

Article

Effective Spectral Efficiency Maximization for Directional Pinching-Antenna-Assisted Multi-User MIMO Systems

Xiaoye Deng ¹, Fengming Xin ^{2,*} and Menghang Liu ¹

¹ Sydney Smart Technology College, Northeastern University, Qinhuangdao 066004, China; dengxiaoye@mails.neu.edu.cn (X.D.); liumh@mails.neu.edu.cn (M.L.)

² Hebei Key Laboratory of Marine Perception Network and Data Processing, School of Computer and Communication Engineering, Northeastern University, Qinhuangdao 066004, China

* Correspondence: 1001007@neuq.edu.cn

Abstract

Pinching-antenna systems (PASSs) have emerged as a promising waveguide-based architecture for high-frequency wireless communications. Recent directional PASS studies have shown that practical pinching antennas (PAs) exhibit directional, pencil-like radiation rather than idealized omnidirectional radiation. However, most existing designs focus on PA placement or instantaneous sum-rate maximization and neglect the reconfiguration time required for PA movement and rotation. This paper investigates reconfiguration-aware joint optimization for a multi-user downlink directional PASS with a finite frame duration. To evaluate transmission performance, an effective spectral efficiency metric is defined to account for both reconfiguration-induced rate gain and effective transmission-time reduction. Based on this metric, a joint optimization problem is formulated for user scheduling, PA positions, PA orientations, and digital beamforming. To tackle this mixed discrete–continuous non-convex problem, a reconfiguration-aware alternating optimization algorithm is developed by combining weighted minimum mean-square error (WMMSE)-based beamforming, local orientation search, projected position update, and restricted user scheduling. Simulation results show that the proposed scheme achieves higher effective spectral efficiency than representative fixed-configuration, sum-rate-oriented, and joint-search schemes. These results indicate that reconfiguration overhead should be considered, since instantaneous-rate-oriented designs may cause excessive PA movement or rotation and degrade effective spectral efficiency.

Keywords: pinching-antenna systems; multi-user MIMO; directional radiation; effective spectral efficiency; reconfiguration-aware optimization



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1. Introduction

With the worldwide deployment of fifth-generation (5G) wireless networks, wireless communication systems have entered an era of enhanced mobile broadband, massive connectivity, and low-latency services. The forthcoming sixth-generation (6G) networks are expected to further support ultra-high data rates, ubiquitous connectivity, high reliability, and intelligent adaptation to dynamic radio environments [1,2]. To realize these ambitious goals, multiple-input multiple-output (MIMO), especially massive MIMO, has been widely recognized as a fundamental technology for improving spectral efficiency and link reliability through spatial multiplexing and diversity gains [3,4]. However, as wireless systems move toward millimeter-wave (mmWave), terahertz (THz), and extremely large-scale antenna deployments, they suffer from severe free-space path loss, high hardware

cost, heavy channel-estimation overhead, and strong susceptibility to line-of-sight (LoS) blockage [5]. These challenges indicate that future wireless systems should not only rely on digital-domain beamforming, but also exploit new antenna architectures capable of reshaping the physical propagation path.

To overcome the limitations of conventional fixed-position antenna arrays, flexible-antenna systems have attracted increasing attention as a new physical-layer paradigm for exploiting additional spatial degrees of freedom. Unlike traditional arrays with fixed antenna positions and radiation structures, flexible-antenna systems can reconfigure the effective radiation locations or radiation states according to the wireless environment, thereby providing an additional means of channel enhancement. Representative examples include fluid antenna systems, which exploit position flexibility within a confined region and have been extended to multiple-access scenarios [6,7], and movable antenna systems, which improve wireless channel conditions by optimizing antenna positions [8,9]. More recently, pinching antennas have been introduced as a waveguide-based flexible-antenna architecture, where radiating points can be flexibly created along dielectric waveguides [10].

Among these flexible-antenna technologies, pinching-antenna systems (PASSs) have recently emerged as a particularly appealing waveguide-based architecture for future high-frequency wireless communications [11]. As a new type of flexible-antenna system, PASS allows radiating points to be flexibly configured along dielectric waveguides, where pinching antennas (PAs) are attached to selected positions to radiate signals into free space [12,13]. By activating PAs close to target users, PASS can shorten the free-space propagation distance and create favorable LoS-dominated links, thereby mitigating large-scale path loss and LoS blockage in mmWave and THz communications [14]. In addition, PASS supports low-cost and scalable deployment, since PAs can be added to or removed from waveguides without redesigning the whole antenna array [15]. Therefore, PASS provides a new communication paradigm that shifts wireless transmission from the conventional “last-mile” perspective toward a “last-meter” perspective [13]. For practical PASS deployment, both PA reconfiguration control signaling and security-sensitive multimedia services require reliable protection, since tampered PA-position and PA-orientation commands may degrade beam alignment, while image and video services involve privacy-sensitive data. Recent studies on image and video encryption and cryptanalysis provide useful references for this aspect [16,17].

Motivated by these advantages, PASS has recently been studied from multiple perspectives, including system modeling, performance analysis, pinching beamforming, multi-user transmission, and practical implementation. Physics-based models have been developed to characterize in-waveguide propagation and PA-waveguide coupling, while performance analysis has shown the potential of PASS in improving outage probability, average rate, and coverage performance [15,18]. PA-position optimization and array-gain analysis have been studied to improve downlink transmission performance, where PA locations affect both large-scale path loss and propagation phases [19,20]. For multi-user transmission, NOMA-assisted PASS, uplink PASS, and multi-waveguide PASS architectures have been investigated under different multiple-access, fairness, and transmission-structure designs [21–23]. In addition, frequency-selective modeling, channel estimation, and beam training have been studied as important issues for practical PASS implementation [24–26].

Although the above studies have significantly advanced PASS research, most existing works mainly exploit the position flexibility of PAs and usually assume that each PA radiates as an omnidirectional antenna. This assumption simplifies the system model, but may not accurately reflect the physical radiation behavior of practical PAs. In reality, a PA can be regarded as a waveguide-based radiator or leaky-wave radiator, whose radiated energy is concentrated within a directional beam rather than uniformly distributed over

space [27]. Moreover, high-frequency wireless channels are highly sensitive to angular-domain propagation characteristics [28]. The recently proposed directional PASS (DiPASS) framework addressed this issue by incorporating the orientation-dependent radiation pattern of PAs into the channel model, showing that the omnidirectional assumption may overestimate the effective radiated power and distort the characterization of coverage regions and interference patterns [29].

In addition to position flexibility, antenna rotation has also been recognized as an important spatial degree of freedom. Rotatable antennas exploit orientation-domain reconfigurability to improve wireless channels [30], while six-dimensional movable antennas further combine position and rotation optimization for enhanced network performance [31,32]. These studies indicate that both position and orientation can be useful design variables for improving wireless transmission. For directional PASS, PA positions affect the propagation distance and phase, while PA orientations affect the alignment of the directional radiation pattern with users. Unlike existing directional PASS studies that mainly optimize PA configurations from an instantaneous-rate perspective, this work further accounts for the non-negligible reconfiguration time required for PA movement and rotation. Therefore, an instantaneous sum-rate-maximizing configuration may not maximize the effective spectral efficiency when the communication time within a frame is limited. This issue becomes more challenging in multi-user scenarios, where PA positions, PA orientations, digital beamforming, and user scheduling are tightly coupled. These observations motivate a reconfiguration-aware design for directional PASS that balances the rate gain achieved by PA position and orientation adaptation against the time cost required for PA movement and rotation.

To further clarify the relationship between existing flexible-antenna studies and the proposed work, Table 1 summarizes representative research directions in terms of antenna reconfigurability, directional radiation modeling, reconfiguration overhead, and optimization objective.

Table 1. Comparison with representative related works.

Research Direction	Reconfigurable Variables	Directional PA Radiation	Reconfiguration Overhead	Main Objective
Fluid antenna systems [6,7]	Antenna position within a confined region	No	Usually not considered	Channel enhancement or diversity gain
Movable antenna systems [8,9]	Antenna position	No PASS-specific radiation model	Usually not considered	Channel condition or rate improvement
Rotatable and six-dimensional movable antennas [30–32]	Antenna orientation or antenna position and orientation	No PASS-specific radiation model	Usually not considered	Spatial channel enhancement
Conventional PASS studies [15,18–20]	PA position or PA activation	Usually without explicit orientation-dependent PA radiation modeling	Usually not considered	Rate, coverage, or outage performance
Directional PASS study [29]	PA–user association and directional PA configuration	Yes	Not explicitly considered	Instantaneous sum-rate enhancement
Proposed RA-AO framework	PA position, PA orientation, user scheduling, and beamforming	Yes	Explicitly considered	Effective spectral efficiency

To address the above issues, this paper investigates a reconfiguration-aware multi-user downlink PASS with directional radiation. Building on existing directional PASS modeling, we consider both PA positions and PA orientations as reconfigurable variables. By jointly considering the rate improvement brought by PA reconfiguration and the resulting reduction in effective transmission time, we adopt the effective spectral efficiency R_{eff} as the optimization objective. Based on this metric, user scheduling, PA positions, PA orientations, and digital beamforming are jointly designed to capture the trade-off between instantaneous-rate enhancement and reconfiguration overhead under a finite frame duration.

The main contributions of this paper are summarized as follows:

1. We define a reconfiguration-aware effective spectral efficiency metric, denoted by R_{eff} , for a multi-user directional PASS with a finite frame duration. Different from the conventional instantaneous sum-rate metric, R_{eff} captures the trade-off between the rate improvement enabled by PA reconfiguration and the reduction in effective transmission time caused by PA movement and rotation.
2. We formulate an R_{eff} maximization problem for multi-user downlink directional PASS. The problem jointly optimizes user scheduling, PA positions, PA orientations, and digital beamforming, which are coupled through the directional PA channel model.
3. We develop a reconfiguration-aware alternating optimization algorithm for the resulting mixed discrete–continuous non-convex problem. The proposed algorithm combines reconfiguration-cost-aware initialization, WMMSE-based beamforming, PA-wise orientation pattern search with re-anchoring, projected finite-difference PA-position search, and rate-aware restricted single-swap user scheduling, so as to improve R_{eff} while satisfying the finite-frame reconfiguration constraint.

The remainder of this paper is organized as follows. Section 2 presents the system model, including the channel model, the signal model, and the problem formulation for R_{eff} maximization. Section 3 presents the proposed alternating optimization algorithm for joint user scheduling, PA position optimization, PA orientation optimization, and beamforming update. Section 4 provides numerical results and performance comparisons. Finally, Section 5 concludes this paper.

