

Enhancing Over-the-Air Computation in Low-Altitude UAV Networks via Pinching-Antenna Systems

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Abstract—In low-altitude networks, unmanned aerial vehicle (UAV) swarms are expected to serve as distributed sensing platforms that continuously collect environmental and operational data, where efficient aggregation of distributed data is critical for latency-critical aerial applications. Over-the-air computation (AirComp) improves spectral efficiency through analog signal superposition, but its performance is often limited by heterogeneous air-to-ground channels and strict UAV peak-power constraints, resulting in computation distortion dominated by the weakest link. This paper studies a pinching-antenna system (PASS) enhancing AirComp in low-altitude UAV network, where the base station (BS) employs dielectric waveguides and can adjust the radiation (pinching) positions to flexibly shape the effective transmission channels. Such a BS-side antenna reconfiguration provides an additional degree of freedom, thereby enhancing the received signal strength and facilitating magnitude alignment. We aim to minimize the computation mean squared error (MSE) by jointly optimizing the BS receive decoding vector, the UAV transmit power, the PASS pinching positions, and the UAV locations. To solve the resulting non-convex problem, we develop an alternating-optimization framework that admits closed-form update for the design of decoding vectors and transmit power, alternating linear search for the pinching positions, and a successive convex approximation algorithm with a trust region for UAV location optimization. Numerical results show that the proposed PASS-aided joint design achieves lower MSE and higher robustness than conventional fixed-antenna baselines, especially in peak-power-limited and noisy regimes.

Index Terms—Over-the-air computation (AirComp), pinching antenna systems (PASS), unmanned aerial vehicle (UAV).

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I. INTRODUCTION

The evolution toward 6G networks is driving tighter integration of terrestrial and non-terrestrial systems, where low-altitude networks (LANs), below 1,000 meters play a key role [1]–[3]. Within this space, unmanned aerial vehicle (UAV) swarms function as distributed sensing platforms, which continuously captures environmental and operational data across diverse scenarios such as smart agriculture, urban logistics, traffic monitoring, and post-disaster response [4]–[6]. Thanks to their high mobility, rapid deployment, and cost efficiency, they are well suited for real-time data collection and on-board processing [7]–[9]. Crucially, the effectiveness of latency-sensitive aerial applications hinges on how efficiently the data gathered across the swarm is aggregated and relayed. Thus, as the number of UAVs and their onboard sensors grows exponentially, the demand for communication links that are both spectrally efficient and highly reliable [10]. Beyond efficient data collection and aggregation, future 6G LANs are also expected to integrate sensing and communication functionalities. Recent studies have shown that even random communication signals can be exploited for sensing tasks and that dedicated precoding designs can further enhance sensing performance, opening new opportunities for integrated sensing and communication (ISAC) in UAV-assisted networks [11]–[13].

Conventional data aggregation for UAV swarms typically relies on orthogonal multiple access (OMA) schemes, such as time division multiple access (TDMA) [14], where the communication and computation are processed sequentially. It thus leads to latency that scales linearly with swarm size, inefficiently using spectrum and impairing latency critical tasks. Therefore, over-the-air computation (AirComp) has been recognized as an efficient solution for fast data aggregation [15], [16]. By exploiting the signal superposition property of multiple-access channels, AirComp enables simultaneous transmissions across distributed devices over the same time–frequency resources [17]. Thus it allows the base station (BS) to directly compute target functions (e.g., sum or average) from the aggregated waveform and thereby largely decouple communication latency from the number of aerial nodes [18], [19]. Building on its information-theoretic foundation for analog function computation over multiple-access channels [15], [20], subsequent research has advanced mean squared error (MSE) oriented transceiver and beamforming design [21], [22], power control strategies [23]–[25], and interference management in multi-cell scenarios [26].

Motivated by recent advances in LAN, prior works have examined UAV-enabled AirComp, where UAV mobility is treated as an additional optimization variable to enhance computation reliability. For instance, the work in [27] jointly optimized UAV positioning and communication parameters under an MSE threshold, showing that proper positioning can reshape large-scale path-loss conditions and facilitate the amplitude alignment required for analog aggregation. Extending to dynamic operation, [28] considered dynamic flight scenarios, co-optimizing time-varying trajectories with transceiver and power control, which showed that maintaining consistent effective channel conditions over time matters more than maximizing average channel strength. Furthermore, [29] showed that mobility and power control should be scheduled according to the sensitivity of computation error to channel variations so as to allocate limited onboard energy to the most error-critical links and periods.

However, reliable AirComp in LANs remains fundamentally limited by both algorithmic requirements and BS hardware design. AirComp requires strict magnitude alignment, and severe path loss may force some UAVs beyond their peak-power limits, causing distortion dominated by weak links [23]. Meanwhile, conventional BS arrays are down-tilted and optimized for ground coverage [4], [30], which is mismatched to aerial links. Although massive multiple-input multiple-output (MIMO) at the BS enhances aggregation quality through array gain and computation-oriented beamforming [21], [22], while intelligent reflecting surface (IRS)/reconfigurable intelligent surface (RIS) reshapes propagation via programmable reflections to strengthen weak links [31]–[33], and movable antenna (MA)/fluid antenna (FA) [34], [35] introduce additional spatial flexibility, which further improve channel conditions by adjusting antenna locations or radiation states. However, these methods mainly offer spatial processing and coverage reshaping, and remain limited in compensating large-scale path loss for severely disadvantaged UAVs under strict peak-power constraints, leaving the weakest-link bottleneck largely unresolved [31], [36].

To overcome this limitation, pinching antenna systems (PASS), first proposed and experimentally demonstrated by NTT DOCOMO [37], [38], offers such a capability by enabling physically relocatable radiation along a low-loss dielectric waveguide [39], [40]. Specifically, PASS guides the radio-frequency signal through a dielectric waveguide that can be deployed on rooftops or building facades, and generates radiation by mechanically pinching the waveguide with a dielectric perturbation element at selectable positions [40], [41]. By moving the pinching (or radiation) point along the waveguide, the transmitter can place the effective aperture closer to the aerial nodes and choose elevation-adaptive radiating locations, thereby reducing large-scale path loss and providing customized upward-looking beamforming. As a result, PASS offers a direct link-budget enhancement that is fundamentally difficult to achieve with IRS-assisted environment shaping or receiver-side MA reconfiguration, especially when straggling UAVs are severely power-limited and perfect channel inversion is infeasible.

Recent PASS studies have expanded from link-level mod-

eling to network-level resource allocation and computation-centric designs. Early studies established physically channel models that incorporate waveguide propagation and radiating position control, enabling joint beamforming and pinching position optimization for precise beam synthesis [42], with follow-up analyses quantifying link reliability under practical conditions [43]. At the system level, PASS reconfigurability has been leveraged to improve multi-user performance [44], [45], where the impact of antenna position on the achievable rate region and user fairness has been studied for downlink sum-rate and uplink minimum-rate optimizations, respectively. In [46], OFDMA-based designs have been considered for PASS to jointly exploit subcarrier scheduling and radiating-position configuration for enhanced spectral efficiency, while PASS has also been combined with non-orthogonal multiple access (NOMA) via antenna activation strategies to improve user separation and robustness [47].

Most relevantly, PASS has been integrated into AirComp, where adjusting pinching positions can reshape effective channels to suppress aggregation distortion [48]. Crucially, unlike IRS which reshapes the propagation environment or reconfigurable antenna techniques MA, PASS provides a lightweight and corrosion-resistant radiating position reconfigurable architecture that can be deployed at the BS side (either TX or RX) to directly boost the effective link budgets via pinching position control. Prior work on PASS aided AirComp has been first studied in [48], where joint transmit power control and pinching antenna positions were joint optimized to reduce aggregation MSE. However, it assumed static users and fixed geometries. In high-mobility LAN, rapidly varying UAV positions induce time-varying path loss that static PASS configurations cannot address, leaving a critical gap in jointly optimizing radiating positions with aerial mobility.

