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RESEARCH ARTICLE

Two-Stage Power Allocation for IRS-Assisted Downlink NOMA: Intra-Group Optimization and Inter-Group Allocation

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ABSTRACT Non-Orthogonal Multiple Access (NOMA) has emerged as a key enabler for massive connectivity in next-generation networks, while Intelligent Reflecting Surfaces (IRS) provide a transformative approach to enhancing spectral efficiency by reconfiguring the wireless propagation environment. However, integrating IRS with downlink NOMA presents significant challenges in power allocation, user grouping, and interference management, with existing methods often struggling to balance power efficiency, quality-of-service (QoS) guarantees, and computational scalability. This paper investigates a two-stage power allocation framework for IRS-assisted downlink NOMA. The first stage performs intra-group optimization, jointly adjusting user-level power allocation and IRS phase shifts to minimize power consumption while meeting QoS requirements based on an iterative optimization procedure. The second stage optimizes inter-group, allocating power across user groups to maximize the number of served users based on a sequential fixing programming procedure. A detailed complexity analysis demonstrates the computational efficiency of the framework, enabling real-time deployment in dynamic networks. The simulation results confirm that the proposed approach achieves superior sum rate performance while minimizing total power consumption and maintaining QoS guarantees.

INDEX TERMS Channel estimation, resource allocation, intelligent reflecting surface, channel conditions, non-orthogonal multiple access, user grouping, power consumption.

I. INTRODUCTION

The exponential growth in data demand and the emergence of diverse applications have motivated the development of Beyond Fifth Generation (B5G) wireless communication systems. These systems are envisioned to achieve high spectral efficiency, improved energy efficiency, and seamless massive connectivity. To meet these requirements, advanced technologies such as Non-Orthogonal Multiple Access (NOMA) and Intelligent Reflecting Surfaces (IRS) have emerged as key enablers in recent years [1], [2], [3].

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NOMA leverages power-domain multiplexing to allow multiple users to share the same frequency resource simultaneously, enhancing system throughput and user fairness. This is achieved using successive interference cancellation (SIC) at the receiver to decode user signals [4]. NOMA has been extensively studied for its ability to address diverse user demands, particularly in scenarios with heterogeneous quality-of-service (QoS) requirements [5], [6], [7]. In contrast, IRS is a revolutionary technology that introduces programmable and passive control of the wireless environment. Comprising a large number of passive reflecting elements, IRS dynamically adjusts the amplitude and phase of incident signals, thus improving signal strength, minimizing interference, and improving energy efficiency.

The integration of IRS with AI has further amplified its adaptability, enabling real-time optimization of wireless channels. These properties make IRS a critical enabler of efficient communication and networking in B5G networks [8], [9], [10].

Integrating IRS with NOMA combines both technologies' strengths, achieving significant improvements in spectral and energy efficiency [11], [12]. However, this integration presents power allocation, user grouping, and interference management challenges. Existing methods primarily focus on joint power allocation and IRS phase shift optimization [13], [14], often relying on iterative algorithms with high computational complexity. Furthermore, previous research has investigated optimal power control in Gaussian broadcast channels, demonstrating significant gains in system capacity when power is efficiently allocated [15]. Furthermore, machine learning-based optimization techniques have been applied to reduce energy consumption in multi-connectivity scenarios, which aligns with the hierarchical power allocation strategy presented in this work [16]. These approaches, while effective, may lack scalability and adaptability in large-scale dynamic environments [17]. This work proposes a two-stage power-allocation framework for IRS-assisted downlink NOMA systems to address these challenges, emphasizing efficient user grouping and resource allocation. The framework consists of the following key components:

- Intra-group optimization that jointly adjusts user-level power allocation and IRS phase shifts within each group to minimize total power consumption while ensuring a set of QoS requirements.
- Inter-group optimization that assigns power across various user groups to maximize the number of served users.
- A scalable and computationally efficient algorithm suitable for real-time deployment in dynamic networks.

The proposed approach is validated through extensive simulations, demonstrating superior sum-rate performance, reduced power consumption, and improved computational efficiency compared to existing solutions [18], [19], [20]. Machine learning-based approaches have been successfully used in various wireless communication applications, including predicting cable length using S-parameters [16] and improving classification performance in head impact detection using neural networks [21]. Inspired by these approaches, the proposed framework leverages iterative optimization to dynamically allocate power among users and adjust IRS phase shifts to maximize spectral efficiency. By optimizing intra- and inter-group power allocation, this work provides a practical solution for deploying IRS-assisted NOMA in B5G systems.

The remainder of this paper is structured as follows. Section II reviews the related work, highlighting recent advances and challenges in integrating IRS and NOMA technologies. Section III details the system model for IRS-assisted downlink NOMA systems. Section IV introduces the problem statement and design constraints of the proposed two-stage power allocation framework. Section V describes the optimization framework for joint power and phase shift allocation. The simulation results are discussed in Section VI, and the conclusions are provided in Section VII.

The notation used throughout this paper is defined as follows: lowercase letters denote scalars, bold lowercase letters denote vectors, bold uppercase letters denote matrices, $(.)^T$ indicates the transpose operator, $(.)^H$ represents the Hermitian transpose operator, $diag(v)$ denotes the diagonal matrix with vector v, v_π indicates the sub-vector containing elements at indexes π, and $\|.\|_p$ signifies the l_p-norm.

II. RELATED WORK

Recently, IRS technology has gained significant attention in wireless communication systems due to its ability to improve spectrum and energy efficiency. IRS-assisted systems have shown the potential to address key challenges in NOMA environments by improving signal quality through passive beamforming. This section reviews existing work on resource allocation and optimization methods designed for IRS-assisted NOMA systems, highlighting their advantages and limitations [8], [14], [18], [22], [23], [24].