2. System Model

Consider a downlink multi-user MIMO system assisted by a pinching-antenna system (PASS), as shown in Figure 1. A base station (BS) feeds N parallel dielectric waveguides, each of which is equipped with M pinching antennas (PAs), to serve K users over a $D_x \times D_y$ service region. The waveguides are deployed at height d , and the n -th waveguide is located at $x_n^W = \frac{2n-1}{2N}D_x$. The coordinate of PA (n, m) is $\mathbf{p}_{n,m} = [x_n^W, y_{n,m}, d]^T$, where $y_{n,m}$ is adjustable along the waveguide, while user k is located at $\mathbf{q}_k = [x_k, y_k, 0]^T$. For notational convenience, define the index sets as $\mathcal{N} = \{1, \dots, N\}$, $\mathcal{M} = \{1, \dots, M\}$, and $\mathcal{K} = \{1, \dots, K\}$. The PA-position vector on waveguide n is denoted by $\mathbf{x}_n = [y_{n,1}, \dots, y_{n,M}]^T$, and the overall position matrix is $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_N]$. Moreover, the orientation of PA (n, m) is characterized by the elevation angle $\theta_{n,m} \in [\pi/2, \pi]$ and the azimuth angle $\phi_{n,m} \in (-\pi, \pi]$. For compactness, all PA orientations are collected as $\boldsymbol{\theta} = \{\theta_{n,m}\}_{n,m}$ and $\boldsymbol{\phi} = \{\phi_{n,m}\}_{n,m}$.

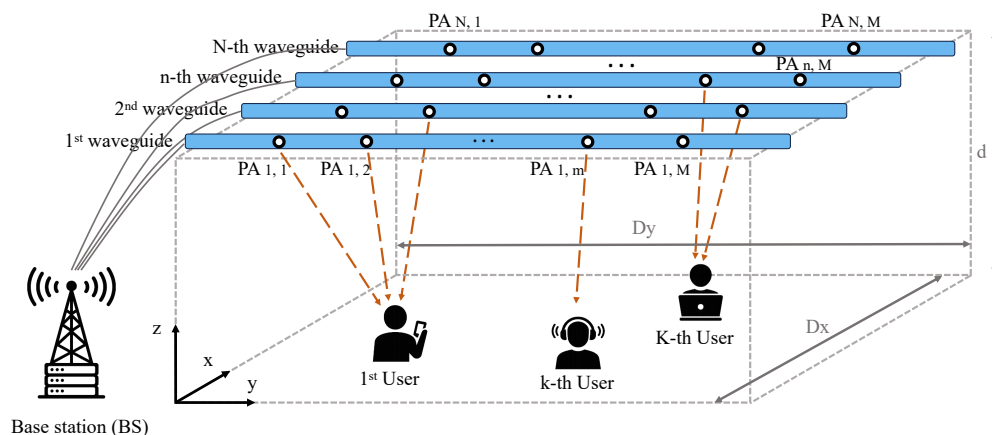


Figure 1. System model of the considered PASS-assisted multi-user downlink system.

2.1. Channel Model

The BS-to-user channel consists of guided-wave and free-space propagation. The guided-wave channel vector of the n -th waveguide is expressed as

$$\mathbf{g}_n(\mathbf{x}_n) = \left[\sqrt{\frac{1}{M}} e^{-\frac{\alpha_W}{2} y_{n,1}} e^{-j \frac{2\pi}{\lambda_g} y_{n,1}}, \dots, \sqrt{\frac{1}{M}} e^{-\frac{\alpha_W}{2} y_{n,M}} e^{-j \frac{2\pi}{\lambda_g} y_{n,M}} \right]^T \in \mathbb{C}^{M \times 1}, \quad (1)$$

where α_W is the waveguide attenuation coefficient and λ_g denotes the wavelength of the guided mode. At each PA, the guided-wave energy is coupled from the waveguide into free space, forming a highly directional radiation pattern. In the local coordinate system of the PA, we adopt the Gaussian-beam radiation pattern in [29], i.e.,

$$Y(x, y, z) = \sqrt{\frac{w_1 w_2}{W_1 W_2}} B \exp \left(-\frac{x^2}{W_1^2} - \frac{z^2}{W_2^2} - j k_0 n_r \left(\frac{x^2}{2R_1} + \frac{z^2}{2R_2} + y \right) + j \frac{\Theta_1 + \Theta_2}{2} \right), \quad (2)$$

where $k_0 = 2\pi/\lambda$, n_r denotes the refractive index, and the remaining Gaussian-beam parameters are defined as in [29]. In particular, the initial Gaussian widths w_1 and w_2 satisfy $w_1/(a\lambda) = w_2/(b\lambda) = v$, where $v \approx 1.1$ is an empirical correction factor related to the normalized waveguide frequency. Hence, a and b affect the beamwidth of the directional PA radiation pattern through w_1 and w_2 .

To evaluate the directional gain from PA (n, m) to user k , the user coordinate is transformed into the local coordinate system of this PA as

$$\tilde{\mathbf{q}}_{k,n,m} = \mathbf{R}_x \left(\theta_{n,m} - \frac{\pi}{2} \right) \mathbf{R}_z \left(\frac{\pi}{2} - \phi_{n,m} \right) (\mathbf{q}_k - \mathbf{p}_{n,m}), \quad (3)$$

where $\tilde{\mathbf{q}}_{k,n,m} = [\tilde{x}_{k,n,m}, \tilde{y}_{k,n,m}, \tilde{z}_{k,n,m}]^T$, and $\mathbf{R}_x(\cdot)$ and $\mathbf{R}_z(\cdot)$ are the rotation matrices around the x - and z -axes, respectively.

Taking into account free-space propagation loss, stochastic LoS blockage, and directional radiation, the free-space channel vector from the PAs on the n -th waveguide to user k is expressed as

$$\tilde{\mathbf{h}}_{k,n}(\mathbf{x}_n, \boldsymbol{\theta}_n, \boldsymbol{\phi}_n) = \left[\sqrt{\eta} \alpha_L^{\|\mathbf{q}_k - \mathbf{p}_{n,1}\|} Y(\tilde{x}_{k,n,1}, \tilde{y}_{k,n,1}, \tilde{z}_{k,n,1}), \dots, \sqrt{\eta} \alpha_L^{\|\mathbf{q}_k - \mathbf{p}_{n,M}\|} Y(\tilde{x}_{k,n,M}, \tilde{y}_{k,n,M}, \tilde{z}_{k,n,M}) \right]^T \in \mathbb{C}^{M \times 1}, \quad (4)$$

where $\eta = \lambda^2 / (4\pi)$, and $\alpha_L \in (0, 1)$ is the LoS existence coefficient.

The composite channel of waveguide n is obtained as $\mathbf{h}_{k,n} = \mathbf{g}_n(\mathbf{x}_n) \odot \tilde{\mathbf{h}}_{k,n}$, where $\odot$ denotes the Hadamard product and $\mathbf{h}_{k,n} \in \mathbb{C}^{M \times 1}$. The overall equivalent channel from all NM PA elements to user k is

$$\mathbf{h}_k = [\mathbf{h}_{k,1}^T, \dots, \mathbf{h}_{k,N}^T]^T \in \mathbb{C}^{NM \times 1}. \quad (5)$$

2.2. Signal Model

Let $\mathcal{S} \subseteq \mathcal{K}$ denote the scheduled user set, where $K_s \leq K$ is the number of simultaneously scheduled users and $|\mathcal{S}| = K_s$. For tractability, we adopt an equivalent PA-domain digital beamforming model, where each PA radiation point is treated as an effective transmit element after guided-wave propagation. For user $k \in \mathcal{S}$, let s_k with $\mathbb{E}\{|s_k|^2\} = 1$ and $\mathbf{w}_k \in \mathbb{C}^{NM \times 1}$ denote the data symbol and the corresponding PA-domain digital beamforming vector, respectively. Let $\mathcal{S} = \{k_1, \dots, k_{K_s}\}$. The beamforming matrix for the scheduled users is defined as $\mathbf{W} = [\mathbf{w}_{k_1}, \dots, \mathbf{w}_{k_{K_s}}] \in \mathbb{C}^{NM \times K_s}$. The received signal at user $k \in \mathcal{S}$ is

$$y_k = \mathbf{h}_k^H \mathbf{w}_k s_k + \sum_{j \in \mathcal{S}, j \neq k} \mathbf{h}_k^H \mathbf{w}_j s_j + n_k, \quad (6)$$

where $n_k \sim \mathcal{CN}(0, \sigma_k^2)$ denotes the additive white Gaussian noise at user k with noise power σ_k^2 . Accordingly, the SINR of user k is

$$\gamma_k = \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{j \in \mathcal{S}, j \neq k} |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma_k^2}. \quad (7)$$

Thus, the corresponding sum spectral efficiency is

$$R_{\text{sum}}(\mathbf{W}, \theta, \phi, \mathbf{X}, \mathcal{S}) = \sum_{k \in \mathcal{S}} \log_2(1 + \gamma_k). \quad (8)$$

2.3. Problem Formulation

Although R_{sum} measures the spectral efficiency after PASS reconfiguration, practical PA movement and rotation consume part of each communication frame. Let $y_{n,m}^0$, $\theta_{n,m}^0$, and $\phi_{n,m}^0$ denote the initial position, elevation angle, and azimuth angle of PA (n, m) , respectively. The corresponding reconfiguration times are defined as

$$\begin{cases} T_X(\mathbf{X}) = \max_{n,m} \frac{|y_{n,m} - y_{n,m}^0|}{v_y}, \\ T_\theta(\theta) = \max_{n,m} \frac{|\theta_{n,m} - \theta_{n,m}^0|}{\omega_\theta}, \\ T_\phi(\phi) = \max_{n,m} \frac{d_\pi(\phi_{n,m}, \phi_{n,m}^0)}{\omega_\phi}, \end{cases} \quad (9)$$

where v_y is the PA moving speed, while ω_θ and ω_ϕ denote the elevation- and azimuth-angle adjustment speeds, respectively. For the periodic azimuth angle $\phi_{n,m} \in (-\pi, \pi]$, $d_\pi(a, b) = |\text{mod}(a - b + \pi, 2\pi) - \pi|$ is used to measure the minimum rotation distance. Since all PA movements and rotations can be carried out in parallel, the total reconfiguration time is

$$T_{\text{rec}}(\theta, \phi, \mathbf{X}) = \max\{T_X(\mathbf{X}), T_\theta(\theta), T_\phi(\phi)\}. \quad (10)$$