Therefore, we propose a new PASS enhancing AirComp in low-altitude UAV networks in this paper. Different from the previous work that regards the transmitter position as fixed, UAVs are considered as terminal devices that transmit data to the BS via AirComp for efficient data aggregation. We use the calculation of the degree of distortion as the evaluation standard of system performance, i.e., the MSE. Therefore, our goal is to jointly optimize pinching antenna (PA) location, UAVs location, and communication resources to minimize the MSE of PASS-aided AirComp. The main contributions of this paper are summarized as follows :

- **Model of PASS-assisted AirComp System:** To the best of our knowledge, this work is the first to investigate PASS enhancing AirComp in a high-mobility UAV swarm scenario. Different from existing PASS-AirComp studies that optimize pinching positions for static/ground terminals, we integrate PASS deployed at the BS with UAV uplink AirComp. By explicitly modeling the waveguide-fed aggregation and the induced equivalent channel, we reveal how flexible pinching positions can actively reshape the effective link budget and reduce the weakest-link dominated aggregation distortion under stringent per-UAV peak-power constraints.
- **Joint optimization solution:** We formulate an MSE minimization problem that jointly optimizes the receive

decoding vector, the UAV transmit power, the PA positions, and the UAV locations variable, subject to the UAV peak power constraints, UAV altitude limitations, as well as PA feasible position and minimum spacing constraints along each waveguide. To solve this highly non-convex problem with highly coupled variables, we develop an alternating optimization (AO)-based framework with closed-form solutions for decoding vector and transmit power updates, alternating linear search for PA positions, and successive convex approximation (SCA) for UAV locations refinement.

- **Performance validation via simulations:** Extensive simulations validate the effectiveness of the proposed design. The results confirm that jointly optimizing the PA positions together with UAV locations and communication resources consistently achieves the lowest AirComp MSE compared with fixed-PA or fixed-UAV baselines, and the gain is particularly pronounced when per-UAV peak-power constraints prevent perfect channel inversion and the aggregation error is dominated by straggling links. The proposed approach remains robust across a broad range of system sizes and power/noise conditions, while the MSE improvement naturally exhibits diminishing returns as the transmit power budget becomes sufficiently large.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, We first describe the considered PASS-enabled AirComp system, channel model, and the AirComp signal aggregation process, and then formulate an optimization problem.

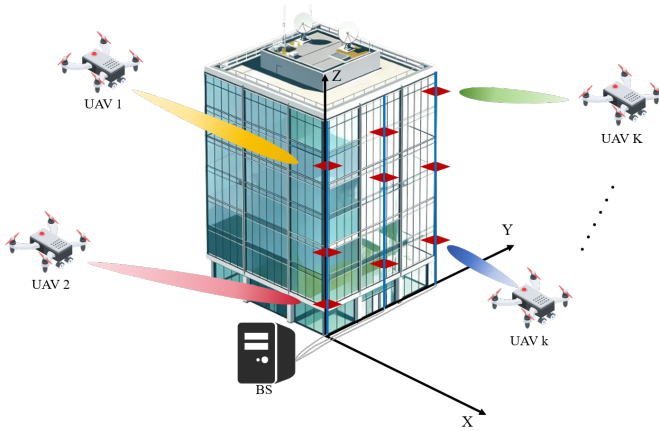


Figure 1. Illustration of PASS-assisted AirComp system model.

A. System Model

We consider a PASS-assisted AirComp system. Specifically, a BS that serves as a fusion center to aggregate sensing data from K UAVs, where the BS is equipped with a set $\mathcal{M} \triangleq \{1, \dots, M\}$ of M dielectric waveguides, and each waveguide is configured with a set $\mathcal{N} \triangleq \{1, \dots, N\}$ of N PAs. Let $\mathcal{K} \triangleq \{1, \dots, K\}$ denote the set of K UAVs. Consider a three-dimensional (3D) coordination system, where

Table I
LIST OF MAIN NOTATIONS

Symbol	Description
$\mathcal{K}$	Set of all UAVs with number of K
$\mathcal{N}$	Set of all PAs on each waveguide with number of N
$\mathcal{M}$	Set of all dielectric waveguide with number of M
$\mathbf{u}_k$	The coordinate of the k -th UAV, $\forall k \in \mathcal{K}$
$v_{m,n}$	The distance between the n -th PA and the feed point on the m -th waveguide, $\forall n \in \mathcal{N}, \forall m \in \mathcal{M}$
$\tilde{\mathbf{v}}_{m,n}$	The coordinate of the n -th PA on the m -th waveguide, $\forall n \in \mathcal{N}, \forall m \in \mathcal{M}$
s_k	Transmission information at UAV $k \in \mathcal{K}$
$h_{k,m,n}$	The channel coefficient between UAV k and the n -th PA on waveguide m , $\forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}$
$g_{m,k}$	The equivalent channel between UAV k and the feeding point $\tilde{\mathbf{v}}_{m,0}$, $\forall k \in \mathcal{K}, \forall m \in \mathcal{M}$
p_k	The transmit power of UAV $k \in \mathcal{K}$
i_r	The refractive index of waveguides
$\mathbf{w}$	The decoding vector
$\mathbf{P}$	The diagonal transmit power matrix
$\mathbf{V}$	The position matrix of all PAs

the UAVs, according to a fixed structure, are distributed over a cuboid area in the x - y - z space with sides L_x , L_y , and L_z , and denote the position of the k -th UAV as $\mathbf{u}_k = (x_k, y_k, z_k)$, where x_k, y_k and z_k are all known linear functions of k , and $z_k \geq 0$. Therefore, only the position of $\mathbf{u}_1$ needs to be obtained to know the positions of all the other UAVs. This fixed UAV formations have already been adopted in a variety of practical applications, such as UAV-based environmental monitoring, disaster surveillance, and drone light shows [49], [50]. Without loss of generality, we assume that the waveguide in PASS is vertically deployed along the outside of the building, and each with a length of L_z . In addition, we set a as the spacing between adjacent waveguides. Thus, we denote the position of the n -th PA on the m -th waveguide as $\tilde{\mathbf{v}}_{m,n} = (0, (m-1)a, v_{m,n})$, where $0 \leq v_{m,n} \leq L_z$, and the feed point of each waveguide is denoted as $\tilde{\mathbf{v}}_{m,0} = (0, (m-1)a, 0)$.

The core task of the BS is to accomplish the recovery of the sum of the transmitted data from all UAVs by means of the waveform superposition characteristic of the wireless MAC. Without loss of generality, we assume that all s_k are independent and identically distributed (IID) random variables with zero mean and unit variance, i.e., $s_k \sim \mathcal{CN}(0, 1), \forall k \in \mathcal{K}$. Thus, the BS is to compute the sum of transmitted data from K UAVs, leading to the following formula

$$s = \sum_{k=1}^K s_k. \quad (1)$$

Since the PASS can establish favorable line-of-sight (LoS) propagation conditions by adjusting the antenna positions and simultaneously shorten the communication distance to the UAVs, it is sufficient to consider only the near-field communication scenario and adopt a free-space propagation channel model. To achieve the aforementioned objective, we next model the uplink transmission process. The channel coefficient between UAV k and the n -th PA on waveguide m is denoted as

$$h_{k,m,n} = \frac{\lambda e^{-j \frac{2\pi}{\lambda} \|\mathbf{u}_k - \tilde{\mathbf{v}}_{m,n}\|}}{4\pi \|\mathbf{u}_k - \tilde{\mathbf{v}}_{m,n}\|}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}, \quad (2)$$

where $\lambda = c/f$ is the wavelength with f and c representing the carrier frequency and the speed of light, respectively. Thus, the received signal at the n -th PA on waveguide m is expressed as

$$r_{m,n} = \sum_{k=1}^K h_{k,m,n} \sqrt{p_k} s_k + z_{m,n}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, \quad (3)$$

where p_k is the transmit power of UAV k , and $z_{m,n}$ is the additive Gaussian white noise (AWGN) with variance σ^2 , i.e., $z_{m,n} \sim \mathcal{CN}(0, \sigma^2)$. We assume that the waveguide is completely passive. In this case, the aggregated signal at feeding point $\tilde{v}_{m,0}$, namely the sum of the signals from N PAs on waveguide m to the feeding point, is expressed as

$$r_m = \sum_{k=1}^K \sqrt{p_k} s_k \left(\sum_{n=1}^N h_{k,m,n} e^{-j\phi_{m,n}} \right) + z_m, \quad (4)$$

where $\phi_{m,n} = \frac{2\pi i_r}{\lambda} \|\tilde{v}_{m,n} - \tilde{v}_{m,0}\|$, i_r is the refractive index of waveguides, and $z_m = \sum_{n \in \mathcal{N}} z_{m,n}$ is the cumulative noise

over all PAs on waveguide m . Let $\mathbf{v}_m = [\tilde{v}_{m,1}, \dots, \tilde{v}_{m,N}]^T \in \mathbb{R}^{N \times 3}$ denote the set of positions of the N PAs on waveguide m and $\mathbf{u} = [\mathbf{u}_1, \dots, \mathbf{u}_K]^T \in \mathbb{R}^{K \times 3}$ denote the set of positions of all K UAVs, where $(\cdot)^T$ is the transpose operation. Then, the equivalent channel between UAV k and the feeding point $\tilde{v}_{m,0}$ denoted by $g_{m,k}(\mathbf{v}_m, \mathbf{u}_k)$ can be expressed as

$$\begin{aligned} g_{m,k}(\mathbf{v}_m, \mathbf{u}_k) &= \sum_{n=1}^N h_{k,m,n} e^{-j\phi_{m,n}} \\ &= \sum_{n=1}^N \frac{\lambda e^{-j\left(\frac{2\pi}{\lambda} \|\mathbf{u}_k - \mathbf{v}_{m,n}\| + \frac{2\pi i_r}{\lambda} \|\mathbf{v}_{m,n} - \mathbf{v}_{m,0}\|\right)}}{4\pi \|\mathbf{u}_k - \mathbf{v}_{m,n}\|} \\ &= \sum_{n=1}^N \frac{\lambda e^{-j\left(\frac{2\pi}{\lambda} \sqrt{(0-x_k)^2 + ((m-1)a-y_k)^2 + (v_{m,n}-z_k)^2} + \frac{2\pi i_r}{\lambda} \tilde{v}_{m,n}\right)}}{4\pi \sqrt{(0-x_k)^2 + ((m-1)a-y_k)^2 + (v_{m,n}-z_k)^2}}. \end{aligned} \quad (5)$$