The authors in [25] proposed a low-complexity resource allocation scheme for IRS-assisted downlink NOMA systems, focusing on reducing computational complexity while achieving near-optimal performance. However, their work primarily addressed static user groupings, limiting their adaptability to dynamic channel conditions. The work in [26] introduced a joint active and passive beamforming framework for IRS-enhanced wireless networks, demonstrating the significant potential of IRS in improving spectral efficiency. However, their proposed scheme was not explicitly designed for NOMA-based systems. The authors in [27] explored resource allocation in IRS-assisted NOMA systems, considering both power allocation and IRS phase-shift optimization. Although their work provided insight into joint optimization, it did not explicitly address user grouping strategies. Similarly, the work in [28] developed energy-efficient IRS-NOMA beamforming schemes, emphasizing green communication but overlooking the dynamic nature of channel conditions when user grouping was performed. The authors in [23] extended the IRS application to mobile edge computing (MEC) systems, integrating dynamic IRS beamforming with NOMA-based offloading. Their unified framework underscored the flexibility of the IRS in handling diverse applications. However, their proposed framework did not address the problem of resource allocation and user grouping. The work in [12] optimized beamforming in IRS-assisted NOMA networks by jointly addressing IRS phase-shift and power allocation. Despite its robustness, their approach lacked scalability for larger user groups and did not consider fairness.

The authors in [5] proposed an energy-efficient design for IRS-NOMA networks, focusing on minimizing power consumption. However, the fixed user grouping in their model restricted its applicability to dynamic environments.

Using a weighted product method, the work in [6] and [29] investigated the energy-spectral efficiency trade-off in IRS-assisted NOMA systems. Although their work provided a balanced approach to optimizing efficiency metrics, it did not address real-time adaptability in resource allocation based on channel dynamics. Recent advances in RIS-assisted systems have explored low-complexity channel estimation under discrete phase-shift constraints [30] and codebook-based solutions for passive beamforming [31]. Although these works address practical implementation challenges, they often overlook dynamic user grouping and hierarchical resource allocation, which are central to the framework proposed in this paper.

In summary, several communication protocols and mechanisms have been proposed for resource allocation in IRS-based NOMA systems. However, most of these protocols were designed assuming static user grouping. This approach limits the adaptability of the proposed protocols and does not adjust the operating parameters based on real-time channel dynamics. Unlike previous works, this paper aims to develop a novel resource allocation framework for IRS-assisted downlink NOMA systems while integrating dynamic user grouping strategies that leverage real-time channel conditions. The proposed approach aims to improve the performance of the system while maintaining fairness and scalability.

III. SYSTEM MODEL

We consider an IRS-assisted downlink NOMA system consisting of a single-antenna base station (BS), U single-antenna user equipments (UEs), and an intelligent reflecting surface (IRS) with N passive reflecting elements. The IRS improves system performance by reconfiguring the wireless propagation environment through phase adjustment of the reflected signals.

The direct channel between the BS and the u-th user is denoted as $h_{Bu} \in \mathbb{C}$, while the channel between the BS and the IRS is modeled as a vector $\mathbf{h}_{BI} \in \mathbb{C}^{N\times 1}$, and the channel between the IRS and the u-th user is given by $\mathbf{h}_{Iu} \in \mathbb{C}^{1\times N}$. The IRS optimizes the signal path by adjusting the phase shifts of its reflecting elements.

The received signal at the u-th user is:

$$y_u = (h_{Bu} + \mathbf{h}_{Iu} 8 \mathbf{h}_{BI}) \sum_{i=1}^{U} \sqrt{P_i} s_i + n_u, \tag{1}$$

where $8 = \mathrm{diag}(e^{j\phi_1}, e^{j\phi_2}, \ldots, e^{j\phi_N})$ is the IRS phase shift matrix with unit-modulus entries, i.e., $|\phi_n| = 1$, and $\phi_n \in [0, 2\pi)$. The variable P_i is the power allocated to the user i, s_i is the normalized transmit signal, and $n_u \sim \mathcal{CN}(0, \sigma^2)$ is the additive white Gaussian noise.

The channel models incorporate large-scale path loss and small-scale fading as follows:

- **BS-to-User:** $h_{Bu} = \sqrt{\beta_{Bu}} g_{Bu}$, with $g_{Bu} \sim \mathcal{CN}(0, 1)$.
- **BS-to-IRS:** $\mathbf{h}_{BI} = \sqrt{\beta_{BI}} \mathbf{g}_{BI}$, with $\mathbf{g}_{BI} \sim \mathcal{CN}(0, \mathbf{I})$ or Rician fading if there is LOS.
- **IRS-to-User:** $\mathbf{h}_{Iu} = \sqrt{\beta_{Iu}} \mathbf{g}_{Iu}$, where $\mathbf{g}_{Iu} \sim \mathcal{CN}(0, \mathbf{I})$ or Rician depending on the scenario.

The IRS consists of N passive reflecting elements, each capable of introducing a phase shift ϕ_n to the incident signal. The phase shift matrix Φ is represented as:

$$\Phi = \mathrm{diag}\left(e^{j\phi_1}, e^{j\phi_2}, \ldots, e^{j\phi_N}\right), \tag{2}$$

where $\phi_n \in [0, 2\pi)$ for all $n = 1, 2, \ldots, N$. Phase shifts should be optimized to enhance the combined channel gain $h_{Bu} + h_{Iu}\Phi h_{BI}$ for each communicating user to improve the overall system performance.

Optimizing 8 improves spectral efficiency. Previous studies used methods such as the Taguchi algorithm for improving antenna directivity [32], and neural networks for high-accuracy localization [33], both of which inspire our IRS control approach.

