t$ can be expressed by

$$
\begin{align*}
\min_{\phi_t} \ & \ v \log \sum_{k \in K_t} \exp \left\{ \frac{f_k - \varepsilon g_k}{\varepsilon} \right\} \\
\text{s.t.} \ & \ |\phi_{t,m}| = 1, \quad \forall m,
\end{align*}
$$

(64a)

$$
\begin{align*}
\min_{\phi_t} \ & \ v \log \sum_{k \in K_t} \exp \left\{ \frac{f_k - \varepsilon g_k}{\varepsilon} \right\} \\
\text{s.t.} \ & \ |\phi_{t,m}| = 1, \quad \forall m,
\end{align*}
$$

(64b)

where $f_k$ and $g_k$ are presented as

$$
f_k \triangleq \gamma_k \left( \sum_{j \neq k} \left| (h_{dk,j}^H + h_{dk,k}^H \Phi_t E_t A) w_j \right|^2 \\
+ \sigma_v^2 \| h_{dk,k}^H E_t A \|^2 + \sigma_v^2 \right), \quad k \in K_t,
$$

(65)

$$
g_k \triangleq \left| (h_{dk,k}^H + h_{dk,k}^H \Phi_t E_t A) w_k \right|^2, \quad k \in K_t.
$$

(66)

The optimal $\varpi_t^*$ can be expressed as [52]

$$
\varpi_t^* = \max \left\{ \frac{f_k}{g_k} \right\}, \quad \forall k \in K_t.
$$

(67)

Likewise, the Euclidean gradient of problem (64) can be derived by

$$
\nabla f = \sum_{k \in K_s} \exp \left\{ \frac{f_k - \varepsilon g_k}{\varepsilon} \right\} (c_k - \varpi_t d_k), \quad k \in K_s,
$$

(68)

where

$$
c_k \triangleq 2\gamma_k \sum_{j \neq k} (r_{k,j} r_{H,k,j}^H \phi_t + r_{k,j} h_{dk,j}^H w_j), \quad k \in K_s,
$$

(69)

$$
d_k \triangleq 2(r_{k,k} r_{H,k,k}^H \phi_t + r_{k,k} h_{dk,k}^H w_k), \quad k \in K_s.
$$

(70)

Therefore, the phase-shift vector $\phi_t$ can be obtained by applying the Riemannian-manifold-based algorithm presented in Algorithm 1. Moreover, since the phase-shift vectors $\phi_t$ and $\phi_t$ are separate, they can be optimized in parallel to reduce computational time.

### Algorithm 4 Joint BS Beamforming and DF-ARIS Design for the Power Minimization Problem

**Input:** $h_{dk,k}^H, h_{dk,k}^H, G, \sigma_v^2, \sigma_v^2, \alpha, \text{SINR}_k, T_{\text{max}}, \delta_\text{th}.

**Output:** $w_k^*, A^*, \Phi_t^*, \Phi_t^*, \varsigma^*.$

1. Initialize $w_k, A, \Phi_t, \delta, t = 1, \delta = \infty, \rho_{\text{temp}} = 0.$
2. while $t \leq T_{\text{max}}$ and $\delta \geq \delta_\text{th}$
3. $\rho_{\text{pre}} = \rho_{\text{temp}}.$
4. Update BS beamforming $w_k^*, \forall k$ by (53).
5. Update amplification matrix $A^*$ by (54).
6. Update phase-shift matrices $\Phi_t^*, \Phi_t^*$ using Algorithm 1.
7. Update amplitude coefficient $\varsigma^*$ using Algorithm 2.
8. $\rho_{\text{temp}} = \alpha \sum_{k=1}^K \| w_k \|^2 + (1 - \alpha) \sum_{k=1}^K \| A G w_k \|^2.$
9. $\delta = \frac{|\rho_{\text{temp}} - \rho_{\text{pre}}|}{\rho_{\text{temp}}}.$
10. $t = t + 1.$
11. end while

### E. Update Amplitude Coefficient

Given other variables, the optimization problem of amplitude coefficient $\varsigma$ can be reformulated as follows

$$
\begin{align*}
\min_{\varsigma} \ & \ v \log \sum_{k \in K} \exp \left\{ \frac{f_k - \varepsilon g_k}{\varepsilon} \right\} \\
\text{s.t.} \ & \ \varsigma_m \in [0,1], \quad \forall m,
\end{align*}
$$

(71a)

(71b)

where $\varpi_t = \frac{f_k}{g_k}, \forall k \in K.$ As we discussed above, we iteratively design each element of the vector $\varsigma$ until convergence.