Let $\mathbf{g}_m(\mathbf{v}_m, \mathbf{u}_1) = \mathbf{g}_m(\mathbf{v}_m, \mathbf{u}) = [g_{m,1}(\mathbf{v}_m, \mathbf{u}_1), \dots, g_{m,K}(\mathbf{v}_m, \mathbf{u}_K)]^T \in \mathbb{C}^{K \times 1}$ denote the equivalent channel vector from all UAVs to the feed point of waveguide m and the received signal in (4) is rewritten as

$$\begin{aligned} r_m &= \sum_{k \in \mathcal{K}} \sqrt{p_k} g_{m,k}(\mathbf{v}_m, \mathbf{u}_k) s_k + z_m \\ &= \mathbf{g}_m^T(\mathbf{v}_m, \mathbf{u}_1) \mathbf{P} \mathbf{s} + z_m, \end{aligned} \quad (6)$$

where $\mathbf{P} = \text{diag}[\sqrt{p_1}, \dots, \sqrt{p_K}] \in \mathbb{C}^{K \times K}$ is the diagonal transmit power matrix, and $\mathbf{s} = [s_1, \dots, s_K]^T \in \mathbb{C}^{K \times 1}$ is a column vector consisting of all signals from K UAVs. Then, we compactly represent the effective uplink channel as

$$\mathbf{r} = \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} \mathbf{s} + \mathbf{z}, \quad (7)$$

where $\mathbf{r} = [r_1, \dots, r_M]^T \in \mathbb{C}^{M \times 1}$, $\mathbf{V} = [\mathbf{v}_1, \dots, \mathbf{v}_M]^T \in \mathbb{R}^{M \times N}$, $\mathbf{G}(\mathbf{V}, \mathbf{u}_1) = \mathbf{G}(\mathbf{V}, \mathbf{u}) = [g_1(\mathbf{v}_1, \mathbf{u}), \dots, g_M(\mathbf{v}_M, \mathbf{u})]^T \in \mathbb{C}^{M \times K}$, and $\mathbf{z} = [z_1, \dots, z_M]^T \in \mathbb{C}^{M \times 1}$.

When the BS receives the signal $\mathbf{r}$, we use the decoding vector $\mathbf{w}$ to restore the sum of the transmitted signal,

$$\hat{\mathbf{s}} = \mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} \mathbf{s} + \mathbf{w}^H \mathbf{z}. \quad (8)$$

Then, the MSE is employed to measure the distortion between $\hat{\mathbf{s}}$ and $\mathbf{s}$, which is given by

$$\begin{aligned} \text{MSE}(\mathbf{w}, \mathbf{V}, \mathbf{P}, \mathbf{u}_1) &\triangleq \mathbb{E}[\|\hat{\mathbf{s}} - \mathbf{s}\|^2] \\ &= \mathbb{E}[\|(\mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} - \mathbf{1}^T) \mathbf{s} + \mathbf{w}^H \mathbf{z}\|^2] \\ &= \|\mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} - \mathbf{1}^T\|^2 + N\sigma^2 \|\mathbf{w}\|^2. \end{aligned} \quad (9)$$

B. Problem Formulation

The aim of our work is to minimize the MSE by jointly optimizing the positions of PAs $\mathbf{V}$ and the position of UAV $\mathbf{u}_1$, as well as the transmit power matrix $\mathbf{P}$ and decoding vector $\mathbf{w}$, subject to transmit power and physical placement constraints on the PAs. The corresponding optimization problem is formulated as

$$\begin{aligned} \text{(P1): } \min_{\mathbf{w}, \mathbf{P}, \mathbf{V}, \mathbf{u}_1} \quad & \|\mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} - \mathbf{1}^T\|^2 + N\sigma^2 \|\mathbf{w}\|^2 \\ \text{s.t.} \quad & \mathbf{P}^2 \preceq \mathbf{P}^{\max} \end{aligned} \quad (10a)$$

$$0 \leq v_{m,n} \leq L_z, \forall m, n \quad (10b)$$

$$v_{m,n} - v_{m,n-1} \geq L_0, \forall m, \forall n = 2, \dots, N \quad (10c)$$

$$z_k \geq 0, \forall k, \quad (10d)$$

where (10a) is the power constraint corresponding to each UAV, where $\mathbf{P}^{\max} = \text{diag}[P_1^{\max}, \dots, P_K^{\max}]$, and $P_k^{\max}$ represents the maximum transmit power of the k -th UAV, (10b) ensures that the moving position of the PA is always on the waveguide, (10c) is the minimum spacing L_0 set to avoid the antenna coupling effect of adjacent PAs on each waveguide, and (10d) is the minimum height constraint set to the UAV based on the ground.

III. OPTIMIZATION DESIGN

Problem (P1) is highly non-convex due to the coupled design variables $\{\mathbf{w}, \mathbf{P}, \mathbf{V}, \mathbf{u}_1\}$ and the nonlinear equivalent channel $\mathbf{G}(\mathbf{V}, \mathbf{u}_1)$. To obtain a tractable solution, we develop an AO algorithm that updates these variables in an iterative manner. In each iteration, we first optimize the decoding vector $\mathbf{w}$ for fixed $\{\mathbf{P}, \mathbf{V}, \mathbf{u}_1\}$, then update the transmit power $\mathbf{P}$ under the peak-power constraints for fixed $\{\mathbf{w}, \mathbf{V}, \mathbf{u}_1\}$, and finally refine the PA pinching positions $\mathbf{V}$ and the UAV location $\mathbf{u}_1$ to improve the effective channels.

A. Optimization of Decoding Vector $\mathbf{w}$

Under the given transmission power $\mathbf{P}$ and PA positions $\mathbf{V}$ and $\mathbf{u}_1$, the decoding vector $\mathbf{w}$ is optimized. Thus, the optimization problem becomes

$$\text{(P2): } \min_{\mathbf{w}} \|\mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} - \mathbf{1}^T\|^2 + N\sigma^2 \|\mathbf{w}\|^2.$$

Problem (P2) is a least squares problem. Therefore, we can solve for the optimal solution of $\mathbf{w}$ by setting the first derivative of the objective function equal to 0, i.e.,

$$\begin{aligned} \frac{\partial \text{MSE}(\mathbf{w})}{\partial \mathbf{w}} &= \\ 2(\mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} \mathbf{P}^T \mathbf{G}^H(\mathbf{V}, \mathbf{u}_1) \mathbf{w} - \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} \mathbf{1} + N\sigma^2 \mathbf{w}) &= 0. \end{aligned} \quad (11)$$

Then, the optimal solution $\mathbf{w}^*$ is denoted as

$$\mathbf{w}^* = \frac{\mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} \mathbf{1}}{\mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} \mathbf{P}^T \mathbf{G}^H(\mathbf{V}, \mathbf{u}_1) + N\sigma^2 \mathbf{I}_M}. \quad (12)$$

B. Optimization of Transmit Power $\mathbf{P}$

With the fixed decoding vector $\mathbf{w}$, the PA positions $\mathbf{V}$, and the UAV $\mathbf{u}_1$ position, we optimize the transmit power. Thus, Problem (P1) is reduced into

$$\begin{aligned} (\text{P3}) : \min_{\mathbf{P}} & \|\mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} - \mathbf{1}^T\|^2 \\ \text{s.t. } & \mathbf{P}^2 \preceq \mathbf{P}^{\max}. \end{aligned}$$

Problem (P3) is a convex quadratically constrained quadratic programming (QCQP) problem, whose optimal solution can be obtained via the Karush-Kuhn-Tucker (KKT) conditions. First, we need to construct the Lagrangian function associated with Problem (P3).

