Reconfigurable Intelligent Surface Assisted mmWave UAV Wireless Cellular Networks

Lisi Jiang*, Hamid Jafarkhani*
*Center for Pervasive Communications & Computing, University of California at Irvine, CA, USA
Email:{lisi.jiang, hamidj}@uci.edu

***Abstract*—In this paper, we consider a RIS-assisted mmWave UAV wireless cellular network, where a UAV is serving several users with the help of multiple RIS. We jointly optimize the deployment, user scheduling, beamforming vector and RIS phases to maximize the sum-rate, with the constraints of the minimum rate, the UAV movement, the analog beamforming and the RIS phases. To solve this complex problem, we use an iterative method, in which when we optimize one variable, we fix the other three variables. When optimizing the deployment, we find the optimal position for the UAV by a sphere search. Then, we formulate an integer linear programming to find the best scheduling. We also design the analog beamforming vector by compensating the phases of the channel which combines the direct path and the RIS paths. When optimizing the RIS phases, we formulate a semi-definite programming to find the best phases. The proposed joint optimization outperforms the system without RIS assistance and the system without deployment optimization.**

I. Introduction

Unmanned aerial vehicles (UAVs) have received increasing attention in the past decade because of their flexible, mobility, and fast deployment [1], [2]. There are several typical applications of UAV-assisted wireless networks including wireless sensor networks (WSNs) [3]–[5], caching aided wireless networks, cloud radio access networks (CRANs) [6], etc. Among these scenarios, UAV-assisted wireless cellular network is a promising technology to enable significantly enhanced UAV-ground communications [7]. In UAV-assisted wireless cellular networks, a UAV can serve as a flying base-station (BS), an aerial radio access point, and an aerial relay to expand wireless coverage and provide data transmission towards physical objects.

Millimeter wave (mmWave) communications are considered in the UAV wireless cellular networks to further enhance the available bandwidth and increase the data rate [1], [8]. The deployment and placement optimization of UAV operating in the mmWave band has been studied in the literature. In [9], a spatial interference channel model is established for UAV groups, and the expression of signal to interference plus noise ratio (SINR), which depends on codebook design and direction of arrival (DOA), is obtained. In [8], a joint optimization of the UAV-BS deployment and beamforming to maximize the achievable sum-rate in a multi-user mmWave-UAV system is proposed.

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Although UAVs bring a lot of flexibility in deploying the networks, their high mobility and instability severely impair the quality of communication. One method to improve the reliability and quality of the UAV networks is to change the wireless scattering environment. Reconfigurable antennas have been proposed to change the transmission states and improve the performance [10]–[12]. Reconfigurable antennas for mmWave systems have been designed and provide similar benefits [13], [14]. Similar to reconfigurable antennas, reconfigurable intelligent surfaces (RIS) can intelligently configure the wireless environment to improve the transmission quality between the transmitter and receiver [15], [16]. However, different from reconfigurable antennas, which use active units to change the transmission state, RIS use passive units which only incur phase shift to the incident signal without power consumption. Moreover, RIS can help improve the channel quality when the line-of-sight (LoS) path is affected by physical obstacles or under hash environments such as rains. In UAV networks, RIS can be implemented on building walls and remotely configured by central controllers to coherently direct the reflected radio waves towards specific users [17]. In [18], the UAV-BS link is assisted by the RIS. In [19], trajectory and beamforming are jointly designed for the scenario where one UAV serves one user.

In this paper, we consider a RIS-assisted mmWave UAV wireless cellular network, where one UAV is serving several users with the help of multiple RIS. We propose a joint optimization problem, which considers the deployment, user scheduling, beamforming vector, and RIS phases to maximize the sum-rate. We consider the constraints of the minimum rate, the movement of the UAV, the analog beamforming, and the RIS phases. To solve this complex problem, we use an iterative method. In our method, we optimize one variable while fixing the other three variables. When optimizing the deployment, we find the optimal position for the UAV by a sphere search. Then, we formulate an integer linear programming to find the best scheduling. We also design the analog beamforming vector by compensating the phases of the channel which combines the direct path and the RIS paths. When optimizing the RIS phases, we formulate a semi-definite programming to find the best phases. The proposed joint optimization outperforms the system without RIS assistance and the system without deployment optimization.