The maximum operator in T_{rec} models a parallel reconfiguration process, where PA displacement, elevation adjustment, and azimuth adjustment are allowed to proceed concurrently. This assumption is applicable when the hardware provides independent

or partially independent actuation mechanisms for different reconfiguration dimensions. If these operations are performed sequentially, a more conservative serial latency can be represented by $T_X(\mathbf{X}) + T_\theta(\boldsymbol{\theta}) + T_\phi(\boldsymbol{\phi})$. The impact of this modeling choice is further evaluated in Section 4. For a frame duration T_f , the remaining interval after reconfiguration is used for data transmission. Thus, the effective number of transmitted bits per Hz within one communication frame is defined as

$$Q_{\text{eff}}(\mathbf{W}, \boldsymbol{\theta}, \boldsymbol{\phi}, \mathbf{X}, \mathcal{S}) = [T_f - T_{\text{rec}}(\boldsymbol{\theta}, \boldsymbol{\phi}, \mathbf{X})]^+ R_{\text{sum}}(\mathbf{W}, \boldsymbol{\theta}, \boldsymbol{\phi}, \mathbf{X}, \mathcal{S}), \quad (11)$$

where $[x]^+ = \max\{x, 0\}$. To remain consistent with the conventional spectral-efficiency metric, the normalized effective spectral efficiency is further defined as

$$R_{\text{eff}}(\mathbf{W}, \boldsymbol{\theta}, \boldsymbol{\phi}, \mathbf{X}, \mathcal{S}) = \left[1 - \frac{T_{\text{rec}}(\boldsymbol{\theta}, \boldsymbol{\phi}, \mathbf{X})}{T_f}\right]^+ R_{\text{sum}}(\mathbf{W}, \boldsymbol{\theta}, \boldsymbol{\phi}, \mathbf{X}, \mathcal{S}). \quad (12)$$

The reconfiguration-aware joint optimization problem is formulated as

$$\max_{\mathbf{W}, \boldsymbol{\theta}, \boldsymbol{\phi}, \mathbf{X}, \mathcal{S}} R_{\text{eff}}(\mathbf{W}, \boldsymbol{\theta}, \boldsymbol{\phi}, \mathbf{X}, \mathcal{S}) \quad (13a)$$

$$\text{s.t.} \quad \sum_{k \in \mathcal{S}} \|\mathbf{w}_k\|_2^2 \leq P_{\text{max}}, \quad (13b)$$

$$\boldsymbol{\theta} \in \Theta, \quad \boldsymbol{\phi} \in \Phi, \quad (13c)$$

$$\mathbf{X} \in \mathcal{X}, \quad (13d)$$

$$\mathcal{S} \subseteq \mathcal{K}, \quad |\mathcal{S}| = K_s, \quad (13e)$$

$$T_{\text{rec}}(\boldsymbol{\theta}, \boldsymbol{\phi}, \mathbf{X}) \leq T_f, \quad (13f)$$

where $\Theta = \{\boldsymbol{\theta} \mid \pi/2 \leq \theta_{n,m} \leq \pi, \forall n, m\}$, $\Phi = \{\boldsymbol{\phi} \mid -\pi < \phi_{n,m} \leq \pi, \forall n, m\}$, and $\mathcal{X} = \{\mathbf{X} \mid \mathbf{x}_n \in \mathcal{X}_n, \forall n \in \mathcal{N}\}$.

The feasible position set of the PAs on waveguide n is defined as

$$\mathcal{X}_n = \{\mathbf{x}_n \in \mathbb{R}^M : 0 \leq y_{n,m} \leq D_y, \forall m \in \mathcal{M}, \\ y_{n,m+1} - y_{n,m} \geq \Delta_y, m = 1, \dots, M-1\}, \quad (14)$$

where Δ_y is the minimum spacing between adjacent PAs on the same waveguide.

Constraint (13b) limits the total transmit power of the BS over all scheduled users to the maximum power budget P_{max} . Constraint (13c) restricts the PA orientations, where the elevation and azimuth angles are constrained within their feasible radiation ranges. Constraint (13d) requires the PA positions on all waveguides to belong to the feasible deployment set $\mathcal{X}$. Specifically, (14) ensures that each PA is located within the waveguide boundary and that the minimum spacing Δ_y between adjacent PAs on the same waveguide is satisfied, so as to avoid physically infeasible deployment. Constraint (13e) selects exactly K_s users from the candidate user set $\mathcal{K}$ for downlink transmission. Finally, constraint (13f) guarantees that the total reconfiguration time caused by PA movement and rotation does not exceed the frame duration T_f , ensuring that a nonnegative transmission interval remains within each frame.

Problem (13) is a mixed discrete–continuous non-convex problem, where the continuous beamforming and PA-geometry variables are coupled with the discrete user scheduling, and the objective is further complicated by the non-smooth reconfiguration time T_{rec} .

3. Algorithm Formulation

To handle the coupled variables in problem (13), we propose a reconfiguration-aware alternating optimization (RA-AO) algorithm, which initializes a feasible solution and then sequentially updates $\mathbf{W}$, (θ, ϕ) , $\mathbf{X}$, and $\mathcal{S}$ based on R_{eff} .

The overall workflow of the proposed RA-AO algorithm is illustrated in Figure 2. It provides a high-level view of the initialization, four alternating update blocks, and convergence check, while the detailed update rules are presented in the following subsections and summarized later in Algorithm 1.

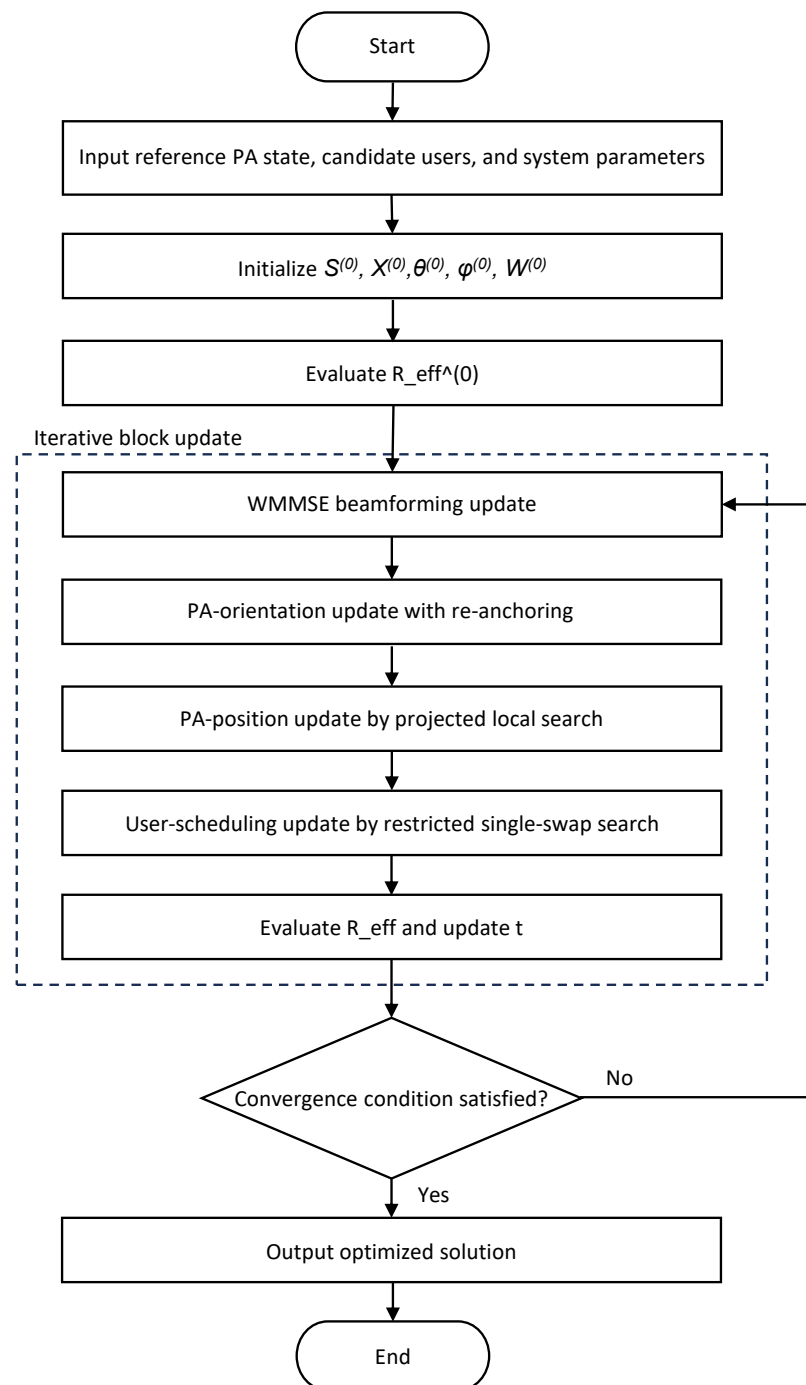


Figure 2. Flowchart of the proposed reconfiguration-aware alternating optimization algorithm.

Algorithm 1 Proposed reconfiguration-aware AO algorithm**Require:** Reference PA state, user set $\mathcal{K}$, and system parameters.**Ensure:** $\mathbf{W}^*, \theta^*, \phi^*, \mathbf{X}^*, \mathcal{S}^*$.

- 1: Initialize the iteration index $t = 0$.
- 2: Construct $\mathcal{S}^{(0)}$ using the peak potential gain $G_k^{\max}$.
- 3: Compute $U_{k,n,m}$ for all k, n, m , and perform displacement-discounted PA–user association.
- 4: Obtain $\mathbf{X}^{(0)}$ by projection, initialize $(\theta^{(0)}, \phi^{(0)})$, and generate $\mathbf{W}^{(0)}$ by MRT.
- 5: **repeat**
- 6: Update $\mathbf{W}^{(t+1)}$ by WMMSE for fixed $(\theta^{(t)}, \phi^{(t)}, \mathbf{X}^{(t)}, \mathcal{S}^{(t)})$.
- 7: Update $(\theta^{(t+1)}, \phi^{(t+1)})$ by sequential PA-wise pattern search with re-anchoring.
- 8: Update $\mathbf{X}^{(t+1)}$ by the projected finite-difference local search.
- 9: Update $\mathcal{S}^{(t+1)}$ by the rate-aware restricted single-swap search.
- 10: During the orientation, position, and user-scheduling updates, accept candidates according to R_{eff} or $R_{\text{usr}}^{(t)}$ with the corresponding feasibility constraints; otherwise, keep the current variables.
- 11: $t \leftarrow t + 1$.
- 12: **until** $|R_{\text{eff}}^{(t)} - R_{\text{eff}}^{(t-1)}| \leq \varepsilon$ or $t \geq I_{\max}$
- 13: Set $(\mathbf{W}^*, \theta^*, \phi^*, \mathbf{X}^*, \mathcal{S}^*) = (\mathbf{W}^{(t)}, \theta^{(t)}, \phi^{(t)}, \mathbf{X}^{(t)}, \mathcal{S}^{(t)})$.