Finally, the joint BS transmit beamforming and DF-ARIS design for the total power minimization problem is straightforward. Similarly, with a proper initialization, the BS beamforming $w_k$, amplification matrix $A$, phase-shift matrices $\Phi_t, \Phi_t$, and amplitude coefficient $\varsigma$ are iteratively optimized until convergence, which is summarized in Algorithm 4.

### F. Complexity Analysis

We also give a brief complexity analysis of the proposed joint BS transmit beamforming and the DF-ARIS design for the power minimization problem. The optimizations of the BS beamforming $w_k$ and the DF-ARIS amplification matrix $A$ have the complexity of approximately $O((KN)^3(M + K))$ and $O(M^3(M + K))^{1.5} + O(M^3(M + K))^{1.5} + O(M^2(M + K))^{1.5} + O(M^2(M + K))^{1.5}$, where the parameters $I_{d1}$ and $I_{d2}$ are the numbers of iterations of updating phase-shift vectors $\phi_t$ and $\phi_t$. Hence, the total computational complexity of Algorithm 4 is approximated by $O(I_{d1}^2 M^2 + I_{d2} M^2 + I_{d2} M^2 + I_{d2} M^2)$, where $I_P$ denotes the required number of iterations for convergence.

### V. Simulation Results

In this section, we provide extensive simulation results to demonstrate the advantages of the proposed DF-ARIS architecture and illustrate the effectiveness of our proposed algorithms. For simplicity, we assume the QoS requirement...
and the noise power at all receivers are the same, i.e., \( \gamma_k = \gamma, \sigma_k^2 = -80 \text{ dBm}, \forall k \). The factor \( \varepsilon \) to maintain the approximation is set as \( 10^{-3} \). The transmit antenna array at the BS is assumed to be a uniform linear array with antenna spacing given by \( \lambda/2 \) where \( \lambda \) denotes the wavelength. The thermal noise power introduced by the DF-ARIS is \( \sigma^2 = -80 \text{dBm} \). The distance-dependent path loss is modeled as:
\[
\text{PL}(d) = C_0 \left( \frac{d_0}{d} \right)^\kappa,
\]
where \( C_0 = -30 \text{dB} \) is the path loss for the reference distance \( d_0 = 1 \text{m} \), \( d \) is the link distance, and \( \kappa \) is the path-loss exponent.

In addition, the channel from the BS to the DF-ARIS is assumed to follow the small-scale Rician fading channel model, which consists of line-of-sight (LoS) and non-LoS (NLoS) components. The channel can be expressed as:
\[
G = \sqrt{\frac{\alpha_g}{\alpha_g + 1}} G^{\text{LoS}} + \sqrt{\frac{1}{\alpha_g + 1}} G^{\text{NLoS}},
\]
where \( \alpha_g \) is the Rician factor set as 3dB, \( G^{\text{LoS}} \) is the LoS component which depends on the geometric settings, and \( G^{\text{NLoS}} \) is the NLoS Rayleigh fading component with a path-loss exponent of 2.5. The channels from the DF-ARIS to users only have NLoS components and the path-loss exponent is 2.0. The path-loss exponent of channels from the BS to users in \( K \) is 3.6. Due to the blockage and severe path loss, the channels from the BS to users in \( K_i \) are weak. Hence, the path-loss exponent is assumed to be 4.2 usually. The BS is equipped with \( N = 16 \) antennas and serves \( K = 4 \) users with two users in \( K_i \) and two users in \( K_t \). We assume that the DF-ARIS equipped with \( M = 128 \) elements is 80m away from the BS, and users are randomly distributed on a circle centered at the DF-ARIS with the radius of 10m, as illustrated in Fig. 4. The simulation results were obtained by averaging over \( 10^4 \) random channel realizations.

We also include two other operation modes for the DF-ARIS: i) Space Division (SD) mode, i.e., elements are divided into two groups. One group operates for the reflection functionality while the other group operates for the transmission functionality. In this mode, the amplitude coefficient \( \varsigma_m \) is fixed as 1 or 0 for these two groups, respectively. ii) Equal Power (EP) mode, i.e., the powers of reflected signal and transmitted signal are fixed at the same value as \( \varsigma_m = 1/\sqrt{2}, \forall m \). Algorithms for optimizing other variables also apply to these modes.
the sum-rate achieved by our proposed DF-ARIS architecture is dramatically greater than the competitor in [31], which is a passive device without signal amplification. In addition, our proposed DF-ARIS also outperforms the traditional FD and HD relay owing to the substantial beamforming gain provided by the RIS. These results support the benefit of deploying the DF-ARIS in wireless communication systems. Since the DoFs of SD and EP modes are limited, the sum-rate achieved by these two schemes is lower than the OP mode, which demonstrates the effectiveness of power splitting.