II. SYSTEM MODEL

We consider a single UAV, multi-RIS and multi-user scenario. The UAV functions as a flying BS to serve the ground users. The RIS are deployed on the ground and are controlled remotely by a central controller to help improve the communication quality between the UAV and ground users. The UAV is equipped with N_t antennas and each user is equipped with a single antenna. The total number of users is K. Each RIS is equipped with N_{RIS} reflecting elements and the total number of RIS is R.

In our system, we assume a quasi-static mobility model. That is, within a timeblock, the UAV is static and then it can move one step. Each timeblock contains M' timeslots. We collect users' locations every M' timeslots.

At each timeblock, we fine tune the position of the UAV to fit in the locations of the users. In each timeblock, we aim to serve all the K users in M timeslots ($M < M'$). Note that the redundant $M' - M$ timelots are used for the data collection and UAV movement. To guarantee that all users can be served, we assume $K \leq M$.

The goal of our system is to maximize the system throughput in each timeblock. To do this, we need to jointly optimize the position of the UAV, design the scheduling, optimize the UAV beams, and adjust the RIS phases. The system model is shown in Fig. 1, where we illustrate a 2-RIS and 5-user system. In Timeslot 3 of the timeblock, the UAV serves User 2 with the help of RIS 1 and RIS 2. In different timeblock, the UAV will fine tune its location to optimize the performance within its users.

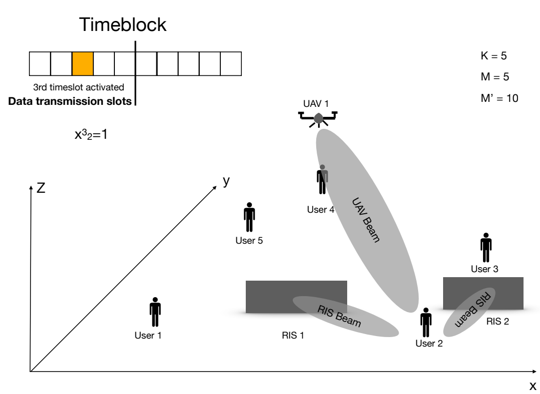

Fig. 1: System model

III. PROBLEM FORMULATION

A. Channel model

1) UAV channel: In our scenario, we assume the UAV is carrying a uniform planar array (UPA) with one RF chain which operates on mmWave band. A multi-path channel

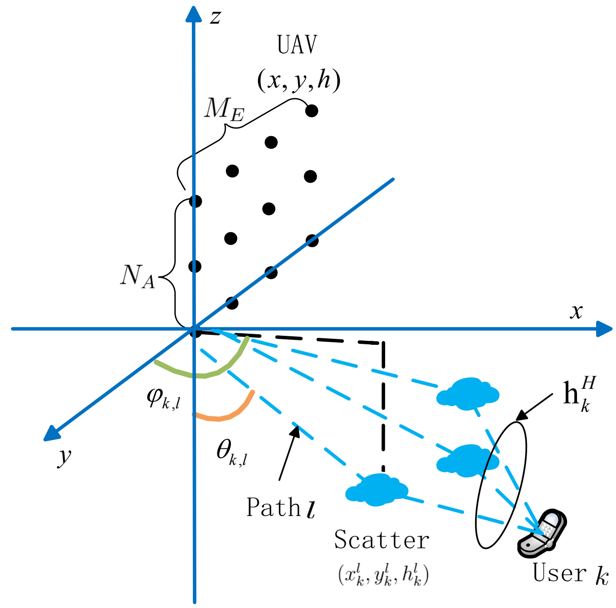

Fig. 2: channel model with three clusters, where the dashed blue lines are the paths formed by reflecting scatters.

(MPC) model is adopted. As Fig. 2 illustrates, we denote $\mathbf{h}_k$ as the channel vector, then it can be expressed as

$$\mathbf{h}_k^H = \sqrt{\frac{N_t}{L_k}} \sum_{l=1}^{L_k} a_{k,l} \alpha(\theta_{k,l}, \varphi_{k,l})^H, \tag{1}$$

where $a_{k,l}$ is the channel gain of the l^{th} path from User k to the UAV, $\theta_{k,l}$ and $\varphi_{k,l}$ are the elevation steering angle and azimuth angle, respectively, of the l^{th} path from User k to the UAV, and L_k is the total number of paths for User k to the UAV. Each path is formed through a scatter. Parameter $\alpha(\theta_{k,l})$ is the steering vector function for the UPA. For an $M_E \times N_A$ ($N_t = M_E N_A$) UPA, the steering vector is defined as

$$\begin{aligned} &\alpha(\theta_{k,l}, \varphi_{k,l}) \\ &= \tfrac{1}{\sqrt{N_t}}[1, \ldots, e^{j\pi \sin(\theta_{k,l})[(M_E-1)\cos(\varphi_{k,l}) + (N_A-1)\sin(\varphi_{k,l})]}]^T \end{aligned} \tag{2}$$