Users are ordered based on descending effective channel gains:

$$|h_{B1} + \mathbf{h}_{I1} 8 \mathbf{h}_{BI}| \geq \cdots \geq |h_{BU} + \mathbf{h}_{IU} 8 \mathbf{h}_{BI}|. \tag{3}$$

In NOMA, the u-th user applies successive interference cancellation (SIC) to decode signals from users with lower ordered channels. The SINR for user u is:

$$\mathrm{SINR}_u = \frac{|h_{Bu} + \mathbf{h}_{Iu} 8 \mathbf{h}_{BI}|^2 P_u}{\sum_{i=1}^{u-1} |h_{Bu} + \mathbf{h}_{Iu} 8 \mathbf{h}_{BI}|^2 P_i + \sigma^2}. \tag{4}$$

IV. PROBLEM DESCRIPTION AND FORMULATION

This section proposes the resource allocation optimization problem for IRS-assisted downlink NOMA systems. The objective is to minimize total power consumption while maximizing the number of served user groups and ensuring that each user meets the imposed QoS requirements and total power budget constraints. The problem is solved in two stages: (1) intra-group optimization for user-level power allocation and IRS phase-shift control, and (2) inter-group optimization for power allocation across groups, considering the varying number of users in each group. User grouping simplifies the resource allocation process by reducing the dimensionality of the optimization problem within each group. By optimizing resources within and across groups, significant improvements in computational efficiency and scalability can be achieved while meeting the system's overall objectives.

A. INTRA-GROUP USER-LEVEL POWER ALLOCATION

For each group of users g, we optimize the allocation of power and IRS phase shifts to minimize power consumption while ensuring that all users in the group achieve the required data rates. The intra-group optimization problem can be formulated as follows:

$$\begin{aligned} \min_{P_g, \Phi_g} \; & \sum_{u\in g} P_u \\ \text{subject to: } & \sum_{u\in g} P_u \leq P_{\max,g}, \\ & R_u \geq r_u, \quad \forall u \in g, \\ & |\phi_n| = 1, \quad \forall n. \end{aligned} \tag{5}$$

where P_u is the power allocated to user u in group g, $P_{\max,g}$ represents the maximum allowable power for group g, and R_u denotes the achievable rate for user u, defined as $R_u = \log_2(1 + \text{SINR}_u)$. Additionally, r_u is the minimum required rate for user u, while Φ_g is the IRS phase shift matrix for group g, with each element constrained to unit modulus.

B. INTER-GROUP POWER ALLOCATION

After completing the intra-group optimization, the next stage involves distributing the total available power among different user groups while maximizing the number of served groups. The goal is to maximize system performance by optimally allocating power between groups while considering system constraints. To achieve this, we introduce the following binary decision variables:

- z_g: Indicates whether group g is active:

$$z_g = \begin{cases} 1, & \text{if group } g \text{ is served,} \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

The inter-group optimization problem that maximizes the number of served groups can be formulated as follows.

$$\begin{aligned} &\max_{z_g, P_{\text{group}}} \sum_{g=1}^{G} z_g \\ &\text{subject to:} \quad \sum_{g=1}^{G} z_g P_{\text{group},g} \leq P_{\max}, \\ &\qquad\qquad z_g \in \{0, 1\}, \quad \forall g. \end{aligned} \tag{7}$$

where G denotes the total number of groups, $P_{\text{group},g}$ represents the total power allocated to group g, and $P_{\max}$ is the total system power budget. The power allocated to each group is determined by $P_{\text{group},g} = \frac{z_g P_{\max}}{\sum_{g=1}^{G} z_g}, \quad \forall g$, ensuring proportional distribution based on the weighting factor z_g.

V. THE OPTIMIZED HIERARCHICAL POWER ALLOCATION FRAMEWORK

We propose the Optimized Hierarchical Power Allocation Framework (OHPAF) to efficiently manage power allocation in IRS-assisted NOMA systems. This framework consists of two sequential optimization stages:

- **Stage 1: Intra-group power allocation** This stage optimizes the power distribution within each user group while ensuring fairness, maximizing spectral efficiency, and satisfying successive interference cancellation (SIC) requirements.
- **Stage 2: Inter-Group Power Allocation.** Once intra-group power allocation is determined, this stage addresses the optimization problem in (7) to determine the active user groups, indicated by z_g.

Using this two-stage approach, the framework ensures a systematic and computationally efficient power allocation process that balances power efficiency, fairness, and overall system performance. The intra-group stage optimizes power distribution at the user level, while the inter-group stage determines which groups are activated and the amount of power allocated to each group, ensuring an adaptive and scalable solution.

A. THE PROPOSED INTRA-GROUP POWER ALLOCATION ALGORITHM

To effectively address the resource allocation problem in (5) for IRS-assisted downlink NOMA systems, we propose an iterative optimization procedure that minimizes power consumption, enhances system performance, and ensures user QoS requirements while adhering to system constraints. This procedure consists of two main processes: power allocation optimization and IRS phase shift optimization, which are executed iteratively. The complete framework follows a systematic approach, starting with solving the power allocation optimization problem using Algorithm 1, followed by optimizing the IRS phase shifts via Algorithm 2, and repeating these steps until convergence is achieved. The two main phases are described in the following subsections.

1) PHASE 1. OPTIMIZING POWER ALLOCATION WITH FIXED IRS PHASE SHIFTS

In the first step, we optimize the power allocation among users while keeping the IRS phase shifts constant. The objective is to minimize total power consumption while ensuring each user meets QoS constraints. The optimization problem is formulated as follows.

$$\begin{aligned} &\min_{P_g} \sum_{u \in g} P_u \\ &\text{subject to:} \sum_{u \in g} P_u \leq P_{\max,g}, \\ &\qquad\qquad R_u \geq r_u, \quad \forall u \in g. \end{aligned} \tag{8}$$

Since this is a convex quadratic program (QP), it can be effectively solved using the Lagrange multiplier method. We define the Lagrangian function as follows.

$$\begin{aligned} \mathcal{L}(P_u, \lambda, \mu_u) = &\sum_{u \in g} P_u + \lambda \left(P_{\max,g} - \sum_{u \in g} P_u \right) \\ &+ \sum_{u \in g} \mu_u (R_u - r_u). \end{aligned} \tag{9}$$

where λ and μ_u are the Lagrange multipliers associated with the power and rate constraints.