Next, we show the achievable sum-rate versus the number of DF-ARIS elements $M$ in Fig. 7. Since the larger RIS can provide larger beamforming gain, we observe that the sum-rate increases for all schemes with increasing $M$. Moreover, the proposed DF-ARIS can achieve satisfactory performance with significantly less RIS elements, which means that the training overhead for channel estimation and complexity of the control link will remarkably decrease in practical scenarios.

In order to illustrate the impact of user distribution, in Fig. 8 we compare the sum-rate versus the number of users in $K_r$. From Fig. 8 we can observe that the sum-rate reaches its maximum when the distribution of users at both sides of the RIS is close to equal. For comparison, we also investigate the performance of current reflective-only active RIS (RO-ARIS) proposed in [20] and [21]. It is noted that, in RO-ARIS assisted communication systems, the sum-rate increases linearly with the number of users in $K_r$, since it can only assist the communication of users within the same half-space as BS. However, the proposed DF-ARIS can always provide satisfactory sum-rate performance for different user distributions.

**B. Power Minimization**

In this subsection, we illustrate the simulation results for the power minimization problem. The power consumption weighted factor $\alpha$ is set as 0.5. The convergence performance shown in Fig. 9 is similar to that observed for the sum-rate maximization problem in Fig. 5. It can be seen from Fig. 9 that all schemes converge around 40 iterations.

In Fig. 10, we show the total power consumption versus the SINR requirement of users. It can be observed that our proposed scheme requires much less total power consumption than the traditional FD relay and STAR-RIS, which validates the advantages of the proposed DF-ARIS scheme in terms of energy efficiency. More interestingly, the passive STAR-RIS
versus the number of users in $K$ can always achieve better performance. Drawn from Fig. 11, that the proposed DF-ARIS architecture exhibited remarkably better performance in terms of sum-rate enhancement and power-saving, which confirmed that the employment of DF-ARIS in wireless communication systems has promising prospects. In the future, we will proceed to investigate the robust design for BS transmit beamforming and DF-ARIS coefficients with imperfect CSI. Specifically, we will adopt the popular deterministic model, in which the CSI error belongs to a given uncertainty set. Matrix properties and successive convex approximations will be utilized to convert the sophisticated optimization problem into tractable convex sub-problems. Then our proposed algorithms can again be invoked straightforwardly.

Next, we present the total power consumption versus the number of DF-ARIS elements in Fig. 11. We observe that as the number of elements increases, the total power consumption is greatly reduced. A similar conclusion can be drawn from Fig. 11 that the proposed DF-ARIS architecture can always achieve better performance.

Finally, in Fig. 12 we show the total power consumption versus the number of users in $K$. The proposed DF-ARIS always has a lower power consumption performance than traditional FD relay and STAR-RIS. The minimum total power consumption is achieved when users are equally located at the two sides of the RIS, i.e. there are 4 users located in $K_r$. When all users are mostly located at the same side of the RIS, the beamforming gain provided by large-scale phase shifters on the other side is limited, which leads to an increase in power consumption.

VI. CONCLUSION

In this paper, we investigated a novel reflection and transmission dual-functional active RIS architecture, which can simultaneously realize reflection and transmission functionalities with signal amplification to enhance the QoS of all users and extend the coverage. In particular, we considered the joint BS transmit beamforming and the DF-ARIS designs for DF-ARIS assisted MU-MISO systems. Efficient iterative algorithms were proposed to solve the sum-rate maximization and power minimization problems, respectively. Simulation results illustrated that our proposed DF-ARIS architecture exhibited remarkably better performance in terms of sum-rate enhancement and power-savings, which confirmed that the employment of DF-ARIS in wireless communication systems has promising prospects. In the future, we will proceed to investigate the robust design for BS transmit beamforming and DF-ARIS coefficients with imperfect CSI. Specifically, we will adopt the popular deterministic model, in which the CSI error belongs to a given uncertainty set. Matrix properties and successive convex approximations will be utilized to convert the sophisticated optimization problem into tractable convex sub-problems. Then our proposed algorithms can again be invoked straightforwardly.