The steering angles $\theta_{k,l}$ and $\varphi_{k,l}$ depend on the location of the UAV and the location of the scatter which forms the path l. We denote (x, y, h) as the location of the UAV and (x_k^l, y_k^l) as the location of the scatter of the l^{th} path for User k. Then, $\theta_{k,l}$ and $\varphi_{k,l}$ can be calculated as

$$\begin{cases} \theta_{k,l} = \arctan\left(\frac{\sqrt{(x_k^l - x)^2 + (y_k^l - y)^2}}{h}\right) \\ \varphi_{k,l} = \arctan\left(\frac{y_k^l - y}{x_k^l - x}\right) \end{cases} \tag{3}$$

Model (1) describes the Non-LoS scenario between User k and the UAV. In most cases, an LoS path exists as well. When there is an LoS path, the channel becomes

$$\mathbf{h}_k^H = \sqrt{N_t} a_k \alpha(\theta_k, \varphi_k)^H, \tag{4}$$

where a_k is the channel gain of the LoS path from User k to the UAV, θ_k and φ_k are the elevation steering angle and azimuth angle of the LoS path from User k to the UAV, respectively.

The LoS path between the UAV and the serving user can be blocked if the propagation environment contains physical obstacles. The probability of existing an LoS component can be described as a function of the angle ξ_k as follows

$$P_{\text{LOS}}(\xi_k) = \frac{1}{1 + a\exp(-b(\xi_k - a))}, \tag{5}$$

where a and b are the positive modeling parameters depending on the propagation environment, e.g., rural, urban, or dense urban. ξ_k is calculated by $\xi_k = \arctan(h/D_k)$ with the horizontal distance from the UAV to User k denoted as $D_k = \sqrt{(x - x_k)^2 + (y - y_k)^2}$. The probability of existing an LoS component increases as the elevation angle increases, and it approaches 1 when h is large enough.

2) RIS channel: We denote the channel between RIS r and the UAV as $\mathbf{G}_r$. The channel between RIS r and User k is denoted by $\mathbf{h}_k^{r,H}$. We use the widely adopted MPC model to model $\mathbf{G}_r$ and $\mathbf{h}_k^{r,H}$. For $\mathbf{h}_k^{r,H}$, it can be expressed as

$$\mathbf{h}_k^{r,H} = \sqrt{\frac{N_{\text{RIS}}}{L_k^r}} \sum_{l=1}^{L_k^r} a_{k,l}^r \alpha(\theta_{k,l}^r, \varphi_{k,l}^r)^H, \tag{6}$$

where $a_{k,l}^r$ is the channel gain of the l^{th} path from RIS r to User k. $\alpha(\theta_{k,l}^r, \varphi_{k,l}^r)$ is the steering vector using the same model as (2).

For $\mathbf{G}_r$, it can be expressed as

$$\mathbf{G}_r = \sqrt{\frac{N_t N_{\text{RIS}}}{L_r}} \sum_{l=1}^{L_r} a_{r,l} \alpha^{\mathbf{r}}(\theta_{\mathbf{r},\mathbf{l}}^{\mathbf{r}}, \varphi_{\mathbf{r},\mathbf{l}}^{\mathbf{r}}) \alpha^t(\theta_{r,l}^t, \varphi_{r,l}^t)^H, \tag{7}$$

where $a_{r,l}$ is the channel gain of the l^{th} path from the UAV to RIS r. $\alpha^t(\theta_{r,l}^t, \varphi_{r,l}^t)$ and $\alpha^r(\theta_{r,l}^r, \varphi_{r,l}^r)$ are the transmitting steering vector and receiving steering vector, respectively.