3.1. Initialization

For user k and waveguide n , the nominal PA position is initialized according to the single-PA placement rule in [29], i.e.,

$$y_{n,m}^*(k) = \left[y_k - \sqrt{\frac{A_{k,n} \alpha_W^2}{(2 \ln \alpha_L)^2 - \alpha_W^2}} \right]^+, \quad (15)$$

where $A_{k,n} = (x_k - x_n^W)^2 + d^2$ denotes the squared distance component between user k and the n -th waveguide in the x - z plane. The corresponding initial potential channel-amplitude metric is evaluated as

$$G_{k,n,m} \triangleq |h_{k,n,m}^*| = \sqrt{\frac{1}{M}} e^{-\frac{\alpha_W}{2} y_{n,m}^*(k)} \alpha_L^{d_{k,n,m}^*} \frac{\lambda n_T v \sqrt{2ab}}{2d_{k,n,m}^*}, \quad (16)$$

where $d_{k,n,m}^* = \|\mathbf{q}_k - [x_n^W, y_{n,m}^*(k), d]^T\|$. For each user k , $G_k^{\max} = \max_{n,m} G_{k,n,m}$ denotes its strongest potential PA–user link. We first construct a candidate pool $\mathcal{C}$ by selecting the $\min\{2K_s, K\}$ users with the largest $G_k^{\max}$. The top K_s users in $\mathcal{C}$ are used as the initial scheduled set $\mathcal{S}^{(0)}$, while the remaining candidates are reserved for the subsequent user-swap update.

To account for the PA movement cost during initialization, we define the displacement-discounted utility as

$$U_{k,n,m} = [1 - \rho D_{k,n,m}]^+ G_{k,n,m}, \quad (17)$$

where $D_{k,n,m} = |y_{n,m}^*(k) - y_{n,m}^0|/D_y$ is the normalized displacement from the pre-reconfiguration PA position. Setting $\rho = 0$ removes the displacement discount and reduces $U_{k,n,m}$ to the channel-amplitude metric $G_{k,n,m}$. As ρ increases, PA–user links with larger normalized displacement $D_{k,n,m}$ receive a stronger discount, so the initialization tends to select links that require shorter PA movement. In this paper, $\rho = 1$ is adopted as the default setting to balance the channel-amplitude metric and the displacement discount.

The PA–user association is initialized according to the displacement-discounted utility $U_{k,n,m}$. Specifically, a one-to-one PA–user matching is first obtained by maximizing the total utility over the scheduled user set $\mathcal{S}^{(0)}$, i.e.,

$$\mathcal{A}^{(0)} = \arg \max_{\mathcal{A}} \sum_{(k,n,m) \in \mathcal{A}} U_{k,n,m}, \quad (18)$$

where $\mathcal{A}$ denotes a one-to-one PA–user matching set over $\mathcal{S}^{(0)}$, and each element $(k, n, m) \in \mathcal{A}$ indicates that scheduled user k is associated with PA (n, m) . For the remaining PAs, the associated user is selected according to the largest utility. Therefore, the final initial association is given by

$$\mu_{n,m}^{(0)} = \arg \max_{k \in \mathcal{S}^{(0)}} U_{k,n,m}. \quad (19)$$

Here, $\mu_{n,m}^{(0)} \in \mathcal{S}^{(0)}$ denotes the user associated with PA (n, m) after the initialization. The nominal initial position of this PA is then given by

$$\bar{y}_{n,m}^{(0)} = y_{n,m}^* (\mu_{n,m}^{(0)}). \quad (20)$$

Since the nominal positions may violate the waveguide boundary or the minimum spacing constraint, the initial PA-position vector on waveguide n is projected onto the feasible set:

$$\mathbf{x}_n^{(0)} = \Pi_{\mathcal{X}_n}([\bar{y}_{n,1}^{(0)}, \dots, \bar{y}_{n,M}^{(0)}]^T). \quad (21)$$

Stacking all waveguides gives the initial PA-position matrix $\mathbf{X}^{(0)} = [\mathbf{x}_1^{(0)}, \dots, \mathbf{x}_N^{(0)}]$. Given $\mathbf{X}^{(0)}$, each PA is initially oriented toward its associated user. Specifically, let $\mathbf{v}_{n,m}^{(0)} = \mathbf{q}_{\mu_{n,m}^{(0)}}^{(0)} - \mathbf{p}_{n,m}^{(0)}$. The initial angles are set as

$$\begin{cases} \theta_{n,m}^{(0)} = \arccos \frac{[\mathbf{v}_{n,m}^{(0)}]_z}{\|\mathbf{v}_{n,m}^{(0)}\|}, \\ \phi_{n,m}^{(0)} = \text{atan2}([\mathbf{v}_{n,m}^{(0)}]_y, [\mathbf{v}_{n,m}^{(0)}]_x). \end{cases} \quad (22)$$

With the initial PA positions $\mathbf{X}^{(0)}$ and orientation angles $(\boldsymbol{\theta}^{(0)}, \boldsymbol{\phi}^{(0)})$, the initial precoding matrix is obtained by MRT based on the corresponding composite channels. Specifically,

$$\mathbf{W}^{(0)} = \beta^{(0)} \left[\frac{\mathbf{h}_{k_1}^{(0)}}{\|\mathbf{h}_{k_1}^{(0)}\|}, \dots, \frac{\mathbf{h}_{k_{|\mathcal{S}^{(0)}|}}^{(0)}}{\|\mathbf{h}_{k_{|\mathcal{S}^{(0)}|}}^{(0)}\|} \right] \in \mathbb{C}^{NM \times K_s}, \quad (23)$$

where $\mathbf{h}_k^{(0)} = \mathbf{h}_k(\mathbf{X}^{(0)}, \boldsymbol{\theta}^{(0)}, \boldsymbol{\phi}^{(0)})$, and $\beta^{(0)}$ is chosen to satisfy the transmit-power constraint $\text{tr}(\mathbf{W}^{(0)}(\mathbf{W}^{(0)})^H) \leq P_{\max}$.

Consequently, the initialization procedure yields $(\mathbf{W}^{(0)}, \boldsymbol{\theta}^{(0)}, \boldsymbol{\phi}^{(0)}, \mathbf{X}^{(0)}, \mathcal{S}^{(0)})$ as a feasible starting point for the subsequent alternating optimization.

3.2. Alternating Optimization

Starting from the initialized solution, the proposed RA-AO algorithm updates the variable blocks in the order

$$\mathbf{W} \rightarrow (\boldsymbol{\theta}, \boldsymbol{\phi}) \rightarrow \mathbf{X} \rightarrow \mathcal{S}. \quad (24)$$

At the t -th iteration, each block update is evaluated using R_{eff} . In the numerical search blocks, small tolerances ϵ_θ , ϵ_X , and ϵ_S are used for the orientation, position, and user-scheduling updates, respectively, to avoid accepting negligible numerical improvements.

(1) *Beamforming update*: For given PA orientations, PA positions, and scheduled users, i.e., $(\theta, \phi, \mathbf{X}, \mathcal{S}) = (\theta^{(t)}, \phi^{(t)}, \mathbf{X}^{(t)}, \mathcal{S}^{(t)})$, the reconfiguration time is fixed and independent of $\mathbf{W}$. Hence, maximizing R_{eff} is equivalent to maximizing the instantaneous sum rate. The beamforming subproblem is given by

$$\begin{aligned} \max_{\mathbf{W}} \quad & \sum_{k \in \mathcal{S}^{(t)}} \log_2(1 + \gamma_k) \\ \text{s.t.} \quad & \sum_{k \in \mathcal{S}^{(t)}} \|\mathbf{w}_k\|_2^2 \leq P_{\max}. \end{aligned} \quad (25)$$

The above problem is solved by the WMMSE method, which is widely used for weighted sum-rate maximization in multi-user MIMO systems [33,34]. For user k , let u_k and v_k denote the receive scalar and the MSE weight, respectively. The MSE is defined as $e_k = \mathbb{E}\{|u_k y_k - s_k|^2\}$, where $y_k = \sum_{j \in \mathcal{S}^{(t)}} \mathbf{h}_k^H \mathbf{w}_j s_j + n_k$. According to the WMMSE transformation, problem (25) can be equivalently handled by minimizing $\sum_{k \in \mathcal{S}^{(t)}} (v_k e_k - \log v_k)$ under the same transmit power constraint.

For fixed $\mathbf{W}$, the optimal receive scalar is

$$u_k = \frac{(\mathbf{h}_k^H \mathbf{w}_k)^*}{\sum_{j \in \mathcal{S}^{(t)}} |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma_k^2}, \quad k \in \mathcal{S}^{(t)}.$$

For fixed u_k , the optimal weight is $v_k = e_k^{-1}$. With $\{u_k\}$ and $\{v_k\}$ fixed, the beamforming vector is updated as

$$\mathbf{w}_k = \left(\sum_{j \in \mathcal{S}^{(t)}} v_j |u_j|^2 \mathbf{h}_j \mathbf{h}_j^H + \mu \mathbf{I} \right)^{-1} v_k u_k^* \mathbf{h}_k, \quad k \in \mathcal{S}^{(t)}, \quad (26)$$

where $\mu \geq 0$ is chosen to satisfy the transmit power constraint. If the unconstrained solution is feasible, $\mu = 0$; otherwise, μ is obtained by bisection. The updates of u_k , v_k , and $\mathbf{w}_k$ are repeated until the inner WMMSE iteration converges, and the resulting beamforming matrix is used as $\mathbf{W}^{(t+1)}$.

(2) *Orientation update*: After updating the digital beamforming matrix to $\mathbf{W}^{(t+1)}$, we optimize the PA orientation angles while keeping the PA positions and scheduled user set fixed as $\mathbf{X}^{(t)}$ and $\mathcal{S}^{(t)}$, respectively. The orientation-angle subproblem is given by

$$\begin{aligned} \max_{\theta, \phi} \quad & R_{\text{eff}}(\mathbf{W}^{(t+1)}, \theta, \phi, \mathbf{X}^{(t)}, \mathcal{S}^{(t)}) \\ \text{s.t.} \quad & \frac{\pi}{2} \leq \theta_{n,m} \leq \pi, \quad -\pi < \phi_{n,m} \leq \pi, \quad \forall n, m, \\ & T_{\text{rec}}(\theta, \phi, \mathbf{X}^{(t)}) \leq T_f. \end{aligned} \quad (27)$$

To solve (27), an eight-direction local search is performed for each PA. For PA (n, m) , let $(\theta_{n,m}^c, \phi_{n,m}^c)$ denote the current search center, and let Δ_θ and Δ_ϕ denote the search step sizes. In each search round, the following polling directions are examined:

$$\mathcal{D} = \{(1, 0), (-1, 0), (0, 1), (0, -1), (1, 1), (1, -1), (-1, 1), (-1, -1)\}. \quad (28)$$

For each $(d_1, d_2) \in \mathcal{D}$, the corresponding candidate angle pair is given by

$$(\theta, \phi) = (\theta_{n,m}^c + d_1 \Delta_\theta, \phi_{n,m}^c + d_2 \Delta_\phi). \quad (29)$$

After projection onto the angular feasible region, candidates violating the frame-duration constraint are discarded. Denote the remaining feasible angle set by $\mathcal{F}_{n,m}^{\text{ang}}$. For compactness, let $R_{n,m}^{\text{ang}}(\theta, \phi)$ denote the effective spectral efficiency obtained by replacing only the orientation of PA (n, m) with (θ, ϕ) , while keeping all other variables fixed. The angle pair of PA (n, m) is updated by

$$(\hat{\theta}_{n,m}, \hat{\phi}_{n,m}) = \arg \max_{(\theta, \phi) \in \mathcal{F}_{n,m}^{\text{ang}}} R_{n,m}^{\text{ang}}(\theta, \phi). \quad (30)$$

If $R_{n,m}^{\text{ang}}(\hat{\theta}_{n,m}, \hat{\phi}_{n,m}) \geq R_{n,m}^{\text{ang}}(\theta_{n,m}^c, \phi_{n,m}^c) + \epsilon_\theta$, the selected candidate is accepted as the new search center. Otherwise, the current search center is retained, and the angular step sizes are reduced as

$$\Delta_\theta^{\text{new}} = \beta_\theta \Delta_\theta, \quad \Delta_\phi^{\text{new}} = \beta_\phi \Delta_\phi, \quad (31)$$

where $0 < \beta_\theta, \beta_\phi < 1$.