To find the optimal power allocation P_u, we take the derivative of $\mathcal{L}$ with respect to P_u and set it to zero:

$$\frac{\partial \mathcal{L}}{\partial P_u} = 1 - \lambda - \mu_u \cdot \frac{1}{(1 + \text{SINR}_u)\ln(2)} = 0. \tag{10}$$

Solving for P_u:

$$P_u = \frac{1 - \lambda}{\mu_u} \cdot (1 + \text{SINR}_u)\ln(2). \tag{11}$$

Using Karush-Kuhn-Tucker (KKT) conditions, we solve for the values of P_u, λ, and μ_u:

Algorithm 1 Power Allocation Optimization With Fixed IRS Phase Shifts

Require: g: Number of users in the group, $P_{\max,g}$: Maximum power budget for group g, γ_u: SINR threshold for each user u, σ^2: Noise power, h_{Bu}, h_{Iu}: Direct and IRS-assisted channel gains, Φ_g: IRS phase shift matrix.

Ensure: P_{optimal}: Optimal power allocation for each user.

Initialization: Set initial power allocation $P_{\text{optimal}}[g] = 0$, $\forall u \in g$.

Compute effective channel gains:

$$\alpha_u = |h_{Bu} + h_{Iu}\Phi_g h_{BI}|^2, \quad \forall u \in g.$$

Formulate Optimization Problem: Solve the optimization problem in (8)

Solve Using Lagrange Multiplier Method: Define the Lagrangian function as in in (9):

Compute the Lagrange derivative and set it to zero. Then, solve for P_u as in (11):

Solve KKT Conditions:

- Primal Feasibility in (12)
- Dual Feasibility in (13)
- Complementary Slackness in (14)

Compute final power allocation P_{optimal}.

Output: Optimized P_{optimal}.

- Primal feasibility:

$$\sum_{u\in g} P_u \le P_{\max,g}, \quad R_u \ge r_u, \quad \forall u \in g. \tag{12}$$

- Dual feasibility:

$$\lambda \ge 0, \quad \mu_u \ge 0, \quad \forall u \in g. \tag{13}$$

- Complementary slackness:

$$\lambda \left(P_{\max,g} - \sum_{u\in g} P_u \right) = 0, \tag{14}$$
$$\mu_u(R_u - r_u) = 0, \quad \forall u \in g.$$

The power-allocation optimization process is detailed in Algorithm 1, where the proposed method iteratively computes the optimal power levels for each user within each group.

2) PHASE 2: OPTIMIZING IRS PHASE SHIFTS WITH FIXED POWER ALLOCATION

After determining the power allocation, the next step is to optimize the IRS phase shifts while keeping the power levels fixed. The goal is to maximize the total SINR across all active users within the selected groups. The optimization problem is formulated as follows.

$$\max_{\Phi_g, z_g, z_{u,g}} \sum_{g=1}^{G} z_g \sum_{u\in g} z_{u,g} \cdot \text{SINR}_u$$
$$\text{subject to:} |\phi_n| = 1, \quad \forall n,$$
$$z_g \in \{0,1\}, \quad z_{u,g} \in \{0,1\}, \quad \forall u, g. \tag{15}$$

where z_g is a binary variable indicating whether group g is active, with $z_g = 1$ if the group is served and $z_g = 0$ otherwise, while $z_{u,g}$ is a binary variable representing whether user u in group g is served, where $z_{u,g} = 1$ if the user is served and $z_{u,g} = 0$ otherwise. The total number of served groups is given by $G_{\text{served}} = \sum_{g=1}^{G} z_g$.

Algorithm 2 IRS Phase Shift Optimization With Fixed Power Allocation

Require:
- N: Number of IRS elements
- G: Number of user groups
- P_u: Fixed power allocation per user
- Channel gains: h_{Bu}, h_{Iu}, h_{BI}
- γ_u: SINR thresholds
- σ^2: Noise power
- α: Step size

Ensure: Optimal IRS phase shifts θ_{opt}

Step 1: Initialization

Initialize IRS phase shifts $\theta[N]$ with random values in $[0, 2\pi)$.

Set activation variables: $z_g = 1$, $z_{u,g} = 1$, $\forall u, g$.

Compute initial SINR values for all users.

Step 2: Iterative Phase Shift Optimization

for iter = 1 to max_iter **do**

  for $n = 1$ to N **do**

    Compute the SINR gradient:

$$\nabla_{\phi_n} = \sum_{g=1}^{G} z_g \sum_{u\in g} z_{u,g} \frac{\partial \text{SINR}_u}{\partial \phi_n}.$$

    Update phase shift using gradient ascent:

$$\phi_n^{(t+1)} = \phi_n^{(t)} + \alpha \nabla_{\phi_n}.$$

    Normalize ϕ_n to ensure unit modulus: $|\phi_n| = 1$.

  end for

  Compute updated SINR values.

  Check for convergence: Stop if:

$$|\text{SINR}^{(t+1)} - \text{SINR}^{(t)}| \le \epsilon.$$

end for

Output: Optimized IRS phase shifts θ_{opt}.

We apply an iterative gradient ascent method to solve the optimization problem in (15), updating the IRS phase shifts based on the SINR gradient. The update rule is expressed as:

$$\phi_n^{(t+1)} = \phi_n^{(t)} + \alpha \sum_{g=1}^{G} z_g \sum_{u\in g} z_{u,g} \frac{\partial \text{SINR}_u}{\partial \phi_n}, \tag{16}$$

where α is the step size and $\frac{\partial \text{SINR}_u}{\partial \phi_n}$ represents the gradient of SINR with respect to the phase shift ϕ_n.

The detailed iterative procedure for optimizing the IRS phase shifts is summarized in Algorithm 2. The phase shifts are iteratively adjusted based on the computed SINR gradient, ensuring unit-modulus constraints and stopping when convergence criteria are met.