The overall channel between User k and the UAV via RIS r can be expressed as

$$\mathbf{h}_{k,r}^H = \mathbf{h}_k^{r,H} \Theta_r \mathbf{G}_r, \tag{8}$$

where $\Theta_r = \text{diag}(e^{j\theta_{r,1}}, \ldots, e^{j\theta_{r,N_{\text{RIS}}}})$ is the phase-shift matrix of the r^{th} RIS. $\theta_{r,m} \in [0, 2\pi]$ denotes the phase shift associated with the m^{th} passive element of the r^{th} RIS.

B. Scheduling

In each timeblock, we have 2 rules for scheduling: (i) in one timeslot, the UAV can only serve at most one user; and (ii) across all timeslots, all K users should be scheduled at least once.

To describe the process of scheduling, we denote the binary variable $x_k^m \in \{0, 1\}$ to indicate whether User k is scheduled by the UAV in Timeslot m, i.e.,

$$x_k^m = \begin{cases} 1, \text{if User } k \text{ is scheduled in Timeslot } m \\ 0, \text{otherwise} \end{cases} \tag{9}$$

For Rule (i), we have

$$0 \leq \sum_{k=1}^{K} x_k^m \leq 1 \tag{10}$$

For Rule (ii), we have

$$\sum_{m=1}^{M} x_k^m \geq 1 \tag{11}$$

C. UAV Beamforming and RIS Reflecting

We denote $\mathbf{w}_k$ as the beamforming vector from the UAV to User k with the constant-modulus constraint $|[\mathbf{w}_k]_m| = \frac{1}{\sqrt{N_t}}, m = 1, \ldots, N_t$. Then, at Timeslot m, the received signal from the UAV to User k is

$$y_k^m = x_k^m \sqrt{P} (\mathbf{h}_k^H + \sum_{r=1}^{R} \mathbf{h}_k^{r,H} \Theta_r \mathbf{G}_r) \mathbf{w}_k \mathbf{s}_k + n_k. \tag{12}$$

The achievable data rate from User k to the UAV at Timeslots m can be expressed as

$$R_k^m = \log_2(1 + \frac{x_k^m P |(\mathbf{h}_k^H + \sum_{r=1}^{R} \mathbf{h}_k^{r,H} \Theta_r \mathbf{G}_r) \mathbf{w}_k|^2}{\sigma^2}), \tag{13}$$

where σ^2 is the power of Gaussian white noise at User k, and P is the total transmission power at the UAV.

D. Joint optimization

In each timeblock, we want to maximize the thoughput of the system. Since we only fine tune the UAV's position in each timeblock, we assume that the UAV only moves one step from the previous timeblock. This means $|\mathbf{p} - \mathbf{p}_{\text{pre}}| = d$ or 0, where $\mathbf{p} \triangleq (x, y, h)$ is the position of the UAV and $\mathbf{p}_{\text{pre}}$ is the position of the UAV in the previous timeblock. The parameter d is decided by the UAV's energy constraint. Then, the optimization problem is described as follows:

$$\begin{aligned}
\underset{\substack{\{\mathbf{p}\}, \{x_k^m\}, \\ \{\mathbf{w}_k\}, \{\Theta_r\}}}{\text{maximize}} \quad & \sum_{m=1}^{M} \sum_{k=1}^{K} R_k^m && \text{(14a)} \\
\text{subject to} \quad & (10)-(11) \quad , && \text{(14b)} \\
& |\mathbf{p} - \mathbf{p}_{\text{pre}}| = d \text{ or } 0 \quad , && \text{(14c)} \\
& \sum_{m=1}^{M} R_k^m \geq \gamma_k \quad , && \text{(14d)} \\
& |[\mathbf{w}_k]_m| = \frac{1}{\sqrt{N_t}}, m = 1, \ldots, N_t \quad , && \text{(14e)} \\
& \Theta_r = \text{diag}(e^{j\theta_{r,1}}, \ldots, e^{j\theta_{r,N_{\text{RIS}}}}). && \text{(14f)}
\end{aligned}$$

Constraint (14d) is the constraint for the minimum data rate for each user. Constraint (14e) is for analog beamforming. Constraint (14f) is for the RIS phases.

IV. Solution

To solve Problem (14), we will iterate among the deployment, scheduling, beamforming, and RIS phases. When we optimize one variable, we fix the other three variables.