When the angle search stagnates, or the scheduled user set has been changed, the search center is re-anchored. The anchor candidates include the current orientation, the default downward direction $(\pi, 0)$, and the geometric directions toward several nearby scheduled users. For an anchor user k , the corresponding geometric direction is computed using the same form as in (22), with $\mathbf{v}_{n,m} = \mathbf{q}_k - \mathbf{p}_{n,m}$ under the current PA position. The best feasible anchor in terms of $R_{n,m}^{\text{ang}}$ is selected as the new search center, and the eight-direction local search in (28)–(30) continues around this reset angle pair. After all PAs are updated sequentially, the obtained angle vectors are denoted by $(\boldsymbol{\theta}^{(t+1)}, \boldsymbol{\phi}^{(t+1)})$.

(3) *Position update*: For fixed $(\mathbf{W}^{(t+1)}, \boldsymbol{\theta}^{(t+1)}, \boldsymbol{\phi}^{(t+1)}, \mathcal{S}^{(t)})$, the PA positions are updated waveguide by waveguide. The position subproblem is

$$\begin{aligned} \max_{\mathbf{X}} \quad & R_{\text{eff}}(\mathbf{W}^{(t+1)}, \boldsymbol{\theta}^{(t+1)}, \boldsymbol{\phi}^{(t+1)}, \mathbf{X}, \mathcal{S}^{(t)}) \\ \text{s.t.} \quad & \mathbf{x}_n \in \mathcal{X}_n, \quad \forall n, \\ & T_{\text{rec}}(\boldsymbol{\theta}^{(t+1)}, \boldsymbol{\phi}^{(t+1)}, \mathbf{X}) \leq T_f. \end{aligned} \quad (32)$$

Since the PA-position subproblem is non-convex, we adopt a projected finite-difference local search. The PA positions are updated sequentially over the waveguides. When the n -th waveguide is updated, the previously updated waveguides keep their latest positions, while the remaining waveguides keep their current positions. Let $\bar{\mathbf{X}}_n^{(t)}$ denote the position matrix before updating the n -th waveguide in the current position-update block. The local objective is defined as

$$f_n(\mathbf{x}_n) = R_{\text{eff}}(\mathbf{W}^{(t+1)}, \boldsymbol{\theta}^{(t+1)}, \boldsymbol{\phi}^{(t+1)}, \bar{\mathbf{X}}_n^{(t)}(\mathbf{x}_n), \mathcal{S}^{(t)}), \quad (33)$$

where $\bar{\mathbf{X}}_n^{(t)}(\mathbf{x}_n)$ is obtained by replacing only the position vector of the n -th waveguide with $\mathbf{x}_n$. A candidate position is feasible only if it satisfies both the position constraints and the frame-duration constraint.

At each inner position-search iteration, the gradient of $f_n(\mathbf{x}_n)$ is approximated by projected finite differences. Specifically, for the m -th coordinate, the perturbed positions are first projected onto $\mathcal{X}_n$, and the gradient component is evaluated as

$$[\nabla f_n(\mathbf{x}_n)]_m \approx \frac{f_n(\Pi_{\mathcal{X}_n}(\mathbf{x}_n + \delta \mathbf{e}_m)) - f_n(\Pi_{\mathcal{X}_n}(\mathbf{x}_n - \delta \mathbf{e}_m))}{2\delta}, \quad (34)$$

where $\mathbf{e}_m$ is the m -th canonical basis vector and δ is the finite-difference step size. If only one perturbed point is feasible, a one-sided difference is used instead; if neither is feasible, the corresponding gradient component is set to zero.

Based on the approximated gradient and the limited-memory curvature information, an L-BFGS-inspired ascent direction is generated by the two-loop recursion. To control the movement scale, the resulting direction is normalized as

$$\mathbf{d}_n = \frac{\mathbf{B}_n \nabla f_n(\mathbf{x}_n)}{\|\mathbf{B}_n \nabla f_n(\mathbf{x}_n)\|}, \quad (35)$$

where $\mathbf{B}_n$ denotes the limited-memory inverse-curvature approximation. If the norm is zero, the current position is retained.

A backtracking line search is then performed along $\mathbf{d}_n$. For a trial step size α , the projected candidate position is

$$\hat{\mathbf{x}}_n(\alpha) = \Pi_{\mathcal{X}_n}(\mathbf{x}_n + \alpha \mathbf{d}_n). \quad (36)$$

The candidate is accepted if it is feasible and satisfies

$$f_n(\hat{\mathbf{x}}_n(\alpha)) \geq f_n(\mathbf{x}_n) + \epsilon_X. \quad (37)$$

Otherwise, the step size is reduced, and the search continues. After each accepted update, the latest position and gradient variations are stored in the limited-memory history. The inner search for the n -th waveguide terminates when no sufficient improvement is obtained or when the maximum number of inner iterations is reached. After all waveguides are updated sequentially, the resulting position matrix is denoted by $\mathbf{X}^{(t+1)}$.

(4) *User-set update:* After updating the position matrix to $\mathbf{X}^{(t+1)}$, we optimize the scheduled user set while keeping $(\mathbf{W}^{(t+1)}, \boldsymbol{\theta}^{(t+1)}, \boldsymbol{\phi}^{(t+1)}, \mathbf{X}^{(t+1)})$ fixed.

In this block, the beamforming matrix is not re-optimized for each candidate user swap in order to preserve the block-wise structure of the proposed alternating optimization algorithm and avoid excessive computational complexity. Instead, candidate swaps are evaluated under the current PA geometry and beamforming structure. Specifically, when a scheduled user is replaced by an external candidate, the candidate user temporarily uses the beamforming column of the replaced user for swap evaluation. Once the user set is updated, the beamforming matrix is re-optimized for the new scheduled user set in the next WMMSE block. For compactness, define the user-set evaluation metric as

$$R_{\text{usr}}^{(t)}(\mathcal{S}) \triangleq R_{\text{eff}}(\mathbf{W}^{(t+1)}, \boldsymbol{\theta}^{(t+1)}, \boldsymbol{\phi}^{(t+1)}, \mathbf{X}^{(t+1)}, \mathcal{S}),$$

where $R_{\text{usr}}^{(t)}(\mathcal{S})$ is used only for evaluating candidate user sets in the current user-selection block with fixed beamforming and PA geometry. Then, the user-set subproblem is written as

$$\begin{aligned} \max_{\mathcal{S}} \quad & R_{\text{usr}}^{(t)}(\mathcal{S}) \\ \text{s.t.} \quad & \mathcal{S} \subseteq \mathcal{K}, \quad |\mathcal{S}| = K_s. \end{aligned} \quad (38)$$

To avoid exhaustive search, a restricted single-swap search is adopted. Specifically, the users in the current scheduled set $\mathcal{S}^{(t)}$ are first evaluated according to their individual rates under the current beamforming and PA geometry. The L_{in} users with the lowest individual rates are selected as the weak-user candidate set $\mathcal{I}_{\text{weak}}^{(t)}$. Meanwhile, the users in the candidate pool $\mathcal{C} \setminus \mathcal{S}^{(t)}$ are sorted in descending order according to the previously defined potential metric G_k^{max} , and the top L_{out} users are selected as the external-candidate

set $\mathcal{J}_{\text{strong}}^{(t)}$. Here, L_{in} and L_{out} are preset search-list sizes for the weak scheduled users and external candidate users, respectively. The algorithm then enumerates single-user swap candidates between these two sets. For each $i \in \mathcal{I}_{\text{weak}}^{(t)}$ and $j \in \mathcal{J}_{\text{strong}}^{(t)}$, the swapped user set is

$$\mathcal{S}_{i,j}^{(t)} = (\mathcal{S}^{(t)} \setminus \{i\}) \cup \{j\}. \quad (39)$$

In the fixed-beamforming evaluation, the external candidate j occupies the beamforming column originally assigned to the replaced user i . The corresponding effective-rate improvement is defined as

$$\Delta_{i,j}^{(t)} = R_{\text{usr}}^{(t)}(\mathcal{S}_{i,j}^{(t)}) - R_{\text{usr}}^{(t)}(\mathcal{S}^{(t)}). \quad (40)$$

Then, the best swap is selected by

$$(i^*, j^*) = \arg \max_{i \in \mathcal{I}_{\text{weak}}^{(t)}, j \in \mathcal{J}_{\text{strong}}^{(t)}} \Delta_{i,j}^{(t)}. \quad (41)$$

If $\Delta_{i^*,j^*}^{(t)} \geq \epsilon_S$, the swap is accepted and $\mathcal{S}^{(t+1)} = \mathcal{S}_{i^*,j^*}^{(t)}$; otherwise, $\mathcal{S}^{(t+1)} = \mathcal{S}^{(t)}$. This acceptance rule is based on the fixed-beamforming user-set evaluation metric $R_{\text{usr}}^{(t)}$, and the beamforming matrix is re-optimized for the updated user set in the next WMMSE block.

Based on the above block updates and acceptance rules, the detailed pseudocode corresponding to the workflow in Figure 2 is summarized in Algorithm 1.

3.3. Convergence and Complexity

We next analyze the convergence and computational complexity of the proposed RA-AO algorithm. Since the updates of (θ, ϕ) and $\mathbf{X}$ are accepted only when R_{eff} is non-decreasing, the user-set update is accepted according to the fixed-beamforming evaluation metric $R_{\text{usr}}^{(t)}$, and the WMMSE step improves or preserves R_{eff} for fixed PA geometry and reconfiguration time, the generated sequence satisfies

$$R_{\text{eff}}^{(t+1)} \geq R_{\text{eff}}^{(t)}. \quad (42)$$

Moreover, R_{eff} is upper bounded due to the finite transmit power, bounded PA feasible region, and finite frame duration. Therefore, the proposed RA-AO algorithm converges to a finite objective value.