REFERENCES

[1] Q. Wu and R. Zhang, “Towards smart and reconﬁgurable environment: Intelligent reﬂecting surface aided wireless network,” IEEE Commun. Mag., vol. 58, no. 1, pp. 106–112, Jan. 2020.
[2] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M. Alouini, and R. Zhang, “Wireless communications through reconﬁgurable intelligent surfaces,” IEEE Access, vol. 7, pp. 11 6753–11 6773, 2019.
[3] W. Ni, X. Liu, Y. Liu, H. Tian, and Y. Chen, “Resource allocation for multi-cell IRS-aided NOMA networks,” IEEE Trans. Wireless Commun., vol. 20, no. 7, pp. 4253–4268, Jul. 2021.
[4] L. Zhang, Y. Wang, W. Tao, Z. Jia, T. Song, and C. Pan, “Intelligent reﬂecting surface aided MIMO cognitive radio systems,” IEEE Trans. Veh. Technol., vol. 69, no. 10, pp. 11 445–11 457, Oct. 2020.
[5] H. Li, W. Cai, Y. Liu, M. Li, Q. Liu, and Q. Wu, “Intelligent reﬂecting surface enhanced wideband MIMO-OFDM communications: From practical model to reﬂection optimization,” IEEE Trans. Commun., vol. 69, no. 7, pp. 4807–4820, Jul. 2021.
[6] X. Mu, Y. Liu, L. Guo, J. Lin, and H. V. Poor, “Intelligent reﬂecting surface enhanced multi-UAV NOMA networks,” IEEE J. Sel. Areas Commun., vol. 39, no. 10, pp. 3051–3066, Oct. 2021.
[7] J. Zuo, Y. Liu, Z. Qin, and N. Al-Dhahir, “Resource allocation in intelligent reﬂecting surface assisted NOMA systems,” IEEE Trans. Commun., vol. 68, no. 11, pp. 7170–7183, Nov. 2020.
[8] S. Hu, F. Rusek, and O. Edfors, “Beyond massive MIMO: The potential of positioning with large intelligent surfaces,” IEEE Trans. Signal Process., vol. 66, no. 7, pp. 1761–1774, Apr. 2018.
[9] M. D. Renzo et al., “Smart radio environments empowered by reconﬁgurable AI meta-surfaces: An idea whose time has come,” EURASIP J. Wireless Commun. Netw., vol. 2019, no. 1, pp. 1–20, Dec. 2019.
[10] S. Liu, M. Li, Q. Liu, and A. L. Swindlehurst, “Joint symbol-level precoding and reﬂecting designs for IRS-enhanced MU-MISO systems,” IEEE Trans. Wireless Commun., vol. 20, no. 2, pp. 798–811, Feb. 2021.
[11] W. Cai, H. Li, M. Li, and Q. Liu, “Practical modeling and beamforming for intelligent reﬂecting surface aided wideband systems,” IEEE Commun. Lett., vol. 24, no. 7, pp. 1568–1571, Jul. 2020.
[12] Y. Liu, J. Zhao, M. Li, and Q. Wu, “Intelligent reﬂecting surface aided MISO uplink communication network: Feasibility and power minimization for perfect and imperfect CSI,” IEEE Trans. Commun., vol. 69, no. 3, pp. 1975–1989, Mar. 2021.
[13] C. Huang, R. Mo, and C. Yuen, “Reconﬁgurable intelligent surface assisted multiuser MISO systems exploiting deep reinforcement learning,” IEEE J. Sel. Areas Commun., vol. 38, no. 8, pp. 1839–1850, Aug. 2020.
[14] K. Feng, Q. Wang, X. Li, and C. Wen, “Deep reinforcement learning based intelligent reﬂecting surface optimization for MISO communication systems,” IEEE Wireless Commun. Lett., vol. 9, no. 5, pp. 745–749, May 2020.
W. Tang et al., “Wireless communications with reconfigurable intelligent surface: Path loss modeling and experimental measurement,” IEEE Access, vol. 9, pp. 44304–44321, 2021.

W. Tang et al., “Wireless communications with reconfigurable intelligent surface: System design, analysis, and implementation,” IEEE J. Sel. Areas Commun., vol. 38, no. 11, pp. 2683–2699, Nov. 2020.

Y. Ma, R. Liu, M. Li, and Q. Liu, “Passive information transmission in intelligent reflecting surface aided MISO systems,” IEEE Commun. Lett., vol. 24, no. 12, pp. 2951–2955, Dec. 2020.

R. Liu, M. Li, Q. Liu, A. L. Swindlehurst, and Q. Wu, “Intelligent reflecting surface based passive information transmission: A symbol-level precoding approach,” IEEE Trans. Veh. Technol., vol. 70, no. 7, pp. 6735–6749, Jul. 2021.