$$\begin{aligned} L(\mathbf{P}, \boldsymbol{\Lambda}) = & \mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} \mathbf{P}^T \mathbf{G}^H(\mathbf{V}, \mathbf{u}_1) \mathbf{w} \\ & - 2\text{Re} \{ \mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} \mathbf{1} \} + \text{tr} (\boldsymbol{\Lambda} (\mathbf{P}^2 - \mathbf{P}^{\max})). \end{aligned} \quad (13)$$

where $\boldsymbol{\Lambda} = \text{diag}[\lambda_1, \dots, \lambda_K]$ is the diagonal matrix composed of Lagrange multipliers corresponding to the K inequality constraints. Therefore, the KKT conditions corresponding to Problem (P3) are expressed as follows:

$$\mathbf{P}^2 - \mathbf{P}^{\max} \preceq \mathbf{0}, \quad (14)$$

$$\boldsymbol{\Lambda} \succeq \mathbf{0}, \quad (15)$$

$$\boldsymbol{\Lambda} (\mathbf{P}^2 - \mathbf{P}^{\max}) = \mathbf{0}, \quad (16)$$

$$\begin{aligned} \frac{\partial L(\mathbf{P}, \boldsymbol{\Lambda})}{\partial \mathbf{P}} = & 2\mathbf{G}^H(\mathbf{V}, \mathbf{u}_1) \mathbf{w} \mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} \\ & - 2\text{Re} (\mathbf{G}^H(\mathbf{V}, \mathbf{u}_1) \mathbf{w} \mathbf{1}^T) + 2\boldsymbol{\Lambda} \mathbf{P} = \mathbf{0}. \end{aligned} \quad (17)$$

According to (17), it is easy to obtain that the optimal transmit power $\mathbf{P}^*$ is

$$\begin{aligned} \mathbf{P}^* = & (\text{diag} (\mathbf{G}^H(\mathbf{V}, \mathbf{u}_1) \mathbf{w} \mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1)) + \boldsymbol{\Lambda})^{-1} \\ & \text{diag} (\text{Re} (\mathbf{G}^H(\mathbf{V}, \mathbf{u}_1) \mathbf{w})). \end{aligned} \quad (18)$$

Noted that the Lagrange multiplier $\boldsymbol{\Lambda}$ must satisfy (15) and (16). Next, by substituting (18) into (16), we can obtain the optimal Lagrange multiplier $\boldsymbol{\Lambda}^*$

$$\begin{aligned} \boldsymbol{\Lambda}^* = & (\text{diag} (\text{Re} (\mathbf{G}^H(\mathbf{V}, \mathbf{u}_1) \mathbf{w})) (\mathbf{P}^{\max})^{-\frac{1}{2}} \\ & - \text{diag} (\mathbf{G}^H(\mathbf{V}, \mathbf{u}_1) \mathbf{w} \mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1)))_+. \end{aligned} \quad (19)$$

where $(\cdot)_+$ refers to the projection onto the non-negative space, which is used to ensure that each Lagrange multiplier λ_k is non-negative.

C. Optimization of UAV Positions $\mathbf{u}_1$

Given the decoding vector $\mathbf{w}$, the transmit power $\mathbf{P}$ and the PA positions $\mathbf{V}$, we optimize the position of the UAV $\mathbf{u}_1$. Then, the optimization problem becomes

$$\begin{aligned} (\text{P4}) : \min_{\mathbf{u}_1} & \|\mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} - \mathbf{1}^T\|^2 \\ \text{s.t. } & z_1 \geq 0. \end{aligned} \quad (20a)$$

To deal with problem (P4), we can solve it using a trust-region-based SCA algorithm. In order to facilitate the subsequent derivation, we set

$$s_k(\mathbf{u}_k) = \sum_{m=1}^M \bar{w}_m \sqrt{p_k} g_{m,k}(\mathbf{v}_m, \mathbf{u}_k), \quad (21)$$

$$g_{m,k}(\mathbf{u}_k) = \sum_{n=1}^N \gamma_{m,n} \frac{e^{-j\frac{2\pi}{\lambda} d_{m,n}(\mathbf{u}_k)}}{d_{m,n}(\mathbf{u}_k)}, \quad (22)$$

$$\gamma_{m,n} = \frac{\lambda}{4\pi} e^{-j\phi_{m,n}}, \quad (23)$$

$$\begin{aligned} d_{m,n}(\mathbf{u}_k) &= \|\mathbf{u}_k - \tilde{\mathbf{v}}_{m,n}\| \\ &= \sqrt{(x_k - 0)^2 + (y_k - (m-1)a)^2 + (z_k - v_{m,n})^2}. \end{aligned} \quad (24)$$

According to (21), we can express the function of the subproblem as

$$\begin{aligned} f(\mathbf{u}_1) &= \|\mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} - \mathbf{1}^T\|^2 \\ &= \sum_{k=1}^K \left| \sum_{m=1}^M \bar{w}_m \sqrt{p_k} g_{m,k}(\mathbf{v}_m, \mathbf{u}_k) - 1 \right|^2 \\ &= \sum_{k=1}^K |s_k(\mathbf{u}_k) - 1|^2. \end{aligned} \quad (26)$$

It is worth noting that we define the relationship between $\mathbf{u}_1$ and $\mathbf{u}_k$ as $\mathbf{u}_k = \mathbf{u}_1 + \eta(k)$, where $\eta(k)$ is a known vector function of k .

Next, we present how to solve for the optimal solution of $\mathbf{u}_1$ using a trust-region-based SCA algorithm, which is primarily implemented through an iterative approach. Considering a specific iteration $i \geq 1$ with a local position point $\mathbf{u}_1^{(i)}$. We first address the non-convex objective problem (P4). By applying a first-order Taylor expansion, it can be approximated as:

$$f(\mathbf{u}_1) \approx f^{(i)}(\mathbf{u}_1) \triangleq f(\mathbf{u}_1^{(i)}) + \frac{\partial f(\mathbf{u}_1^{(i)})}{\partial \mathbf{u}_1^{(i)}} (\mathbf{u}_1^{(i+1)} - \mathbf{u}_1^{(i)}), \quad (27)$$

where substitute variable $\mathbf{u}_1$ in $f(\mathbf{u}_1)$ with $\mathbf{u}_1^{(i)}$ to obtain (28). Then we compute the first-order derivative of $f(\mathbf{u}_1^{(i)})$ with respect to $\mathbf{u}_1^{(i)}$. Next, we will give the specific derivation process of $\frac{\partial f(\mathbf{u}_1^{(i)})}{\partial \mathbf{u}_1^{(i)}}$.

Since $\eta(k)$ is known, we have $\frac{\partial f(\mathbf{u}_1)}{\partial \mathbf{u}_1} = \frac{\partial f(\mathbf{u}_1)}{\partial \mathbf{u}_k}$. Using the identity

$$\frac{\partial |x|^2}{\partial \mathbf{u}_1^{(i)}} = 2\text{Re} \left\{ \bar{x} \frac{\partial x}{\partial \mathbf{u}_1^{(i)}} \right\}, \quad (29)$$

and letting $x = s_k(\mathbf{u}_k^{(i)}) - 1$, we obtain

$$\frac{\partial f(\mathbf{u}_1^{(i)})}{\partial \mathbf{u}_1^{(i)}} = \sum_{k=1}^K 2\text{Re} \left\{ \overline{(s_k(\mathbf{u}_k^{(i)}) - 1)} \frac{\partial s_k(\mathbf{u}_k^{(i)})}{\partial \mathbf{u}_1^{(i)}} \right\}. \quad (30)$$

Moreover, by (21) and (22),

$$\begin{aligned} \frac{\partial s_k(\mathbf{u}_k^{(i)})}{\partial \mathbf{u}_1^{(i)}} &= \sum_{m=1}^M \bar{w}_m \sqrt{p_k} \frac{\partial g_{m,k}(\mathbf{u}_k^{(i)})}{\partial \mathbf{u}_k^{(i)}} \\ &= \sum_{m=1}^M \bar{w}_m \sqrt{p_k} \sum_{n=1}^N \gamma_{m,n} \frac{\partial}{\partial \mathbf{u}_k^{(i)}} \left(\frac{e^{-j\kappa d_{m,n}(\mathbf{u}_k^{(i)})}}{d_{m,n}(\mathbf{u}_k^{(i)})} \right). \end{aligned} \quad (31)$$

where $\kappa = \frac{2\pi}{\lambda}$.