The complexity per outer iteration mainly comes from the WMMSE update, the PA-wise angle search, the projected position search, and the restricted user-scheduling search. Let $N_{\text{PA}} = NM$, and let I_W , I_{ang} , and I_{pos} denote the numbers of inner iterations for the WMMSE update, angle search, and position search, respectively. Let L_μ be the maximum number of bisection iterations in the WMMSE update, L_{bt} be the maximum number of backtracking steps in the position search, and C_R be the complexity of evaluating R_{eff} . In addition, let C_{ang} denote the maximum number of R_{eff} evaluations required in one inner angle-search round for one PA, including polling and possible re-anchoring, and let C_{usr} denote the maximum number of candidate swaps evaluated in the user-scheduling block. Then, the per-outer-iteration complexity can be roughly written as

$$\mathcal{O}\left(I_W\left((L_\mu + 1)N_{\text{PA}}^3 + K_s N_{\text{PA}}^2\right) + (I_{\text{ang}}N_{\text{PA}}C_{\text{ang}} + I_{\text{pos}}N(2M + L_{\text{bt}}) + C_{\text{usr}})C_R\right). \quad (43)$$

To provide a quantitative comparison of computational effort, Table 2 reports the average number of iterations, average achieved R_{eff} , and normalized runtime under the default simulation setup. Since absolute runtime may vary with the computing platform

and implementation details, the runtime is reported after normalization to the fixed PA-S scheme under the same implementation.

As shown in Table 2, the fixed PA-S scheme has the lowest computational burden because the PA positions and orientations are fixed, but it also yields the lowest R_{eff} . By further re-optimizing the beamforming matrix during user scheduling, the fixed PA-S + WMMSE scheme improves R_{eff} at the cost of a higher normalized runtime. The HG-SR scheme achieves a relatively low normalized runtime due to its structured PA–user assignment procedure, but its R_{eff} remains lower than that of the proposed RA-AO. The SA joint search requires 5000 annealing iterations and still obtains a lower R_{eff} , indicating that stochastic search may be inefficient for the considered mixed discrete–continuous problem. The proposed RA-AO incurs the highest normalized runtime because it jointly updates beamforming, PA orientations, PA positions, and user scheduling. Nevertheless, it converges within a small number of outer iterations and achieves the highest average R_{eff} , demonstrating the performance benefit of the proposed reconfiguration-aware block-wise optimization.

Table 2. Computational effort comparison under the default simulation setup.

Scheme	Dominant Computational Modules	Avg. Iterations	Avg. R_{eff}	Norm. Runtime
Fixed PA-S	User scheduling and beamforming under fixed PA configuration	1.97	4.92	1.00
Fixed PA-S + WMMSE	Fixed-configuration user scheduling with WMMSE-based beamforming re-optimization	7.07	21.53	57.24
HG-SR	Hungarian-greedy PA–user assignment and beamforming update	1.00	25.57	5.05
SA joint search	Annealing-based joint search over PA configuration and user scheduling	5000.00	23.37	103.09
Proposed RA-AO	WMMSE beamforming, PA-orientation search, PA-position search, and restricted single-swap user scheduling	8.66	27.52	321.56

4. Simulation Results

In this section, we provide simulation results to evaluate the proposed reconfiguration-aware AO (RA-AO) algorithm and demonstrate the importance of accounting for reconfiguration overhead in effective spectral efficiency maximization. Unless otherwise specified, the reported performance curves are obtained from synthetically generated Monte Carlo instances. In each realization, user locations are randomly generated, and the same user-location realization is used for all benchmark schemes under the same parameter setting. The reported curves show the sample mean over N_{MC} realizations, and for statistical performance figures, the error bars denote the 95% confidence intervals computed as $\bar{z} \pm 1.96s_z / \sqrt{N_{\text{MC}}}$, where s_z is the sample standard deviation. This error-bar convention applies to all figures where error bars are shown. Here, T_f is interpreted as the PASS reconfiguration frame duration, and v_y denotes the effective PA moving speed along the waveguide. The average effective spectral efficiency R_{eff} is adopted as the performance metric.

For comparison, four benchmark schemes are considered. The *fixed PA-S* scheme fixes the PA positions and orientations, and updates only $\mathbf{W}$ and $\mathcal{S}$. The *fixed PA-S with WMMSE precoding (fixed PA-S + WMMSE)* scheme further re-optimizes $\mathbf{W}$ by WMMSE for each candidate user-set swap, so that the swap decision is evaluated after beamforming adaptation. This benchmark is included to examine the effect of beamforming re-optimization during user-set evaluation. The *Hungarian-greedy sum-rate maximization (HG-SR)* scheme adopts the sum-rate-oriented Hungarian-greedy PA–user assignment in [29] under the directional PA channel model, while finite-frame reconfiguration time is not explicitly considered. The *SA joint search* scheme jointly optimizes the PA configuration and scheduled user set through simulated annealing.

We first examine the influence of the Gaussian-beam parameters a and b on the PA radiation pattern.

As shown in Figure 3, a larger beam-sharpness parameter leads to a more concentrated high-gain region, whereas a smaller beam-sharpness parameter results in a wider coverage region on the ground plane. For $a = 0.50$ and $b = 0.30$, the sharper beam provides a higher peak directional gain, which is advantageous when PA positions and orientations are accurately optimized. In contrast, for $a = 0.30$ and $b = 0.18$, the broader beam reduces the peak gain but improves the tolerance to orientation mismatch, thereby providing more robust coverage for fixed or insufficiently optimized PA configurations.

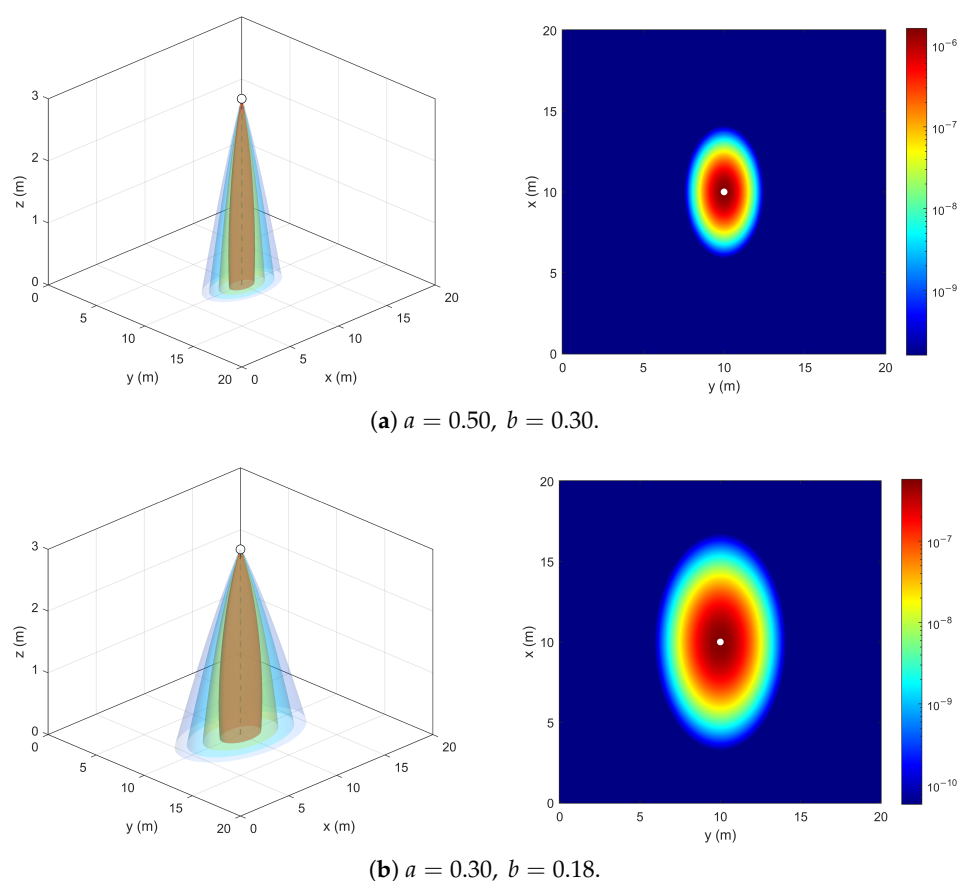


Figure 3. Effective channel power-gain patterns under different beam-sharpness parameters. The (left panels) show three-dimensional isosurfaces of the squared equivalent PA-to-point channel magnitude, and the (right panels) show the ground-plane power distribution at $z = 0$.

Figure 4 compares the effective spectral efficiency R_{eff} under two beam-sharpness settings. Overall, the proposed RA-AO scheme achieves the highest R_{eff} in both cases. The HG-SR, fixed PA-S with WMMSE precoding, and SA joint search schemes achieve

intermediate performance, whereas fixed PA-S gives the lowest performance in the considered settings. This is because fixed PA-S only adapts the user set and beamforming under fixed PA positions and orientations, which limits its ability to exploit directional PA radiation.

When a and b decrease, the wider beam improves the robustness of fixed PA-S by alleviating pointing mismatch. In contrast, the proposed RA-AO, HG-SR, and SA joint search schemes achieve lower R_{eff} under the wider-beam setting because the reduced beam sharpness lowers the peak directional gain. This result indicates that sharp beams are more beneficial when PA reconfiguration is available, whereas wider beams provide better robustness for fixed PA configurations.

In the following simulations, unless otherwise specified, we use $a = 0.50$ and $b = 0.30$ as the default beam-sharpness parameters.

Figure 5 shows the convergence behavior of different schemes. It is observed that the proposed RA-AO algorithm converges within 10 iterations and achieves the highest R_{eff} . The HG-SR scheme also converges fast, but its final performance is lower since it is mainly driven by sum-rate-based PA–user assignment rather than the effective-rate objective. The fixed PA-S and fixed PA-S with WMMSE precoding schemes converge quickly due to the limited number of optimized variables, but their achievable R_{eff} is much lower. In contrast, the SA joint search requires a much larger number of iterations and still converges to a lower value than the proposed RA-AO algorithm. The relatively lower performance of SA joint search is mainly due to its stochastic exploration of the large mixed discrete–continuous search space under a finite annealing budget, which may lead to convergence to a local solution. In contrast, HG-SR uses a structured Hungarian-greedy PA–user assignment under the directional PA channel model, and therefore may obtain a stronger sum-rate-oriented configuration in some cases. This verifies the efficiency of the proposed reconfiguration-aware block-wise optimization.