B. STAGE 2: THE PROPOSED INTER-GROUP POWER ALLOCATION ALGORITHM

The optimization problem in (7) constitutes a binary linear programming problem (BLP), which is generally NP-hard [34]. To solve this problem, we adopt the sequential fixing linear procedure (SFLP) in [35]. To efficiently solve the NP-hard BLP problem in (7), we use SFLP as proposed in [36]. SFLP is a practical optimization technique

Algorithm 3 Inter-Group Power Allocation

Require: G: Number of user groups, $P_{\max}$: Total system power,
Ensure: z_g: Active groups, $P_{\text{group},g}$: Power allocation per group.
1: **Step 1: Initialization**
2: Set $z_g = 1$ for all groups.
3: Compute the initial power allocation: $P_{\text{group},g} = \frac{P_{\max}}{G}$.
4: **Step 2: Check Power Constraint**
5: Compute total power usage:

$$P_{\text{total}} = \sum_{g=1}^{G} z_g P_{\text{group},g}.$$

6: If $P_{\text{total}} \leq P_{\max}$, continue. Otherwise, deactivate the group with the lowest performance metric.
7: **Step 3: Update Power Allocation**
8: Compute $G_{\text{served}} = \sum_{g=1}^{G} z_g$.
9: Allocate power per group:

$$P_{\text{group},g} = \frac{P_{\max}}{G_{\text{served}}}, \quad \forall g.$$

10: **Step 4: Output Results**
11: Return active groups z_g and allocated power per group $P_{\text{group},g}$.

that iteratively refines the solution by sequentially fixing selected binary variables based on an optimality criterion, thereby reducing the problem complexity at each step. The procedure begins by solving a relaxed version of the original BLP, where binary constraints are temporarily relaxed to continuous values. Based on the solution of this relaxed problem, a subset of variables is fixed to ensure convergence toward an optimal or near-optimal solution. This iterative approach significantly improves computational efficiency while maintaining solution accuracy. By leveraging SFLP, the optimization problem is transformed into a series of smaller, more manageable linear subproblems, making it well-suited for large-scale IRS-NOMA resource allocation scenarios.

C. COMPUTATIONAL COMPLEXITY

The proposed OHPAF framework consists of two sequential optimization stages: *intra-group power allocation* and *inter-group power allocation*. Each stage involves solving an optimization problem with different levels of computational complexity. In this section, we analyze the computational cost of each stage and provide an overall complexity assessment. Bayesian classification techniques have been widely applied in biological sequence analysis to optimize pattern recognition [33]. Similarly, information-theoretic approaches have been employed for gene detection, demonstrating the effectiveness of iterative optimization algorithms in improving classification accuracy [21]. Our proposed power allocation framework adopts similar iterative strategies to refine power control decisions and improve system performance.

1) COMPLEXITY OF INTRA-GROUP POWER ALLOCATION

The intra-group power allocation problem involves optimizing the power distribution among users within each group while satisfying fairness constraints and SIC conditions. The primary computational steps include:

- Solving a convex optimization problem per group typically requires an iterative method such as the Lagrange multiplier method or a water-filling algorithm.
- Verification and enforcement of SIC constraints involve comparing the SINR values of the users in the group.

Let U_g denote the number of users in group g. The power allocation problem for each group requires $O(U_g^2)$ operations due to iterative updates in convex solvers. Since there are G groups, the total complexity for this stage is:

$$O\left(GU_g^2\right). \tag{17}$$

This complexity remains computationally feasible for large-scale networks, where the number of users per group is relatively small compared to the total number of users.

2) COMPLEXITY OF INTER-GROUP POWER ALLOCATION

The inter-group power allocation problem is formulated as a BLP problem, known to be NP-hard. Solving it directly is impractical for large-scale networks. To address this, we employ the SFLP, which iteratively refines the solution by fixing binary decision variables based on optimality criteria.

The key computational steps in SFLP include the following:

- Solving a *relaxed* LP problem in each iteration.
- Sequentially fixing the binary variables to 0 or 1 based on threshold criteria.
- Iterating until all binary variables are fixed.

Let G be the total number of user groups. The complexity of solving a relaxed LP problem is approximately $O(G^3)$ using interior-point methods. In practice, SFLP converges within a small number of iterations (denoted as I_{SFLP}), leading to a total complexity of:

$$O\left(I_{\text{SFLP}} G^3\right). \tag{18}$$

Since I_{SFLP} is typically much smaller than G, the iterative refinement ensures that computational overhead is significantly reduced compared to brute-force approaches.

3) OVERALL COMPUTATIONAL COMPLEXITY

The overall computational complexity of OHPAF is derived by combining the complexities of intra-group and inter-group power allocation:

$$O\left(GU_g^2\right) + O\left(I_{\text{SFLP}} G^3\right). \tag{19}$$

This ensures that OHPAF remains scalable and efficient for practical IRS-NOMA deployments.

4) SCALABILITY AND PRACTICAL CONSIDERATIONS

The proposed framework is designed to scale well for large network sizes due to the following.

- **Efficient intra-group power allocation:** Since power allocation within groups is convex, it is efficiently solvable in polynomial time.

TABLE 1. Simulation parameters.

Parameter	Value
Number of Users (U)	2 and 3
Number of IRS Reflecting Elements (N)	10 to 40
SINR Range	1 to 6 dB
Channel Model	Rayleigh fading (direct and IRS-assisted links)
Noise Variance (σ^2)	1
Initial IRS Phase Shifts	Zero and Random phase shifts

- **Iterative inter-group refinement:** By leveraging SFLP, the complexity of solving the binary linear programming problem is significantly reduced.
- **Parallelization potential:** The intra-group power allocation step can be executed independently between groups, making it suitable for parallel processing techniques in real-time applications.

Thus, OHPAF provides a computationally efficient and scalable solution for power allocation in large-scale IRS-assisted NOMA systems.

The computational complexity analysis highlights the efficiency of OHPAF in handling intra-group and inter-group power allocation. Although the inter-group optimization problem is inherently complex, adopting SFLP significantly reduces computational overhead. The complexity remains manageable for large-scale networks, making the framework practical for real-time wireless communication systems. The convergence of the proposed Optimized Hierarchical Power Allocation Framework (OHPAF) is mathematically established by demonstrating monotonic improvement, bounded optimization, and fixed-point conditions for both intra-group and inter-group power allocation stages, as detailed in the Appendix A.