Z. Zhang et al., “Active RIS vs. passive RIS: Which will prevail in 6G?” IEEE Trans. Commun., vol. 71, no. 3, pp. 1707–1725, Mar. 2023.

R. Long, Y. Liang, Y. Pei, and E. G. Larsson, “Active reconfigurable intelligent surface-aired wireless communications,” IEEE Wireless Commun., vol. 20, no. 8, pp. 4962–4975, Aug. 2021.

Q. Wu and R. Zhang, “Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming,” IEEE Trans. Wireless Commun., vol. 18, no. 11, pp. 5394–5409, Nov. 2019.

Q. Wu and R. Zhang, “Beamforming optimization for wireless network aided by intelligent reflecting surface with discrete phase shifts,” IEEE Trans. Commun., vol. 68, no. 3, pp. 1838–1851, Mar. 2020.

E. Björnson, Ö. Özdogan, and E. G. Larsson, “Intelligent reflecting surface versus decode-and-forward: How large surfaces are needed to beat relaying?” IEEE Wireless Commun. Lett., vol. 9, no. 2, pp. 244–248, Feb. 2020.

K. Nootin, M. Di Renzo, and F. Lazarakis, “On the rate and energy efficiency comparison of reconfigurable intelligent surfaces with relays,” in Proc. IEEE 21st Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC), May 2020, pp. 1–5.

Z. Wang, L. Liu, and S. Cui, “Channel estimation for intelligent reflecting surface assisted multiuser communications: Framework, algorithms, and analysis,” IEEE Trans. Wireless Commun., vol. 19, no. 10, pp. 6607–6620, Oct. 2020.

X. Cheng and Y. He, “Channel modeling and analysis of ULA massive MIMO systems,” in Proc. 20th Int. Conf. Adv. Commun. Technol. (ICACT), Feb. 2018, p. 1.

C. You, B. Zheng, and R. Zhang, “Channel estimation and passive beamforming for intelligent reflecting surface: Discrete phase shift and progressive refinement,” IEEE J. Sel. Areas Commun., vol. 38, no. 11, pp. 2604–2620, Nov. 2020.

X. Ying, U. Demirhan, and A. Alkhateeb, “Relay aided intelligent reconfigurable surfaces: Achieving the potential without so many antennas,” arXiv:2006.06644.

N. T. Nguyen, Q. Vu, K. Lee, and M. Juntti, “Hybrid relay-reflecting intelligent surface-assisted wireless communications,” IEEE Trans. Veh. Technol., vol. 71, no. 6, pp. 6228–6242, Jun. 2022.

J. Xu, Y. Liu, X. Mu, and O. A. Dobre, “STAR-RISs: Simultaneous transmitting and reflecting reconfigurable intelligent surfaces,” IEEE Commun. Lett., vol. 25, no. 9, pp. 3134–3138, Sep. 2021.

Y. Liu et al., “STAR: Simultaneous transmission and reflection for 360° coverage by intelligent surfaces,” IEEE Wireless Commun., vol. 28, no. 6, pp. 102–109, Dec. 2021.

X. Mu, Y. Liu, L. Guo, J. Lin, and R. Schober, “Simultaneously transmitting and reflecting (STAR) RIS aided wireless communications,” IEEE Trans. Wireless Commun., vol. 21, no. 5, pp. 3083–3098, May 2022.

F. Amato, C. W. Peterson, B. P. Degnan, and G. D. Durgin, “Tunneling RFID tags for long-range and low-power microwave applications,” IEEE J. Radio Freq. Ident., vol. 2, no. 2, pp. 93–103, Jun. 2018.

J. Lomas, Z. Ipu, and S. Harbar, “Ultra thin active polarization selectives metasurface at X-band frequencies,” Phys. Rev. B, Condens. Matter, vol. 100, no. 7, Oct. 2019, Art. no. 075131.

K. K. Kishor and S. V. Hum, “An amplifying reflective reconfigurable antenna,” IEEE Trans. Antennas Propag., vol. 60, no. 1, pp. 197–205, Jan. 2012.

M. Jereminov, A. Pandey, D. M. Bromberg, X. Li, G. Hug, and L. Pileggi, “Steady-state analysis of power system harmonics using equivalent split-circuit models,” in Proc. IEEE PES Innov. Smart Grid Techn. Conf. Eur. (ISGT-Eur.), Ljubljana, Slovenia, Oct. 2016, pp. 1–6.

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