Then, we define $h(d_{m,n}(\mathbf{u}_k)) \triangleq \frac{e^{-j\kappa d_{m,n}(\mathbf{u}_k)}}{d_{m,n}(\mathbf{u}_k)}$, and take derivative with respect to $d_{m,n}(\mathbf{u}_k)$

$$\begin{aligned} \frac{\partial h(d_{m,n}(\mathbf{u}_k))}{\partial d_{m,n}(\mathbf{u}_k)} &= \frac{\partial}{\partial d_{m,n}(\mathbf{u}_k)} \left(\frac{e^{-j\kappa d_{m,n}(\mathbf{u}_k)}}{d_{m,n}(\mathbf{u}_k)} \right) \\ &= -\frac{e^{-j\kappa d_{m,n}(\mathbf{u}_k)}}{d_{m,n}(\mathbf{u}_k)} \left(\frac{1}{d_{m,n}(\mathbf{u}_k)} + j\kappa \right). \end{aligned} \quad (32)$$

Then we continue to derive (21) with respect to $\mathbf{u}_k$

$$\frac{\partial d_{m,n}(\mathbf{u}_k)}{\partial \mathbf{u}_k} = \frac{\mathbf{u}_k - \tilde{\mathbf{v}}_{m,n}}{\|\mathbf{u}_k - \tilde{\mathbf{v}}_{m,n}\|} = \frac{\mathbf{u}_k - \tilde{\mathbf{v}}_{m,n}}{d_{m,n}(\mathbf{u}_k)}. \quad (33)$$

According to the chain rule of derivative, we get

$$\begin{aligned} \frac{\partial}{\partial \mathbf{u}_k} \left(\frac{e^{-j\kappa d_{m,n}(\mathbf{u}_k)}}{d_{m,n}(\mathbf{u}_k)} \right) \\ = -\frac{e^{-j\kappa d_{m,n}(\mathbf{u}_k)}}{d_{m,n}(\mathbf{u}_k)} \left(\frac{1}{d_{m,n}(\mathbf{u}_k)} + j\kappa \right) \frac{\mathbf{u}_k - \tilde{\mathbf{v}}_{m,n}}{d_{m,n}(\mathbf{u}_k)}. \end{aligned} \quad (34)$$

Substituting $\mathbf{u}_k = \mathbf{u}_k^{(i)}$, and $d_{m,n}(\mathbf{u}_k) = d_{m,n}(\mathbf{u}_k^{(i)})$ into (34), and then substituting the result into (31) and (30), yields (35). Additionally, it is worth noting that in (35), $\mathbf{u}_k^{(i)} = \mathbf{u}_1^{(i)} + \eta(k)$.

Since the constraint of P4 is convex in itself, it can be directly retained. To ensure the approximation accuracy, we add a series of trust region constraints as follows:

$$\|\mathbf{u}_1^{(i)} - \mathbf{u}_1^{(i-1)}\| \leq \psi^{(i)}, \quad (36)$$

where $\psi^{(i)}$ denotes the trust region radius.

So far, we replace the non-convex objective function of P4 with the approximate form of (22), retain its convex constraints, and add the trust region constraint (26). Finally, we obtain the approximate convex version problem (P5) of Problem (P4) after the l -th iteration, which can be efficiently solved using CVX to find the optimal solution of $\mathbf{u}_1$.

$$\begin{aligned} \text{(P5.i)} : \min_{\mathbf{u}_1} f^{(i)}(\mathbf{u}_1) \\ \text{s.t. (20a) and (36).} \end{aligned}$$

It should be noted that theoretically, the convergence of the iteration can be ensured as long as the trust region radius is sufficiently small. However, in practice, we need to perform the following operations: if the objective value of (P5.i) does not decrease compared with the previous iteration, we need to reduce the trust region radius to $\psi^{(i)} = \frac{\psi^{(i-1)}}{2}$ and then resolve (P5.i). The iteration terminates when $\psi^{(i)}$ is less than a preset threshold ϵ , and the solution from the last iteration is the optimal solution of $\mathbf{u}_1^*$.

$$f(\mathbf{u}_1^{(i)}) = \sum_{k=1}^K \left| \sum_{m=1}^M \bar{w}_m \sqrt{p_k} \sum_{n=1}^N \gamma_{m,n} \frac{e^{-j\frac{2\pi}{\lambda} \|\mathbf{u}_k^{(i)} - \tilde{\mathbf{v}}_{m,n}\|}}{\|\mathbf{u}_k^{(i)} - \tilde{\mathbf{v}}_{m,n}\|} - 1 \right|^2. \quad (28)$$

$$\frac{\partial f(\mathbf{u}_1^{(i)})}{\partial \mathbf{u}_1^{(i)}} = \sum_{k=1}^K 2\text{Re} \left(\overline{(s_k(\mathbf{u}_k^{(i)})) - 1} \sum_{m=1}^M \bar{w}_m \sqrt{p_k} \sum_{n=1}^N \gamma_{m,n} \left[-\frac{e^{-j\frac{2\pi}{\lambda} d_{m,n}(\mathbf{u}_k^{(i)})}}{d_{m,n}(\mathbf{u}_k^{(i)})} \left(\frac{1}{d_{m,n}(\mathbf{u}_k^{(i)})} + j\frac{2\pi}{\lambda} \right) \frac{\mathbf{u}_k^{(i)} - \tilde{\mathbf{v}}_{m,n}}{d_{m,n}(\mathbf{u}_k^{(i)})} \right] \right). \quad (35)$$

D. Optimization of PA Positions $\mathbf{V}$

With the fixed encoding vector $\mathbf{w}$, transmit power $\mathbf{P}$ and UAV position $\mathbf{u}$, we optimize the PA positions $\mathbf{V}$, then the optimization problem is expressed as

$$\begin{aligned} \text{(P6)} : \min_{\mathbf{V}} \|\mathbf{w}^H \mathbf{G}(\mathbf{V}, \mathbf{u}_1) \mathbf{P} - \mathbf{1}^T\|^2 \\ \text{s.t. (10b) and (10c).} \end{aligned}$$

To solve Problem (P6), we adopt an alternating linear search, whose core idea is to optimize each PA position individually in sequence while keeping other PA positions fixed. Specifically, we first optimize the position of the n -th PA on waveguide m , i.e., $\tilde{\mathbf{v}}_{m,n}$, and fix all other PA positions $\tilde{\mathbf{v}}_{m',n'}$, where $(m', n') \neq (m, n)$. At this point, $\mathbf{G}(\mathbf{V}, \mathbf{u}_1)$ is a function of $\tilde{\mathbf{v}}_{m,n}$, and we can rewrite Problem (P6) as

$$\begin{aligned} \text{(P7)} : \min_{\tilde{\mathbf{v}}_{m,n}} \|\mathbf{w}^H \mathbf{G}(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1) \mathbf{P} - \mathbf{1}^T\|^2 \\ \text{s.t. } v_{m,\tilde{n}} - v_{m,\tilde{n}-1} \geq L_0, \tilde{n} = n, n+1 \quad (37a) \\ (10b), \end{aligned}$$

where $\mathbf{G}(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1) = [\mathbf{g}_1, \dots, \mathbf{g}_{m-1}, \mathbf{g}_m(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1), \mathbf{g}_{m+1}, \dots, \mathbf{g}_M]^T$, with $\mathbf{g}_{m'}, \forall m' \neq m$ are constant values independent of $\tilde{\mathbf{v}}_{m,n}$, $\mathbf{g}_m(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1) = [\mathbf{g}_{m,1}(\tilde{\mathbf{v}}, \mathbf{u}_1), \dots, \mathbf{g}_{m,k}(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1), \dots, \mathbf{g}_{m,K}(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1)]^T$, and L_0 is the minimum spacing between adjacent PAs. For the convenience of subsequent processing, we first denote $\mathbf{g}_{m,k}(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1)$ as

$$\mathbf{g}_{m,k}(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1) = \mathbf{W}_{m,k}(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_k) + \mathbf{M}_{m,k}, \quad (38)$$

with $\mathbf{M}_{m,k} = \sum_{n', n' \neq n} \mathbf{W}_{m,k}(\tilde{\mathbf{v}}_{m,n'}, \mathbf{u}_k)$ and $\mathbf{W}_{m,k}(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_k) = \frac{\lambda e^{-j\left(\frac{2\pi}{\lambda} \sqrt{(0-x_k)^2 + ((m-1)a-y_k)^2 + ((v_{m,n}-z_k)^2 + \frac{2\pi i r}{\lambda} \tilde{\mathbf{v}}_{m,n})}\right)}}{4\pi \sqrt{(0-x_k)^2 + ((m-1)a-y_k)^2 + ((v_{m,n}-z_k)^2 + \frac{2\pi i r}{\lambda} \tilde{\mathbf{v}}_{m,n})}}$. Next, we rewrite the objective function of Problem (P7) as

$$\min_{\tilde{\mathbf{v}}_{m,n}} \|(\bar{w}_m \mathbf{g}_m^T(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1) + \mathbf{e}) \mathbf{P} - \mathbf{1}^T\|^2, \quad (39)$$