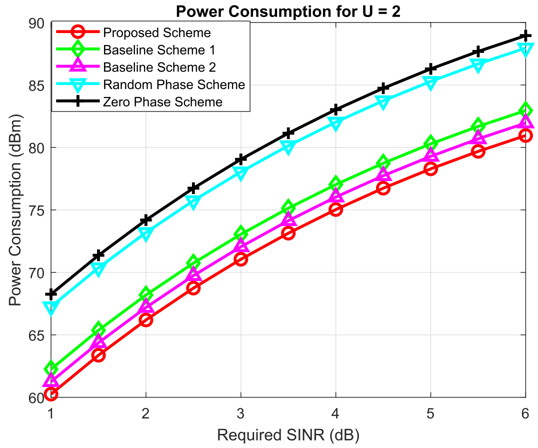
VI. SIMULATION RESULTS

This section presents the simulation setup and results to evaluate the proposed low-complexity resource allocation scheme in IRS-assisted NOMA systems. The evaluation focuses on key performance metrics, including sum rate, power consumption, convergence behavior, and computational complexity. The following performance metrics are used in our evaluation.

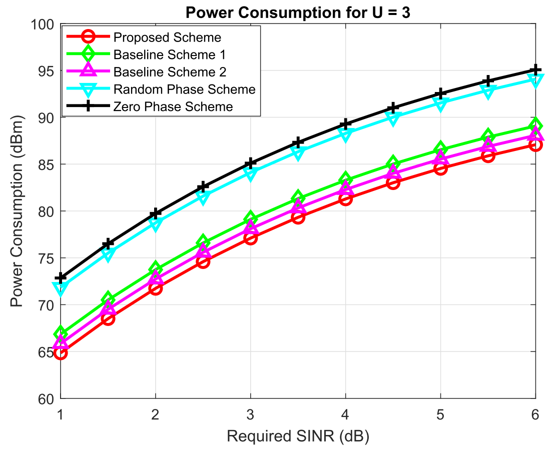
- **Sum Rate:** The total achievable rate of all users.
- **Power Consumption:** The total power allocated to users while satisfying a set of imposed QoS requirements.
- **Convergence Behavior:** The number of iterations required for the proposed scheme to converge to an optimal solution.
- **Computational Complexity:** The time required to execute the optimization algorithm for the proposed and baseline schemes.

A. COMPARISON SCHEMES

The schemes used for comparison are as follows.



(a) Power consumption for $U = 2, N = 32$.



(b) Power consumption for $U = 3\ \ N = 32$

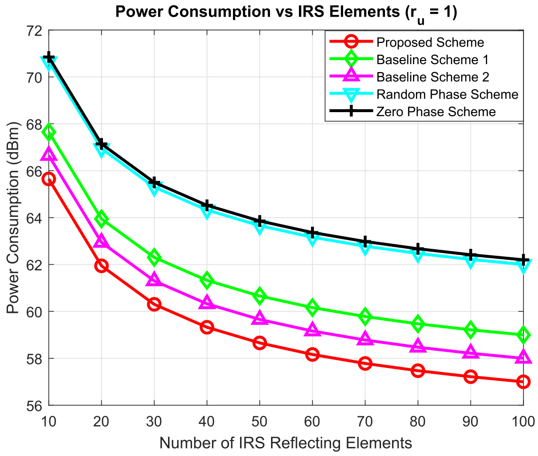
FIGURE 1. Comparison of power consumption for different numbers of users and IRS reflecting elements.

- **Baseline Scheme 1:** This scheme, proposed by Wang et al. [7], optimizes power allocation in IRS-assisted systems using a low-complexity approach for phase shift design.
- **Baseline Scheme 2:** This scheme, introduced by Zhu et al. [13], incorporates user grouping techniques to further enhance system efficiency while optimizing power allocation and IRS phase shifts.
- **Random/Zero Phase Schemes:** These represent baseline scenarios in which the IRS reflecting elements are initialized with random phase shifts or all set to zero, providing a benchmark for evaluating the effectiveness of phase-shift optimization.

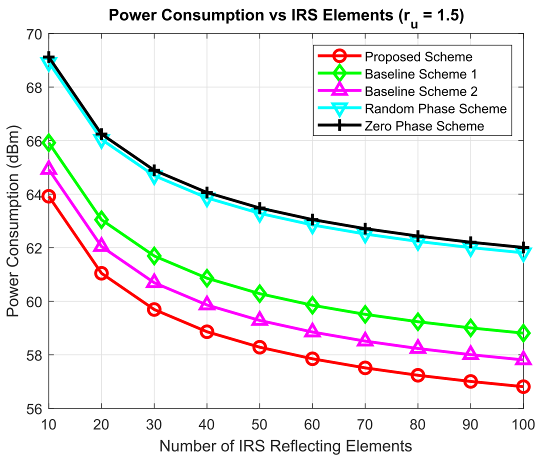
B. SIMULATION SETUP AND METRICS

The simulations were conducted in MATLAB using the parameters summarized in Table 1.

The channel model follows a Rayleigh distribution, and AWG is assumed to have a mean of 0 and a variance of 1. Two initialization cases for IRS phase shifts (Zero and Random)



(a) Power consumption with $U = 3$, $r_u = 1$.



(b) Power consumption with $U = 3$, $r_u = 1.5$.

FIGURE 2. Total power consumption versus the number of IRS reflecting elements for four schemes with $U = 3$.

are considered to evaluate the proposed scheme's robustness and convergence.

C. SIMULATION RESULTS

Fig. 1 explores the power consumption of four schemes with $N = 32$, where $U = 2$ is depicted in Fig. 1 and $U = 3$ in Fig. 1b. The x-axis represents the required SINR for each user. The power consumption for all schemes increases as the SINR increases.