A. Deployment

When optimizing the deployment, we fix the scheduling, the beamforming vector, and the RIS phases. We denote the index of the scheduled user at Timeslot m by i_m, then the sub-problem for deployment can be expressed as

$$\begin{aligned}
\underset{\mathbf{p}}{\text{maximize}} \quad & \sum_{m=1}^{M} R_{i_m} && \text{(15a)}\\
\text{subject to} \quad & |\mathbf{p}-\mathbf{p}_{\text{pre}}| = d \text{ or } 0, && \text{(15b)}\\
& R_{i_m} \geq \gamma_m \quad , && \text{(15c)}
\end{aligned}$$

where $R_{i_m} = \log_2(1+\frac{P|\tilde{\mathbf{h}}_{i_m}^H \mathbf{w}_{i_m}|^2}{\sigma^2})$, $\tilde{\mathbf{h}}_{i_m}^H = \mathbf{h}_{i_m}^H + \sum_{r=1}^{R} \mathbf{h}_{i_m}^{r,H} \Theta_r \mathbf{G}_r$, and γ_m is calculated by $\gamma_{i_m}/(\sum_{n=1}^{M} x_{i_m}^n)$.

The position of the moved UAV can be expressed as

$$\mathbf{p} = \mathbf{p}_{\text{pre}} + d[\sin\theta_{\text{mv}}\cos\varphi_{\text{mv}}, \sin\theta_{\text{mv}}\sin\varphi_{\text{mv}}, \cos\theta_{\text{mv}}]^T, \quad (16)$$

where θ_{mv} and φ_{mv} are the movement elevation angle and azimuth from $\mathbf{p}$ to $\mathbf{p}_{\text{pre}}$, respectively. To find the best position for the UAV, we perform a sphere search for $\mathbf{p}$ based on $\mathbf{p}_{\text{pre}}$, i.e., we find the optimal moving direction from $\mathbf{p}_{\text{pre}}$ to $\mathbf{p}$. The detailed algorithm is described in Alg. 1.

Algorithm 1 Best deployment

Input:
Searching step size Δ, $\mathbf{p}_{\text{pre}}$ and the sum-rate of the previous timeblock $R_{\text{sum}}^{\text{pre}}$;
$\mathbf{p}^{\text{opt}} \leftarrow \mathbf{p}_{\text{pre}}$, $R_{\text{sum}}^{\max} \leftarrow R_{\text{sum}}^{\text{pre}}$;
for $\theta_{\text{mv}} = 0:\Delta:2\pi$ **do**
  for $\varphi_{\text{mv}} = 0:\Delta:2\pi$ **do**
    Update $\mathbf{p}$ and R_{sum};
    if $R_{\text{sum}} \geq R_{\text{sum}}^{\max}$ and Constraint (15c) is satisfied **then**
      $\mathbf{p}^{\text{opt}} \leftarrow \mathbf{p}$, $R_{\text{sum}}^{\max} \leftarrow R_{\text{sum}}$;
    end if
  end for
end for
Return the optimal $\mathbf{p}^{\text{opt}}$.

B. Scheduling

When the deployment, beamforming, and RIS phases are fixed, the throughput maximization with respect to the scheduling is formulated as

$$\begin{aligned}
\underset{\mathbf{x}}{\text{maximize}} \quad & \sum_{k=1}^{K}[R_k \sum_{m=1}^{M} x_k^m] && \text{(17a)}\\
\text{subject to} \quad & (10)-(11) \quad , && \text{(17b)}\\
& \sum_{m=1}^{M} x_k^m R_k \geq \gamma_k, && \text{(17c)}
\end{aligned}$$

where $\mathbf{x} = \{x_k^n[m]\}$ is the set of scheduling indicators and $R_k = \log_2(1+\frac{P|\tilde{\mathbf{h}}_k^H \mathbf{w}_k|^2}{\sigma^2})$. Problem (17) is an integer linear programming (ILP) since all variables are binary and all constraints are linear. Optimizers such as the Gurobi [20] can be employed to obtain the optimal solution to Problem (17).