where $(\cdot)$ is the conjugate operation, and $\mathbf{e} = \sum_{m', m' \neq m} \bar{w}_{m'} \mathbf{g}_{m'}^T$. To further simplify the computation, we define the equality $\mathbf{E} \triangleq \mathbf{e} \mathbf{P} - \mathbf{1}^T$, then we can rewrite (38) as

$$\begin{aligned} \min_{\tilde{\mathbf{v}}_{m,n}} \|\bar{w}_m \mathbf{g}_m^T(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1) \mathbf{P} + \mathbf{E}\|^2 \\ = \min_{\tilde{\mathbf{v}}_{m,n}} |w_m|^2 \mathbf{g}_m^T(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1) \mathbf{P}^2 \bar{\mathbf{g}}_m(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1) \\ + 2\text{Re}(\bar{w}_m \mathbf{g}_m^T(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1) \mathbf{P} \mathbf{E}^H) \\ = \min_{\tilde{\mathbf{v}}_{m,n}} \sum_k (|w_m|^2 p_k |\mathbf{g}_{m,k}(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1)|^2 \\ + 2\text{Re}(\bar{w}_m \sqrt{p_k} \mathbf{g}_{m,k}(\tilde{\mathbf{v}}_{m,n}, \mathbf{u}_1) \bar{\mathbf{E}}_k)). \end{aligned} \quad (40)$$

Then, Problem (P7) becomes as

$$\begin{aligned} \text{(P8)} : \min_{\tilde{v}_{m,n}} & \sum_k (A_k |W_{m,k}(\tilde{v}_{m,n}, \mathbf{u}_1)|^2 \\ & + 2\text{Re}(B_k W_{m,k}(\tilde{v}_{m,n}, \mathbf{u}_1))) \\ \text{s.t.} & \text{ (10b) and (37a),} \end{aligned}$$

where $A_k = |w_m|^2 p_k$, $B_k = |w_m|^2 p_k M_{m,k} + \bar{w}_m \sqrt{p_k} \bar{E}_k$.

Problem (P8) is a scalar optimization problem over a closed interval, which can be efficiently solved using grid search. Specifically, we first divide the interval $[0, L_z]$ into D equally spaced points, forming the set $\mathcal{D}_m$:

$$\mathcal{D}_m \triangleq \left\{ 0, \frac{L_z}{D-1}, \frac{2L_z}{D-1}, \dots, L_z \right\}. \quad (41)$$

Then, we substitute each value in set $\mathcal{D}$ into the objective function of (P8) for evaluation thus, the optimal $v_{m,n}^*$ can be obtained as

$$\begin{aligned} \tilde{v}_{m,n}^* = \arg \min_{\tilde{v}_{m,n} \in \mathcal{D}_m} & \sum_k (A_k |W_{m,k}(\tilde{v}_{m,n}, \mathbf{u}_1)|^2 \\ & + 2\text{Re}(B_k W_{m,k}(\tilde{v}_{m,n}, \mathbf{u}_1))), \end{aligned} \quad (42)$$

where $\hat{\mathcal{D}}_m$ is the feasible search region of $v_{m,n}$ satisfying (10b) and (37a), i.e.,

$$\hat{\mathcal{D}}_m = \mathcal{D}_m \cap [v_{m,n-1} + L_0, L_z] \cap [0, v_{m,n+1} - L_0]. \quad (43)$$

Based on the above analysis, the decoding vector $\mathbf{w}$, the transmit power P , the UAV position $\mathbf{u}_1$, and the PA positions $\mathbf{V}$ are updated iteratively according to Algorithm 1 until the objective value falls below a predefined threshold. During the iterative process, the objective values corresponding to the variable set $\{\mathbf{w}^*, \mathbf{P}^*, \mathbf{u}_1^*, \mathbf{V}^*\}$ are monotonically non-increasing. Therefore, the convergence of the proposed optimization framework is guaranteed.

E. Complexity Analysis

The solutions to Problems (P2) and (P3) can be obtained through the first-order derivatives of the objective functions and the KKT conditions, which lead to semi-closed form solutions. Thus, we primarily analyze the complexity of the SCA algorithm for solving the UAV position $\mathbf{u}_1$ and the alternating linear search for solving the PA positions $\mathbf{V}$.

Problem (P4) can be solved by using the trust-region SCA algorithm, which attains the optimal solution of $\mathbf{u}_1$ with only $\mathcal{O}(\log \frac{\psi}{\epsilon})$ iterations. In each iteration, the function $f(\mathbf{u}_1^{(i)})$ and its first-order $\frac{\partial f(\mathbf{u}_1^{(i)})}{\partial \mathbf{u}_1^{(i)}}$ derivative need to be computed, with computational complexities $\mathcal{O}(KM^2N^2)$ and $\mathcal{O}(KM^2N^2)$, respectively. After that, CVX is employed to solve the first-order Taylor expansion of the original objective function. Therefore, the overall computational complexity of optimizing $\mathbf{u}_1$ is $\mathcal{O}((KM^2N^2 + 3KM^2N^2) \log \frac{\psi}{\epsilon})$.

Problem (P6) is solved using an alternating linear search. Specifically, when optimizing the PA located at (m, n) , the positions of all other PAs $(m', n') \neq (m, n)$ are fixed. A grid search method is applied by uniformly partitioning the waveguide into D segments to optimize the variable $v_{m,n}$. As a result, the computational complexity for optimizing a

single PA position is $\mathcal{O}(K^2(MN-1)^2D)$. Therefore, the total computational complexity for completing one full optimization over all PA positions $\mathbf{V}$ is $\mathcal{O}(K^2(MN-1)^2DMN)$.

The above complexity analysis reveals a clear trade-off between performance and computational complexity. The proposed AO framework improves the MSE by jointly optimizing the decoding vector, transmit power, PA positions, and UAV positions, at the cost of iterative updates and grid-based PA search. In practice, the system can balance performance and complexity by selecting different optimization modes according to latency and hardware constraints. For example, fixing either the UAV positions or the PA positions can significantly reduce the computational overhead while retaining most of the MSE gain.

IV. NUMERICAL RESULTS

In this section, we evaluate the performance of the proposed PASS-enabled AirComp with respect to the joint design of PA positions, UAV positions, and communication design. The performance evaluation is conducted strictly in accordance with the system and channel models described in Section 2, where the channel coefficients from each UAV to each PA are given by Equation (2). This model comprehensively accounts for the free-space path loss and phase delay. The signals received by all PAs on each waveguide undergo coherent combining at the feeding point, and the equivalent channel response is provided by Equation (5). This response is a function of the PA positions and incorporates the propagation phase induced by the waveguide refractive index i_r . Specifically, we consider a PASS parallel to the wall covering the $L_y = 10m$ and $L_z = 20m$ plane, where the carrier frequency $f = 28GHz$, the waveguide refractive index $i_r = 1.44$, and the noise power $\sigma^2 = -90$ dBm. M waveguides are placed vertically to the ground and parallel to the wall with a spacing of $a = L_y/(M-1)$. Each waveguide is equipped with N PAs to serve K UAVs, with a minimum spacing of $L_0 = \lambda/2$ between adjacent PAs. The K UAVs adopt a fixed configuration. We consider the following benchmark schemes are compared with the proposed scheme.

- **Fixed PAs and UAVs:** Fixing the initial positions of PAs and UAVs, we only optimize the decoding vector w and the transmit power P to solve Problem (P1).
- **Fixed PAs position:** Fixing the initial positions of PAs, we solve Problem (P1) by optimizing the decoding vector w , the transmit power P , and the UAV positions $\mathbf{u}$ via the trust-region-based SCA algorithm.
- **Fixed UAVs position:** Fixing the initial positions of UAVs, we solve Problem (P1) by optimizing the decoding vector w , the transmit power P , and the PAs positions $\mathbf{V}$ via the alternating linear search.