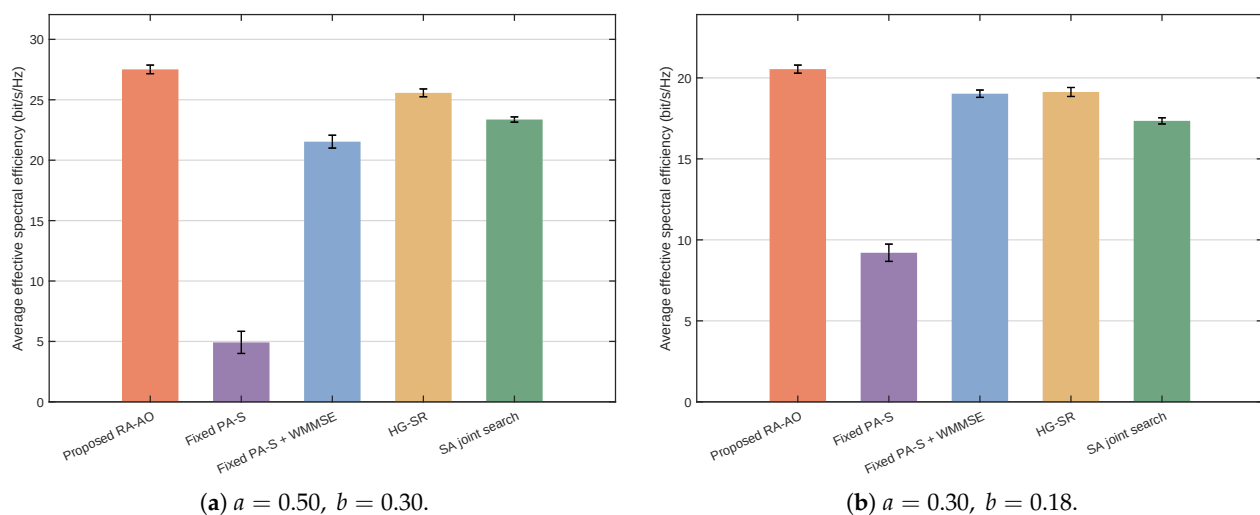


Figure 4. Average effective spectral efficiency under different beam-sharpness parameters with other parameters fixed at their default values.

Figure 6 plots the average effective spectral efficiency versus SNR. The zero-reconfiguration upper-bound curve is obtained by evaluating the solution generated by the proposed RA-AO algorithm with the reconfiguration-time penalty removed, so that R_{eff} reduces to the instantaneous sum spectral efficiency of the same solution. The proposed RA-AO algorithm consistently outperforms the benchmark schemes over the whole SNR range. At low SNR, the performance gap between RA-AO and HG-SR is relatively small, since the system is mainly noise-limited. As the SNR increases, the advantage of RA-AO

becomes more evident, which shows the benefit of jointly optimizing the PA positions, PA orientations, scheduled users, and beamforming matrix under the effective-rate objective. The fixed PA-S scheme gives the worst performance. Although fixed PA-S with WMMSE precoding improves the performance by re-optimizing the beamforming matrix during user-set evaluation, it still cannot fully exploit the spatial reconfigurability of PAs.

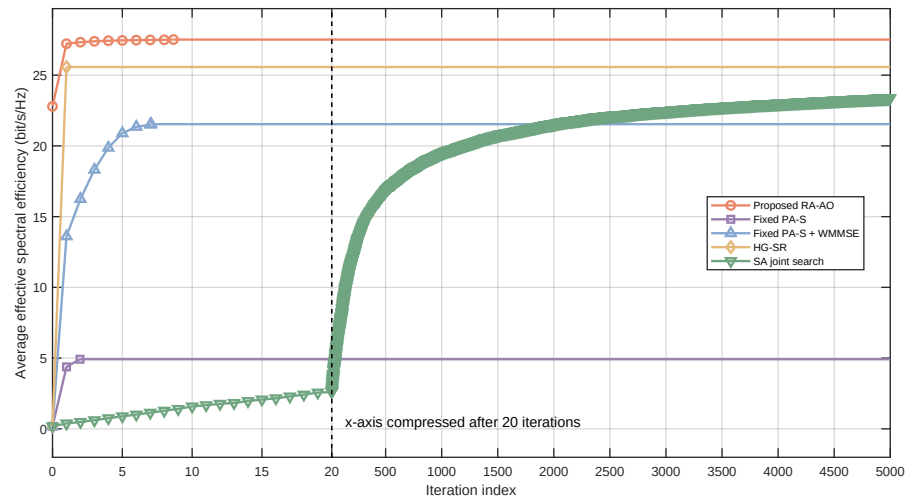


Figure 5. Convergence behavior of different schemes under the default setting.

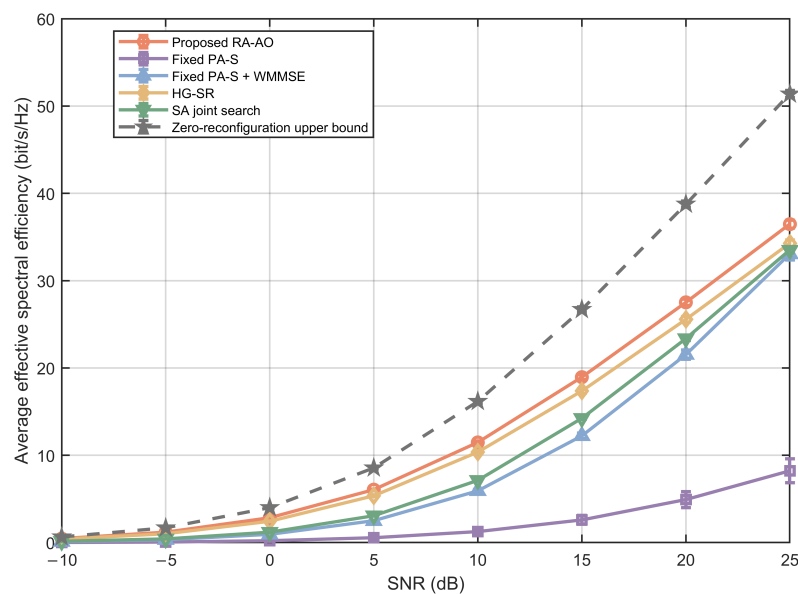


Figure 6. Average effective spectral efficiency versus SNR with other parameters fixed at their default values.

To further examine the role of reconfiguration overhead, we next compare different reconfiguration-time accounting models and evaluate the sensitivity to frame duration and reconfiguration speed.

Figure 7 compares the effective spectral efficiency of the proposed RA-AO algorithm under different reconfiguration-time accounting models, with all system parameters fixed at their default values. The parallel-reconfiguration case corresponds to the proposed model in (10), where the total reconfiguration time is determined by the maximum latency among PA displacement, elevation rotation, and azimuth rotation. The serial-reconfiguration case assumes that these three operations are performed sequentially and therefore uses the sum of the three latency components, while the zero-reconfiguration case is shown as a

no-latency reference. The serial model leads to a lower effective spectral efficiency than the parallel model, which is consistent with its longer reconfiguration time and shorter remaining transmission interval. This comparison shows that the latency-accounting model has a non-negligible impact on R_{eff} , and further supports the need to explicitly include reconfiguration time in directional PASS optimization.

Figure 8 evaluates the sensitivity of different schemes to the frame duration and reconfiguration speed. Only the x-axis parameter is varied in each subfigure, while the other system parameters are fixed at their default values in Table 3. As shown in Figure 8a, increasing T_f reduces the relative time loss caused by PA movement and rotation, and therefore improves the effective spectral efficiency of reconfiguration-based schemes. In contrast, fixed-configuration schemes are nearly insensitive to T_f , since their PA positions and orientations are not reconfigured.

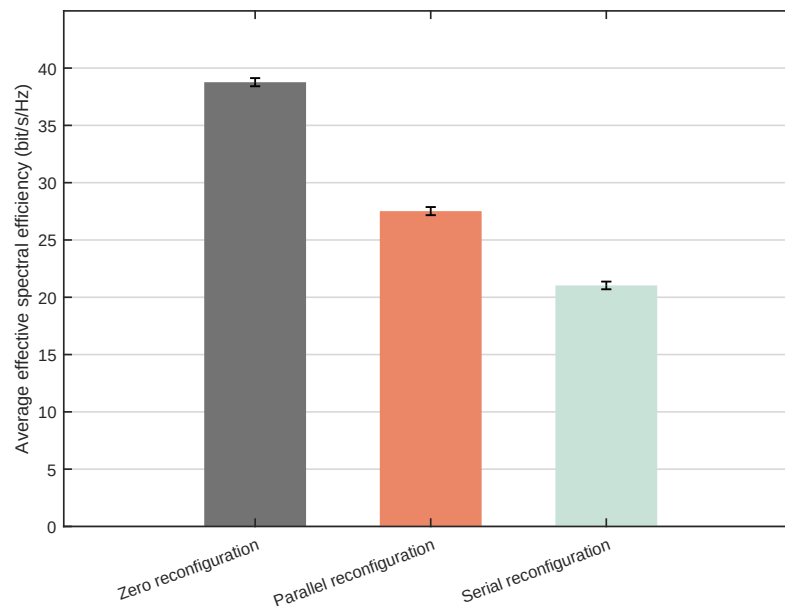


Figure 7. Average effective spectral efficiency under different reconfiguration-time accounting models under the default setting.

Table 3. Default simulation parameters.

Parameter	Symbol	Value
Number of waveguides	N	8
Number of PAs per waveguide	M	4
Number of candidate users	K	32
Number of scheduled users	K_s	8
Frame duration	T_f	5 s
Effective PA moving speed	v_y	10 m/s
Elevation rotation speed	ω_θ	5 rad/s
Azimuth rotation speed	ω_ϕ	5 rad/s
Displacement penalty coefficient	ρ	1
Number of Monte Carlo realizations	N_{MC}	100

In Figure 8b, the reconfiguration-speed scaling factor ζ multiplies the default values of all three speed parameters, i.e., $v_y = \zeta v_y^{\text{def}}$, $\omega_\theta = \zeta \omega_\theta^{\text{def}}$, and $\omega_\phi = \zeta \omega_\phi^{\text{def}}$. A larger ζ shortens the reconfiguration latency and improves R_{eff} , while the improvement becomes less pronounced at larger ζ , indicating a diminishing marginal benefit of further increasing the reconfiguration speed under the considered setup.

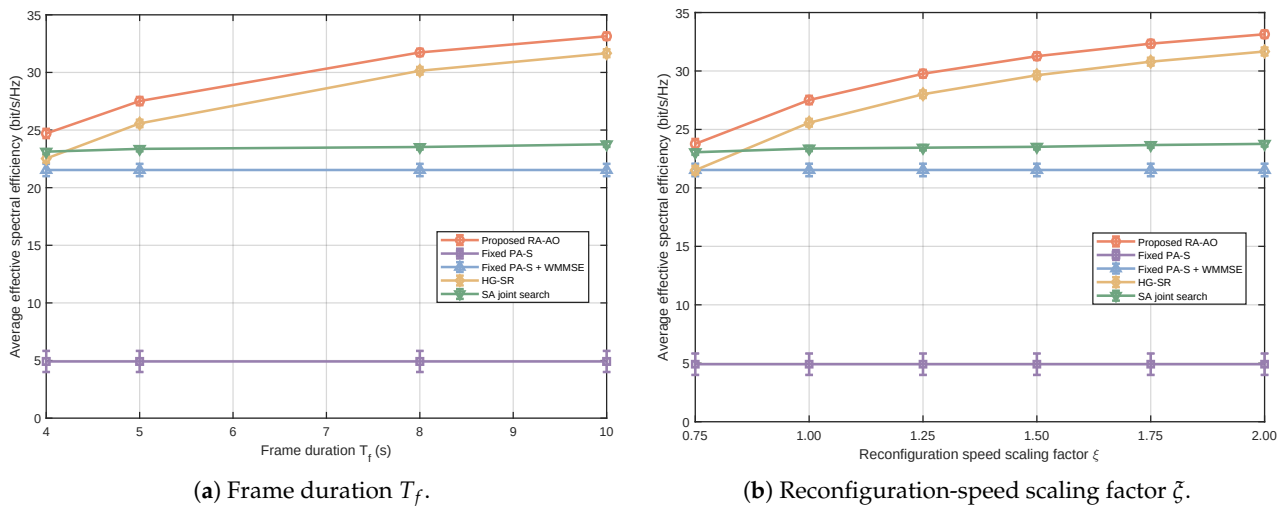


Figure 8. Sensitivity of average effective spectral efficiency to frame duration and reconfiguration speed with other parameters fixed at their default values.