C. Beamforming vector optimization

Given the scheduling order, the optimal deployment and the RIS phases, we can simplify the beamforming vector design problem into

$$\begin{aligned}
\underset{\{\mathbf{w}_k\}}{\text{maximize}} \quad & \sum_{m=1}^{M} R_{i_m} && \text{(18a)}\\
\text{subject to} \quad & R_{i_m} \geq \gamma_m \quad , && \text{(18b)}\\
& |[\mathbf{w}_k]_m| = \frac{1}{\sqrt{N_t}}, m = 1,...,N_t. && \text{(18c)}
\end{aligned}$$

To further simplify the problem, we decouple Problem (18) by timeslots. At Timeslot m, we need to design the beamforming vector for the scheduled user according to

$$\begin{aligned}
\underset{\mathbf{w}_{i_m}}{\text{maximize}} \quad & R_{i_m} && \text{(19a)}\\
\text{subject to} \quad & R_{i_m^n} \geq \gamma_{i_m} \quad , && \text{(19b)}\\
& |[\mathbf{w}_{i_m}]_t| = \frac{1}{\sqrt{N_t}}, t = 1,...,N_t. && \text{(19c)}
\end{aligned}$$

Since we are maximizing the rate R_{i_m} in (19), we can drop the lower-bound constraint (19b) to simplify the problem. Note that maximizing R_{i_m} is equivalent to maximizing the power of the receiving signal, since there is no interference. Then, we can re-formulate the optimization problem as

$$\begin{aligned}
\underset{\mathbf{w}_{i_m}}{\text{maximize}} \quad & |\tilde{\mathbf{h}}_{i_m}^H \mathbf{w}_{i_m}|^2 && \text{(20a)}\\
\text{subject to} \quad & |[\mathbf{w}_{i_m}]_t| = \frac{1}{\sqrt{N_t}}, t = 1,...,N_t, n = 1,...,N. && \text{(20b)}
\end{aligned}$$

According to the Cauchy-Schwartz inequality, the optimal $\mathbf{w}_{i_m}^{\text{opt}}$ is the one which compensates the phases of the channel, i.e.,

$$\mathbf{w}_{i_m}^{\text{opt}} = \frac{1}{\sqrt{N_t}} e^{j\arg(\tilde{h}_{i_m})} \quad (21)$$

D. RIS phase design

When designing the RIS phases, similar to the beamforming vector designing, we decompose the problem by timeslots. At Timeslot m, we reformulate the optimization problem as

$$\begin{aligned}
\underset{\{\Theta_r\}}{\text{maximize}} \quad & \sum_{r}^{R} \mathrm{Tr}(\mathbf{G}_r^H \Theta_r^H \mathbf{h}_{i_m}^r \mathbf{h}_{i_m}^{r,H} \Theta_r \mathbf{G}_r \mathbf{W}_{i_m}) && \text{(22a)}\\
\text{subject to} \quad & \Theta_r = \text{diag}(e^{j\theta_{r,1}},...,e^{j\theta_{r,N_{\text{RIS}}}}), && \text{(22b)}
\end{aligned}$$

where we ignore the term $\mathbf{w}_{i_m}^H \mathbf{h}_{i_m} \mathbf{w}_{i_m}$, since it is a constant term for fixed $\mathbf{w}_{i_m}$. To simplify the optimization problem, we define $\mathbf{H}_{i_m^n}^{\text{RIS},H} = [\mathbf{h}_{i_m^n}^{1,H},...,\mathbf{h}_{i_m^n}^{R,H}] \in \mathcal{C}^{1\times RN_{RIS}}$, $\mathbf{\Theta} = \text{diag}(\Theta_1,...,\Theta_R) \in \mathcal{C}^{RN_{RIS}\times RN_{RIS}}$ and $\mathbf{G}_{\text{RIS}} = [\mathbf{G}_1^H,...,\mathbf{G}_R^H]^H \in \mathcal{C}^{RN_{RIS}\times N_t}$. Then, the objective in (22) can be re-formulated as $\mathrm{Tr}(\mathbf{\Theta}^H \mathbf{H}_{\text{RIS}} \mathbf{H}_{i_m^n}^{\text{RIS},H} \mathbf{\Theta} \mathbf{G}_{\text{RIS}} \mathbf{W}_{i_m} \mathbf{G}_{\text{RIS}}^H)$. Further, by defining $\mathbf{v}_\Theta$ as the vector collecting the diagonal elements of $\mathbf{\Theta}$, according to [21], we can transform the objective into $\mathbf{v}_\Theta^H \mathbf{E} \mathbf{v}_\Theta$, where $\mathbf{E} = (\mathbf{H}_{\text{RIS}} \mathbf{H}_{i_m^n}^{\text{RIS},H}) \odot (\mathbf{G}_{\text{RIS}} \mathbf{W}_{i_m} \mathbf{G}_{\text{RIS}}^H)$. Operator $\odot$ represents the Hadamard product.