Fig. 1a illustrates the power consumption for $U = 2$ and $N = 32$, showing the efficiency of the proposed scheme in minimizing power usage. Fig. 1b shows the power consumption of $U = 3$ and $N = 32$, highlighting the increased power requirements for a larger number of users and the effectiveness of the proposed scheme in managing these requirements.

The proposed scheme exhibits lower power consumption than the schemes discussed in [7] and [13], which are more efficient than the IRS-assisted NOMA schemes with random and zero phase shifts. In particular, the proposed scheme achieves a power reduction of more than 5 dBm compared to [7] and [13]. Furthermore, the power consumption for the proposed scheme remains consistent regardless of whether the initial IRS phase shifts are zero or random, indicating that the initial phase shifts do not impact its performance. When comparing Fig. 1a and Fig. 1b, it is clear that the power consumption is higher for $U = 3$ than for $U = 2$. This increase is due to the higher required power to meet the SINR needs of the additional user. Furthermore, the scalability of the scheme is evident in its consistent improvement in power consumption performance with an increased number of users, from $U = 2$ to $U = 3$, indicating its ability to manage larger user groups without significant performance degradation.

Fig.2 presents the total power consumption required by the four schemes versus the number of IRS reflecting elements with $U = 3$. The x-axis denotes the number of IRS reflecting elements. As the number of IRS reflecting elements increases, the gaps between the curves become more noticeable, yet they all exhibit a general downward trend. Moreover, as can be observed, the power consumption of the proposed scheme is lower than that of the other three schemes, and the power consumption of each scheme decreases as the number of IRS-reflecting elements increases. This is due to the enhanced received signal power provided by the larger number of reflecting elements. The trend observed in Fig. 2a shows a decrease in power consumption as the number of IRS elements increases, indicating the effectiveness of additional reflecting elements in enhancing received signal power. The proposed schemes consistently exhibit lower power consumption than others, underscoring their efficiency in utilizing IRS technology. In addition, the slight disparity in power use between the Proposed (Zero) and Proposed (Random) strategies implies that the early phase changes have a minor influence on the total performance. Figure 2b illustrates a continuous pattern of declining power use as the number of IRS elements increases to a value of r_u equal to 1.5. Significantly, the power usage for $r_u = 1.5$ is often lower than that for $r_u = 1$, indicating that the system functions more effectively when higher rate requirements are imposed. The suggested designs regularly demonstrate superior power efficiency compared to other schemes, highlighting their resilience and effectiveness.

The proposed approach improves performance by employing iterative optimization to efficiently adjust the IRS phase shift. This optimizes signal strength and reduces interference/power consumption. This strategy improves efficiency by optimizing resource allocation for each group and incorporating user grouping based on channel conditions. Conventional optimization methods guarantee optimal and computationally efficient solutions for power distribution within a group, further reducing power consumption. The technique exhibits robustness by maintaining high performance independently of early IRS phase changes. It also shows scalability by efficiently managing an increasing number of users, as seen by the continuous reduction in power usage from $U = 2$ to $U = 3$. In addition, the increased

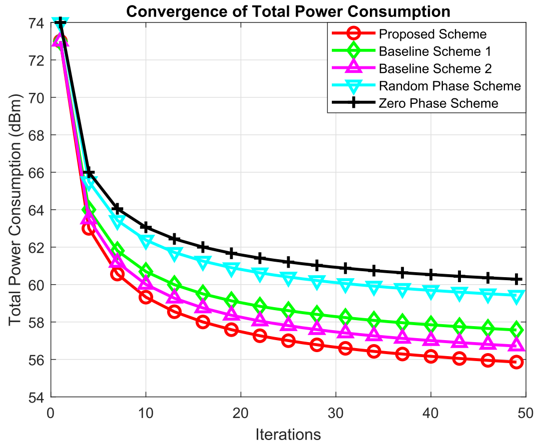


FIGURE 3. Convergence behavior of total power consumption for the proposed and benchmark schemes.

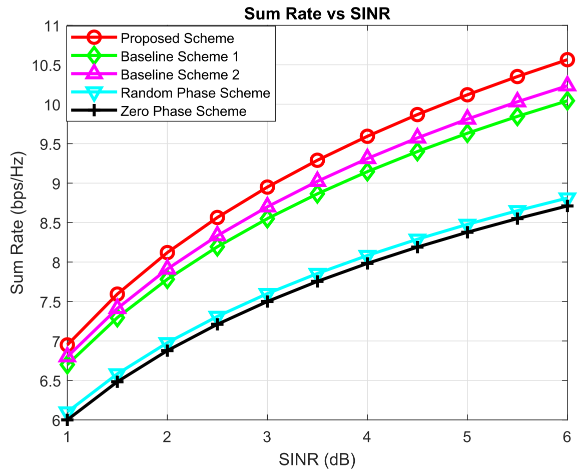


FIGURE 4. Comparison of the sum rate and signal-to-interference-plus-noise ratio (SINR) between the proposed scheme and other schemes.

power consumption reported for $r_u = 1.5$ compared to $r_u = 1$ results from the more power required to meet the higher rate demands.

Figure 3 illustrates that the proposed scheme exhibits faster convergence in terms of overall power usage compared to the other schemes. This suggests that the suggested approach is more effective in identifying the most favorable option.

Figure 4 illustrates the relationship between the sum-rate and the SINR for the proposed design and three existing schemes. Empirical evidence demonstrates that the suggested method consistently achieves a higher sum rate at all SINR levels compared to the other systems. Adjusted IRS phase shifts and appropriate user grouping enhance signal strength and reduce interference. The logarithmic correlation between SINR and total rate is apparent, suggesting effective use of the given SINR range.