Figure 9 shows the cumulative distribution function (CDF) of the per-user rate. Here, the per-user rate corresponds to the individual term $\log_2(1 + \gamma_k)$ in the post-reconfiguration sum spectral efficiency R_{sum} , rather than the normalized effective spectral efficiency R_{eff} . The CDF curves of the proposed RA-AO and HG-SR schemes are shifted toward the high-rate region, indicating that PA reconfiguration can significantly improve the user-level rate distribution. In comparison, fixed PA-S exhibits a large probability mass near zero rate, which means that many users cannot be effectively served when the PA configuration is fixed. Fixed PA-S with WMMSE precoding and SA joint search improve the distribution to different extents, but their curves remain clearly left-shifted compared with the proposed RA-AO. Therefore, the proposed RA-AO not only achieves a higher average R_{eff} , but also provides a more favorable per-user rate distribution.

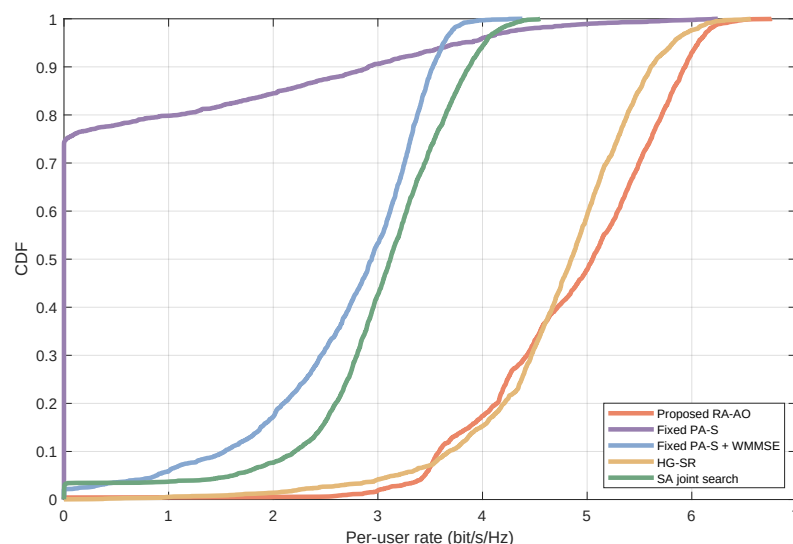


Figure 9. Cumulative distribution function (CDF) of per-user rate for different schemes under the default setting.

Figure 10 shows the impact of the number of waveguides N on R_{eff} . As N increases, all schemes generally achieve higher effective spectral efficiency, since more waveguides provide additional spatial degrees of freedom and more flexible PA–user matching opportunities. The proposed RA-AO scheme consistently achieves the highest R_{eff} , increasing

from about 20.4 bit/s/Hz at $N = 2$ to about 30.0 bit/s/Hz at $N = 12$. This confirms that the proposed algorithm can effectively exploit the additional waveguide resources through joint PA reconfiguration, user scheduling, and beamforming.

Figure 11 illustrates the effect of the waveguide length on R_{eff} . For the proposed RA-AO scheme, R_{eff} first increases as the waveguide length grows from 4 m to 8 m, because a moderate extension provides more flexibility for PA placement and improves the spatial matching between PAs and users. However, further increasing the waveguide length reduces R_{eff} , mainly because the larger feasible movement range may lead to higher reconfiguration overhead and thus reduce the effective transmission time. This result indicates that a longer waveguide is not always beneficial, and its length should be properly designed to balance spatial flexibility and reconfiguration cost.

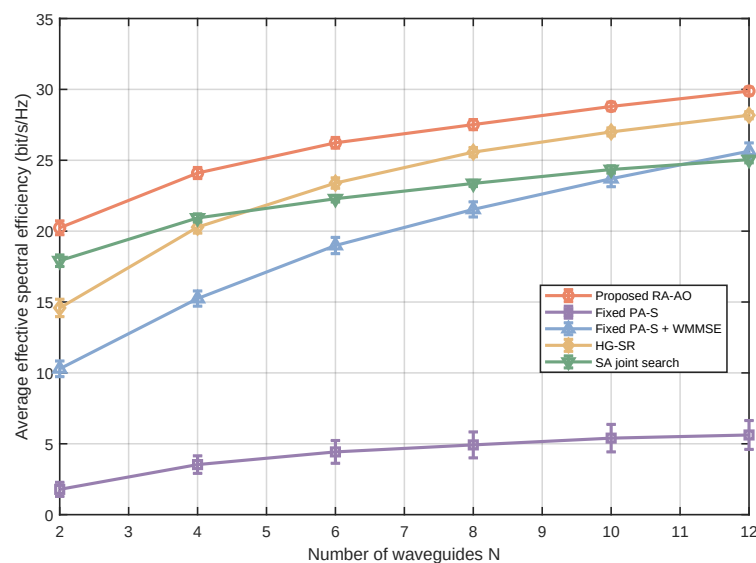


Figure 10. Average effective spectral efficiency versus the number of waveguides with other parameters fixed at their default values.

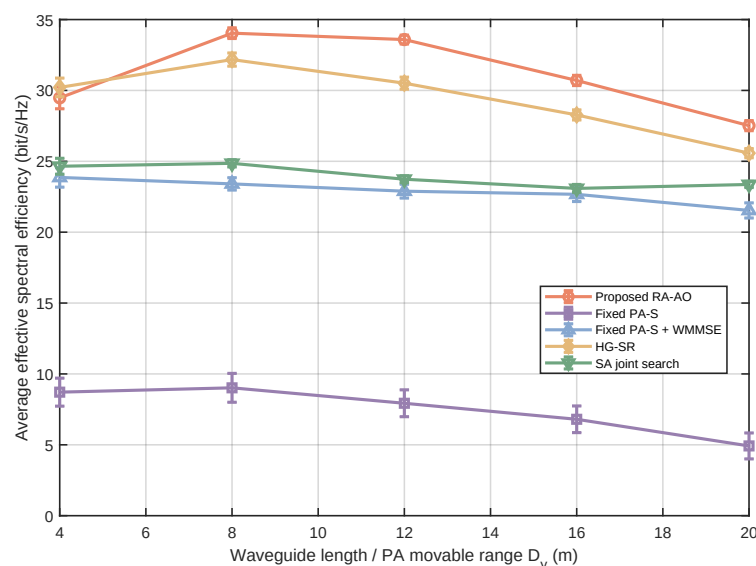


Figure 11. Average effective spectral efficiency versus the waveguide length with other parameters fixed at their default values.

Figure 12 shows the influence of the number of PAs per waveguide M . The proposed RA-AO scheme maintains the best performance and exhibits a mild improvement as M increases, since more PAs provide more candidate radiation points for serving users.

Nevertheless, the gain gradually saturates, indicating that simply increasing PA density does not lead to proportional performance improvement. For some benchmark schemes, R_{eff} even decreases when M becomes large, suggesting that the performance gain brought by additional PAs may saturate under limited favorable PA–user matching opportunities and practical PA deployment constraints.

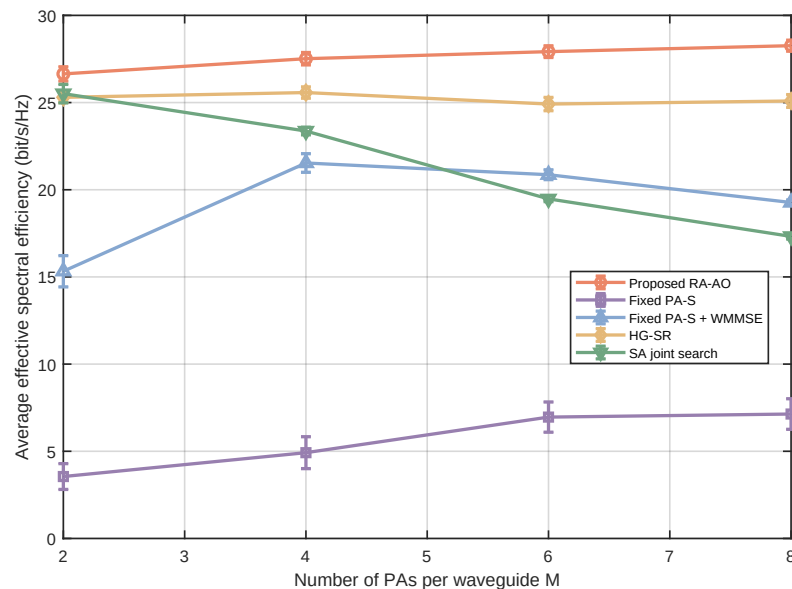


Figure 12. Average effective spectral efficiency versus the number of PAs per waveguide with other parameters fixed at their default values.

5. Conclusions

In this paper, we investigated reconfiguration-aware joint optimization for a multi-user downlink PASS with directional radiation. Both PA positions and PA orientations were treated as reconfigurable variables, since they affect the propagation distance, phase, and alignment of the directional radiation pattern. By jointly considering the rate gain brought by PA reconfiguration and the resulting reduction in effective transmission time, we defined the effective spectral efficiency metric R_{eff} and formulated a joint optimization problem over user scheduling, PA positions, PA orientations, and digital beamforming.

To solve the resulting mixed discrete–continuous non-convex optimization problem, we developed a reconfiguration-aware alternating optimization algorithm that combines cost-aware initialization, WMMSE-based beamforming, PA-orientation search, PA-position update, and restricted user scheduling. Simulation results showed that the proposed design consistently achieved higher average effective spectral efficiency than representative benchmark schemes across different radiation-pattern and system-parameter settings. The CDF results further indicated an improved per-user rate distribution, while the parameter-sensitivity results showed that increasing the waveguide length or the number of PAs does not necessarily bring proportional performance gains. These results confirm the importance of considering reconfiguration overhead in directional PASS design.

Future work may extend the proposed framework to mobility-aware scenarios, imperfect CSI, hardware-constrained PA movement and rotation, low-complexity and scalable reconfiguration-aware algorithms, secure PA-control signaling and multimedia-service support, and wideband or multi-BS PASS architectures.

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