We can transform the RIS phase design problem into a semi-definite program (SDP) as follows:

$$\underset{\mathbf{V}_\Theta}{\text{maximize}} \quad \mathrm{Tr}(\mathbf{E}\mathbf{V}_\Theta) \tag{23a}$$
$$\text{subject to} \quad [\mathbf{V}_\Theta]_{t,t} = 1, t = 1,...,RN_{RIS}, \tag{23b}$$
$$\mathbf{V}_\Theta \succeq 0 \quad , \tag{23c}$$
$$\mathrm{rank}(\mathbf{V}_\Theta) = 1 \quad , \tag{23d}$$

where $\mathbf{V}_\Theta \triangleq \mathbf{v}_\Theta \mathbf{v}_\Theta^H$. To deal with the rank-one constraint in (23), we introduce the semi-definite programming relaxation (SDR) technique by dropping the rank-one constraint to solve the optimization problem below

$$\underset{\mathbf{V}_\Theta}{\text{maximize}} \quad \mathrm{Tr}(\mathbf{E}\mathbf{V}_\Theta) \tag{24a}$$
$$\text{subject to} \quad [\mathbf{V}_\Theta]_{t,t} = 1, t = 1,...,RN_{RIS}, \tag{24b}$$
$$\mathbf{V}_\Theta \succeq 0 \tag{24c}$$

Problem (24) provides an upper bound for Problem (23) and its optimal solution can be found by standard tools of mathematical programming such as CVX [22]. Note that Problem (24) is the relaxed version of Problem (23), which means we cannot guarantee $\mathbf{V}_\Theta^{\text{opt}}$ is rank-one. When the rank of $\mathbf{V}_\Theta^{\text{opt}}$ is larger than one, we cannot recover $\mathbf{v}_\Theta^{\text{opt}}$ from $\mathbf{V}_\Theta^{\text{opt}}$ straightforwardly. In such cases, we use the same technique as [23], in which we generate a set of candidates which obey the distribution of $\mathcal{CN}(\mathbf{0},\mathbf{V}_\Theta^{\text{opt}})$. Then, we normalize the vector elements of each candidate. At last, we pick the normalized candidate $\mathbf{v}_\Theta^{\text{opt}}$ which maximizes $\mathrm{Tr}(\mathbf{E}\mathbf{v}_\Theta^{\text{opt}}\mathbf{v}_\Theta^{\text{opt}^H})$.

E. Joint optimization

The details of the joint optimization algorithm are described in Alg. 2. Obviously, Alg. 2 converges, since we generate a monotonically increasing sequence with an upper bound (the maximum sum-rate).

Algorithm 2 Joint Optimization

Set the sum-rate $R_{\text{sum}}[-1] \leftarrow 0$, the maximal iteration number $k_{max} \leftarrow 1000$ and the convergence threshold $\epsilon \leftarrow 10^{-3}$;
Choose feasible start points $\mathbf{p}^{\text{opt}}[0]$, $\mathbf{x}^{\text{opt}}[0]$, $\{\mathbf{w}_k^{\text{opt}}[0]\}$, and $\mathbf{\Theta}^{\text{opt}}[0]$;
while $R_{\text{sum}}[k] - R_{\text{sum}}[k-1] \geq \epsilon R_{\text{sum}}[k-1]$ and $k \leq k_{max}$ **do**
    $k \leftarrow k+1$;
    Use Alg. 1 to find the optimal deployment;
    Solve (17) to obtain the optimal scheduling;
    Obtain the optimal beamforming vector by (21);
    Solve (23) to get the optimal RIS phases;
    Calculate $R_{\text{sum}}[k]$;
end while
Return $\mathbf{p}^{\text{opt}}$, $\mathbf{x}^{\text{opt}}$, $\{\mathbf{w}_k^{\text{opt}}\}$, and $\mathbf{\Theta}^{\text{opt}}$.