Fig. 2 illustrates the convergence behavior of the proposed scheme compared with the three benchmark schemes. It demonstrates that the proposed scheme can rapidly reduce the MSE with the number of iterations increasing and achieve stable convergence within approximately 10 iterations, which shows the algorithmic efficiency. In contrast, other three benchmark schemes are observed to converge to a local point

Algorithm 1 Overall algorithm for solving problem (P1)

```

1: Initialization: decoding vector  $\mathbf{w}^{(o)}$ , transmit power  $\mathbf{P}^{(o)}$ ,
   UAV positions  $\mathbf{u}_1^{(o)}$  and PA positions  $\mathbf{V}^{(o)}$ , set iteration
   index  $o = 1$ .
2: repeat
3: Let  $l = 1$ ,  $\mathbf{w}^{(l-1)} = \mathbf{w}^{(o-1)}$ ,  $\mathbf{P}^{(l-1)} = \mathbf{P}^{(o-1)}$ ,  $\mathbf{u}_1^{(l-1)} = \mathbf{u}_1^{(o-1)}$ .
4: while the decrease of the MSE  $>$  the threshold  $\epsilon$  do
5:   Optimize the decoding vector  $\mathbf{w}^{(l)}$  by solving Problem
     (P2) under  $\mathbf{P}^{(l-1)}$ ,  $\mathbf{u}_1^{(l-1)}$ , and  $\mathbf{V}^{(o-1)}$ .
6:   Optimize the transmit power  $\mathbf{P}^{(l)}$  by solving Problem
     (P3) under  $\mathbf{w}^{(l)}$ ,  $\mathbf{u}_1^{(l-1)}$ , and  $\mathbf{V}^{(o-1)}$ .
7:   Let  $i = 1$ ,  $\mathbf{u}_1^{(i-1)} = \mathbf{u}_1^{(l-1)}$ .
8:   while  $\psi > \epsilon$  do
9:     Compute  $f^{(i-1)}(\mathbf{u}_1^{(i-1)})$  and its first-order derivative
       using (28) and (35) under  $\mathbf{u}_1^{(i-1)}$ ,  $\mathbf{w}^{(l)}$ ,  $\mathbf{P}^{(l)}$ ,  $\mathbf{V}^{(o-1)}$ ,
       respectively.
10:    Obtain  $\mathbf{u}_1^{(i-1)*}$  by use CVX to solve problem (P5.i)
       under  $\mathbf{u}_1^{(i-1)}$ ,  $\mathbf{w}^{(l)}$ ,  $\mathbf{P}^{(l)}$ , and  $\mathbf{V}^{(o-1)}$ .
11:    if the objective value of problem (P4) increases then
12:       $\mathbf{u}_1^{(i)} = \mathbf{u}_1^{(i-1)*}$ .
13:    else
14:       $\psi^{(i)} = \frac{\psi^{(i-1)}}{2}$ .
15:    end if
16:     $i = i + 1$ .
17:  end while
18:   $\mathbf{u}_1^{(l)} = \mathbf{u}_1^{(i)}$ ,  $l = l + 1$ .
19: end while
20: update  $\mathbf{w}^{(o)} = \mathbf{w}^{(l)}$ ,  $\mathbf{P}^{(o)} = \mathbf{P}^{(l)}$ ,  $\mathbf{u}_1^{(o)} = \mathbf{u}_1^{(l)}$ .
21: while the decrease of the MSE  $>$  the threshold  $\epsilon$  do
22:   for each PA do
23:     Fix  $v_{m',n'}^{(o-1)}$ ,  $\forall (m',n') \neq (m,n)$ .
24:     Divide the  $m$ -th waveguide of length  $L_z$  into  $D$  equal
       segments, resulting in the set (41).
25:     According to (43), determine the feasible search
       region for  $v_{m,n}^{(o-1)}$ .
26:     According to (42), use grid search to obtain the
       optimal solution for  $v_{m,n}^{(o-1)*}$ .
27:   end for
28: end while
29: PA positions Optimization complete, output  $\mathbf{V}^{(o)} = \mathbf{V}^{(o-1)*}$ .
30: Calculate the MSE under  $\mathbf{w}^{(o)}$ ,  $\mathbf{P}^{(o)}$ ,  $\mathbf{u}_1^{(o)}$  and  $\mathbf{V}^{(o)}$ .
31:  $o = o + 1$ .
32: until the decrease of the MSE is below a threshold.

```

with slower speeds. Specifically, the proposed scheme can achieve a lower MSE compared with other three benchmark schemes. This shows the advantages of the proposed scheme in terms of system degrees of freedom and resource collaborative optimization.

Fig. 3 depicts the MSE performance versus the variation of waveguide length L_z . It is observed that the fixed-PAs-and-UAVs and fixed-PAs position schemes exhibit a straight line, namely that their MSE is unaffected by the waveguide length. This is because the PA positions are fixed throughout,

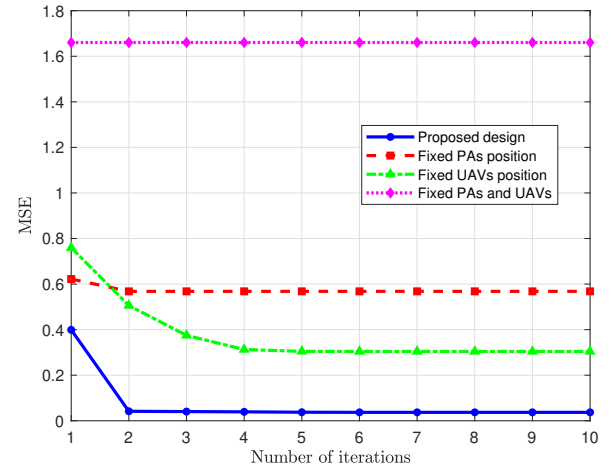


Figure 2. Comparison of Convergence Performance.

so the PASS architecture remains unchanged. In contrast, when we optimize the PA positions, the MSE decreases as the waveguide length increases. The reason is that a longer waveguide provides higher positional degrees of freedom for the PAs, enabling them to better approach the UAV positions and thereby improving the channel conditions. When we jointly optimize the PA and UAV positions, it can be observed that even with a short waveguide length, the MSE can still achieve extremely good performance. This is because when the PA positions are sufficiently optimized, they are still constrained by the waveguide length, at this point, the additional optimization of UAV positions allows the UAVs to move closer to the PA positions, thus establishing favorable channel conditions.

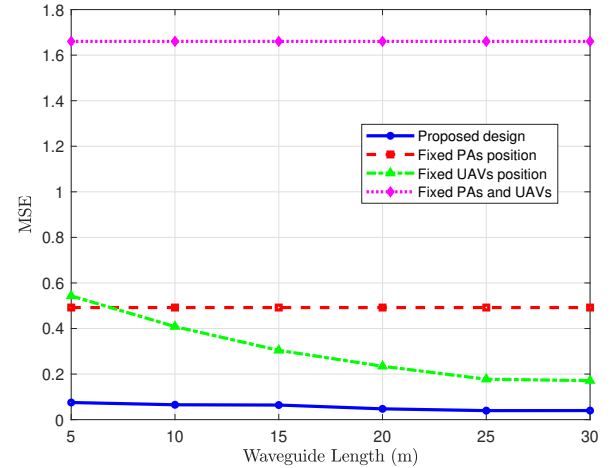


Figure 3. MSE w.r.t. the waveguide length.

Fig. 4 illustrates the variation of the MSE performance as the number of PAs N deployed on the waveguide increases. Overall, the MSE of all schemes decreases significantly with growing N . This trend can be attributed to two main factors. First, a larger number of PAs provides higher beamforming degrees of freedom, enabling more accurate synthesis of the desired field pattern while suppressing sidelobe energy. Second, increasing the number of antenna elements enhances spatial

diversity, thereby improving the system's robustness against channel fluctuations and model inaccuracies. A comparison among the schemes shows that the proposed joint optimization approach consistently outperforms the three benchmark schemes across the entire range of N . This demonstrates that simultaneously optimizing both PA and UAV positions plays a crucial role in reducing estimation errors, whereas schemes with fixed PA or fixed UAV positions exhibit higher MSE, indicating that single-dimensional optimization cannot fully exploit the additional transmitting elements. A closer inspection of the curve slopes reveals that when N increases from a small to a moderate value, the MSE drops rapidly, however, the decreasing trend gradually becomes flatter as N continues to grow. This behavior reflects a typical diminishing marginal gain: each additional PA provides more substantial improvement when the array size is small, while the benefit becomes less pronounced at larger values of N .

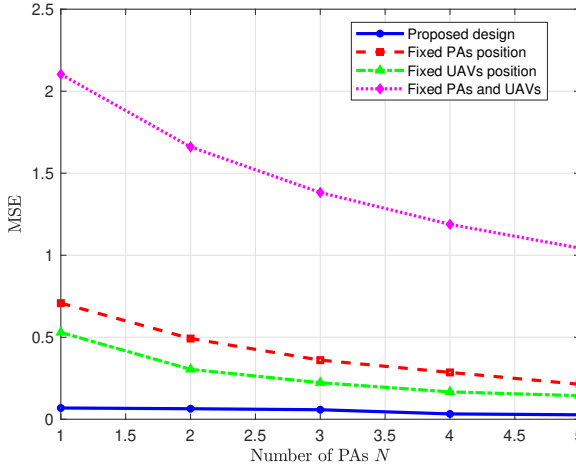


Figure 4. MSE w.r.t. the number of PAs.