The sum rate is shown in Fig. 5 as a function of the number of IRS reflecting elements. The findings indicate that the sum rate positively correlates with the number of reflecting components in all designs. The suggested technique achieves

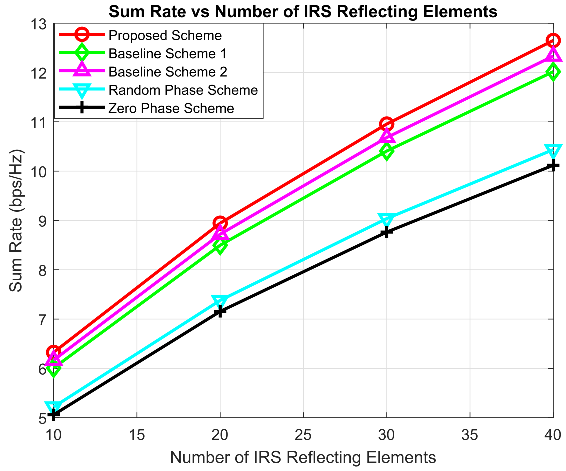


FIGURE 5. Comparison of the sum rate with the number of IRS reflecting elements for the proposed scheme and other schemes.

the maximum sum rate by leveraging the amplified received signal power resulting from the augmented IRS components. The proposed approach demonstrates its scalability by its exceptional performance as the number of pieces increases.

In addition to assessing the total rate performance, we analyzed the power consumption needed for the proposed system and compared it to existing schemes. Power consumption was evaluated in several situations, considering the varied quantities of IRS-reflecting elements and the SINR values. The suggested method consistently exhibited reduced power consumption compared to the process in [19], the scheme in [20], and the IRS-assisted NOMA schemes with random and zero phase shifts. The decrease in power consumption may be due to the effective optimization of IRS phase shifts and resource allocation algorithms, which limit superfluous power use while improving signal quality.

VII. CONCLUSION

The research extensively analyzes a new, more straightforward resource allocation technique for NOMA systems that integrates Intelligent Reflecting Surfaces (IRS). The proposed solution entails iteratively optimizing the IRS's phase shifts, grouping the channels, and utilizing convex optimization. This combined approach improves power consumption efficiency and the system's overall performance. Simulations provide evidence that this technology surpasses current alternatives in terms of performance. The proposed method's capability to sustain performance throughout initial IRS phase transitions and adjust to changing network conditions renders it highly suitable for forthcoming wireless communication networks. The results suggest that NOMA systems, which the IRS helps, can attain enhanced energy and spectrum efficiency by implementing this approach. Subsequent investigations may go into the application of sophisticated machine learning methodologies to improve resource allocation and adapt more effectively to changing circumstances.

APPENDIX A CONVERGENCE ANALYSIS OF OHPAF

This appendix provides the convergence analysis of the proposed OHPAF framework, which includes two sequential stages: intra-group and inter-group power allocation, as well as IRS phase-shift optimization. Convergence is established by demonstrating the following conditions:

1) Monotonic improvement of objective functions.
2) Boundedness of the optimization variables.
3) Satisfaction with fixed-point convergence conditions.

A. MONOTONIC IMPROVEMENT

The OHPAF algorithm sequentially optimizes power allocation and IRS phase shifts.

1) STAGE 1: INTRA-GROUP POWER ALLOCATION

At iteration t, the intra-group power allocation objective is expressed as:

$$f_1^{(t)} = \sum_{g=1}^{G} \sum_{u \in g} P_u^{(t)}. \tag{20}$$

Given the convex nature of this problem, each iteration satisfies:

$$f_1^{(t+1)} \leq f_1^{(t)}, \tag{21}$$

ensuring monotonic convergence for intra-group allocation.

2) STAGE 2: INTER-GROUP POWER ALLOCATION

Using the Sequential Fixing Linear Procedure (SFLP) [35], the inter-group objective is:

$$f_2^{(t)} = \sum_{g=1}^{G} z_g^{(t)} P_{\text{group},g}^{(t)}. \tag{22}$$

Since SFLP refines power allocation while fixing binary variables, the process guarantees:

$$f_2^{(t+1)} \geq f_2^{(t)}. \tag{23}$$

3) IRS PHASE SHIFT OPTIMIZATION

IRS phase shifts aim to maximize the sum SINR:

$$f_3^{(t)} = \sum_{g=1}^{G} \sum_{u \in g} \text{SINR}_u^{(t)}. \tag{24}$$

Using gradient ascent, we ensure:

$$f_3^{(t+1)} \geq f_3^{(t)}. \tag{25}$$

B. BOUNDED OPTIMIZATION

All optimization variables are constrained as follows.

1) POWER ALLOCATION BOUNDS

$$0 \leq f_1^{(t)} \leq P_{\max}, \quad 0 \leq f_2^{(t)} \leq P_{\max}. \tag{26}$$

2) IRS PHASE SHIFT BOUNDS

$$|\phi_n| = 1, \quad \forall n. \tag{27}$$

SINR values are practically bounded:

$$0 \leq f_3^{(t)} \leq \text{SINR}_{\max}. \tag{28}$$

C. FIXED-POINT CONDITION AND STOPPING CRITERION

The algorithm halts when the changes in objective values satisfy:

$$|f_1^{(t+1)} - f_1^{(t)}| \leq \epsilon, \; |f_2^{(t+1)} - f_2^{(t)}| \leq \epsilon, \; |f_3^{(t+1)} - f_3^{(t)}| \leq \epsilon. \tag{29}$$

This implies convergence of the optimization variables:

$$P_u^{(t+1)} = P_u^{(t)}, \quad P_{\text{group},g}^{(t+1)} = P_{\text{group},g}^{(t)}, \quad \phi_n^{(t+1)} = \phi_n^{(t)}. \tag{30}$$

D. CONVERGENCE SUMMARY

The convergence of OHPAF is ensured by:

- **Monotonic Objective Functions:** Each subproblem improves or maintains its metric.
- **Bounded Variables:** Optimization variables remain within predefined limits.
- **Fixed-Point Criteria:** Convergence is declared when iteration changes are below a threshold.

Given that intra-group allocation is convex, inter-group optimization uses SFLP, and IRS tuning applies gradient ascent, OHPAF reliably converges to a local optimum. This ensures robustness and practical efficiency in IRS-NOMA systems.

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