V. Simulation results

In this section, we provide some simulation results for our proposed joint optimization algorithm. We consider a scenario where a UAV serves 4 users in 10 timeslots with the assistance of 2 RIS. The UAV serves the users using a mmWave carrier. We choose 28 GHz as the carrier's frequency, since 28 GHz is a typical frequency band in urban areas [24]. The parameters in Eq. (5) are set as $a = 11.95$ and $b = 0.14$. The channel gain coefficient a_k^n is generated according to a complex Gaussian distribution $a_k^n \sim \mathcal{CN}(0,10^{-0.1\kappa})$, where $\kappa = e + 10f\log_{10}(s) + \eta$. Parameter s is the distance between the UAV and the user. We calculate s according to the UAV's position in the previous timeblock. Parameters f and e are constants and $\eta \sim \mathcal{N}(0,\sigma_\eta)$. When the channel is an LoS channel, $f = 2$, $e = 61.4$ and $\sigma_\eta = 5.8$. When the channel is a Non-LoS channel, $f = 2.92$, $e = 72$ and $\sigma_\eta = 8.7$.

In our simulations, the positions of the RIS are $(10,10,0)$ and $(40,40,0)$. The UAV and the RIS are all equipped with a 64 (16×4) antenna array. We set the amplitude of the moving step for the UAV to be 5 meters. The initial position $\mathbf{p}[0] = (25,25,50)$. At each timblock, we randomly generate the positions of the users. The total number of timeblocks is 1000. We use the averaged sum-rate and minimum rate per timeblock as the measurements of our system.

In Figs. 3 and 4, we compare the sum-rate and the minimum rate among the system which uses our proposed joint optimization method, the system that optimizes the deployment without the assistance of RIS, the system which optimizes the beamforming vector and RIS phases but not the deployment, and the system without the best deployment and the optimal beamforming vector and RIS phases. The power of the Gaussian white noise is set to be -100 dBm and the minimum rate constraint is 1 bit/Hz. The results show that our joint optimization method brings great gains over the other three systems in both the sum-rate and the minimum rate.

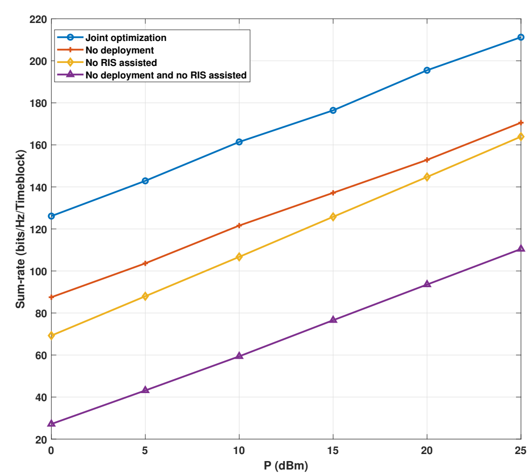

Fig. 3: Sum-rate comparison

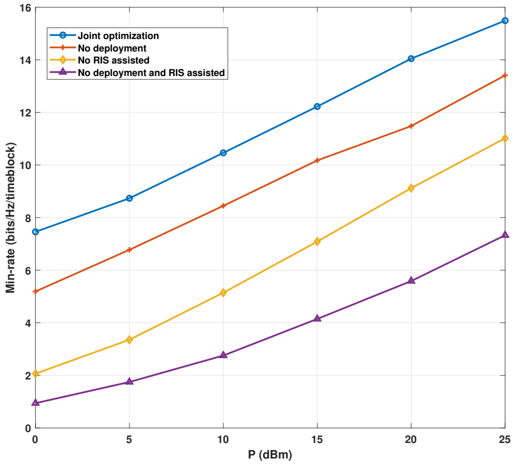

Fig. 4: Minimum rate comparison

VI. Conclusion

In this paper, we jointly optimized the deployment, user scheduling, beamforming vector, and RIS phases in a RIS assisted UAV wireless network. To solve the problem, we iterated among the 4 variables. While optimizing one variable, we fixed the other 3 variables. For the deployment, we found the optimal position by a sphere search. Then, we formulated an integer linear programming to find the best scheduling. We also designed the analog beamforming vector by compensating the phases of the channel. When optimizing the RIS phases, we formulated a semi-definite programming to find the best phases. The proposed joint optimization outperforms the system without RIS assistance, and the system without deployment optimization.

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