Next, Fig. 5 shows the MSE curves with respect to the number of UAVs K . It can be observed that the MSE of all schemes increases as K grows. This behavior is primarily due to the cumulative uplink interference introduced by multiple UAVs simultaneously accessing the system. As the number of active UAVs increases, their transmitted signals become more difficult to spatially separate, which degrades the quality of the aggregated received signal. Even so, the proposed joint optimization scheme consistently outperforms the three benchmark schemes across the entire range of K . Compared with single-dimensional optimization strategies such as fixing the PA positions or fixing the UAV positions, the joint optimization approach can adjust both UAV and PA locations at the same time. This allows the system to construct more effective customized beams under increasing interference, achieving gains in both interference suppression and energy focusing. As a result, the proposed scheme maintains the lowest MSE even in high-interference scenarios with a large number of users, demonstrating stronger robustness and interference management capability.

Finally, Fig. 6 illustrates the MSE performance under different numbers of waveguides M . As shown in the figure, the MSE exhibits a steady downward trend with the increase in the

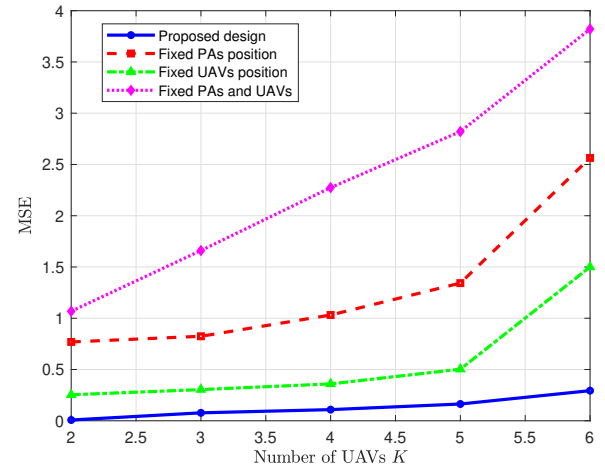


Figure 5. MSE w.r.t. the number of UAVs.

number of waveguides M . This is because more waveguides expand the antenna coverage area and provide higher degrees of freedom for the system, facilitating more precise control of signal propagation and interference suppression, thereby effectively improving the precision of signal aggregation and reducing errors. Meanwhile, it can be observed that for different values of M , the proposed scheme consistently achieves the best performance, with its MSE curve being significantly lower than the three benchmark schemes. This further verifies the effectiveness and robustness of the proposed scheme under different hardware configuration conditions.

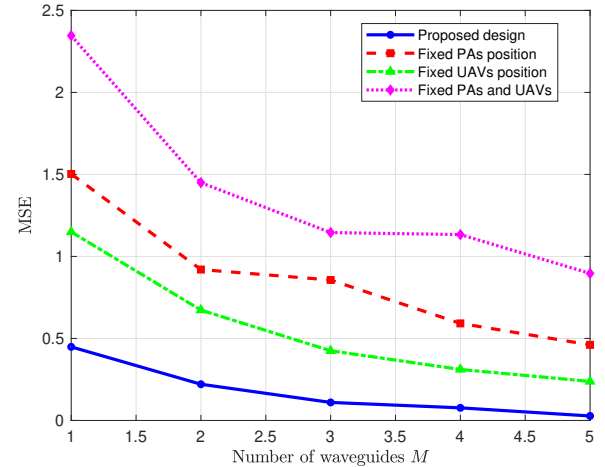


Figure 6. MSE w.r.t. the number of waveguides.

Fig. 7 illustrates the relationship between the maximum transmit power $P^{\max}$ and the MSE. From the figure, it can be observed that as $P^{\max}$ increases, the MSE of all schemes continuously decreases. This trend is in line with theoretical expectations, i.e., in the absence of power consumption constraints, the system improves signal quality by increasing the transmission power, thereby reducing the MSE. However, it is noteworthy that the proposed scheme consistently outperforms the three benchmark schemes, indicating that, at the same power level, the proposed scheme provides better communication quality. Further analysis reveals that although increasing

the transmit power helps reduce the MSE, the system's performance gain gradually stabilizes as the power increases. This suggests that, beyond a certain power level, the reduction in MSE becomes less significant, reflecting diminishing marginal returns between power and communication quality. Therefore, under scenarios with less stringent communication quality requirements, the proposed scheme can effectively reduce energy consumption while still ensuring high communication quality.

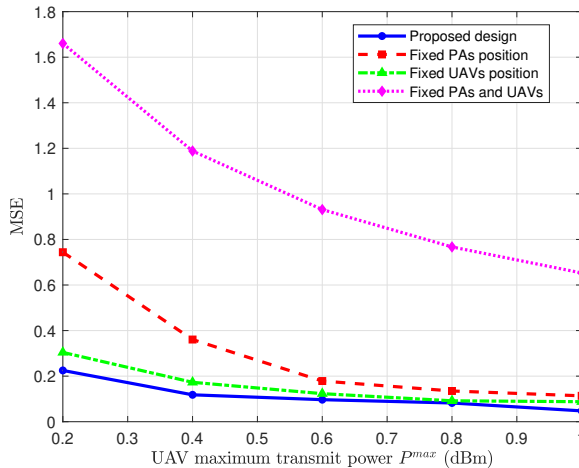


Figure 7. The MSE performance versus the maximum transmit power.

Fig. 8 depicts the MSE performance versus the noise power σ^2 . As expected, the MSE of all schemes increases monotonically with σ^2 , since stronger receiver noise directly reduces the effective signal-to-noise ratio (SNR) after analog aggregation and thus deteriorates the accuracy of magnitude alignment required by AirComp. In the low-noise regime, the MSE is mainly dominated by the signal misalignment caused by heterogeneous channel gains and the peak-power limitation that prevents perfect channel inversion for disadvantaged UAVs; hence, the proposed joint design achieves a clear advantage by flexibly adjusting both PA pinching positions and UAV locations to equalize the effective channels. In the high-noise regime, noise becomes the dominant impairment and all curves exhibit a steeper increase, yet the proposed scheme still maintains the lowest MSE because its PA/UAV placement optimization improves the equivalent channel strength, which enhances the post-combining SNR and makes the aggregation more robust to noise.

V. CONCLUSIONS

This paper investigated a PASS enhancing AirComp in low-altitude UAV uplink, where the BS deploys multiple dielectric waveguides and adjusts the pinching positions to flexibly reshape the effective air-to-ground channels. To mitigate the AirComp straggler effect under stringent per-UAV peak-power constraints, we formulated an MSE-minimization problem that jointly optimizes the BS receive decoding vector, the UAV transmit powers, the PASS pinching positions, and the UAV locations. To tackle the resulting coupled non-convex design, we developed an alternating-optimization framework with closed-form updates for the decoding vector and power control, an

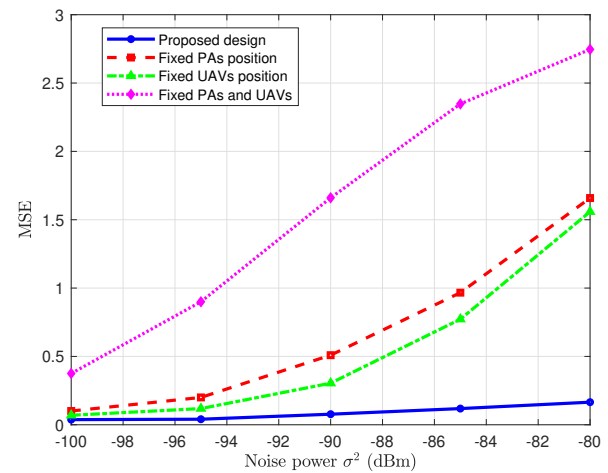


Figure 8. The MSE performance versus the noise power.

alternating linear search for the PA pinching positions, and an SCA method with a trust region for refining UAV locations.

Simulation results demonstrated that the proposed PASS-enabled joint design consistently achieves lower computation MSE than representative baselines with fixed PA placement and/or fixed UAV locations, and the performance gain is particularly pronounced in peak-power-limited and noisy regimes. Moreover, the proposed algorithm shows reliable convergence and provides robust improvements under different system sizes, including varying numbers of UAVs and waveguides.

Future work will extend the proposed framework to more practical communication scenarios involving hybrid near-field/far-field users, multipath fading channels, and Non-line-of-sight (NLOS) or hybrid LoS/NLoS propagation environments with broader UAV distributions. Such extensions require redesigning the joint optimization framework under more realistic channel models while addressing challenges arising from channel estimation uncertainty, stronger variable coupling, and increased computational complexity. In addition, practical PASS deployment issues, including the appropriate selection of waveguide length and the performance impact of different waveguide arrangements, will be systematically investigated.

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