On Energy Efficiency and Fairness Maximization in RIS-Assisted MU-MISO mmWave Communications

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Abstract—Reconfigurable intelligent surfaces (RISs) are considered to be a promising solution to overcome the blockage issue in the millimeter-wave (mmWave) band. Energy efficiency is an important performance metric in RIS-assisted mmWave systems with a large number of antennas. However, due to the severe path loss in mmWave systems, resource allocation algorithms tend to allocate most of the resources for the benefit of the users with higher channel gains. In this paper, we propose a lexicographic-based approach to find the optimal power allocation, RIS passive beamforming matrix, and analog precoders that maximize both energy efficiency and user fairness. We solve the corresponding multi-objective optimization problem in two stages. In the first stage, we maximize the energy efficiency, and in the second stage we maximize the fairness subject to a minimum energy efficiency constraint. We propose an alternating optimization procedure to solve the optimization problem in each stage. The optimal power allocation is found using Dinkelbach’s method and convex optimization techniques in the first and second stage respectively, the RIS phase shift matrix is found using a gradient ascent algorithm, and the analog precoder is determined using beam alignment. Numerical results show that the proposed algorithm can achieve an excellent trade-off between the energy efficiency and fairness by boosting the minimum weighted rate with a minor and controllable reduction in the energy efficiency.

Keywords—Reconfigurable intelligent surfaces, mmWave communications, energy efficiency, user fairness, lexicographic approach, Dinkelbach’s method.

I. INTRODUCTION

To cope with the ever-increasing demand for better connectivity and higher data rates, the use of the millimeter-wave (mmWave) band has been investigated for the existing fifth-generation (5G) and the upcoming sixth-generation (6G) of cellular wireless communication networks [1], [2]. To address the high sensitivity to blockages in the mmWave band, the use of reconfigurable intelligent surfaces (RISs) has been proposed to create a programmable propagation environment by controlling the phase of the incident signals using low-cost nearly-passive reflecting elements [3]. Recent research contributions draw more attention to the energy efficiency of mmWave systems [4], where the spectral efficiency should be enhanced at a minimal expense in additional power consumption. Two solutions for EE maximization were proposed in [5]; one is gradient-based and the other uses a sequential fractional programming based alternating optimization approach. A genetic approach was proposed in [6] based on a covariance matrix adaptation evolution strategy and Dinkelbach’s method to maximize the EE in mmWave and terahertz systems. The optimal beamformer design was obtained in [7] along with an asymptotic channel capacity characterization under hardware impairments. Furthermore, a long short-term memory (LSTM) deep neural network was utilized to boost the EE in [8].

Due to the high path loss in mmWave systems, users served by the same base station (BS) can have significantly different channel strengths. When user fairness is ignored, EE optimization algorithms tend to offer a very low quality of service (QoS) to users with weaker channels, as such users make only a minor contribution to the EE objective function. One solution to avoid this is to incorporate QoS constraints into the optimization problem, e.g., by forcing the rate of each user to be greater than a specific threshold. However, determining these threshold rates can be problematic as it can make the optimization problem infeasible. Moreover, the results in [5] showed that setting high thresholds can severely impact the EE of the system. To avoid this, a multi-objective function was formulated in [9] which combines the sum rate and Jain’s fairness index; a successive convex approximation method was proposed to solve the resulting non-convex optimization problem. The minimum rate in the system was maximized in [10] whereas the minimum EE of the individual users was targeted in [11].

In this paper, we target the maximization of both EE and fairness in an RIS-assisted multiuser multiple-input single-output (MU-MISO) mmWave system. First, we formulate a multi-objective optimization problem which focuses on maximizing the system’s EE as well as the fairness between users, which is expressed in terms of proportional rates. The former is an important aspect of system design while the latter is crucial to ensure the QoS of end users. Next, we use a lexicographic method to divide the optimization problem into two stages. In the first stage, we maximize the EE only, and in the second stage, we maximize the fairness subject to an EE constraint derived from the solution found in the first stage. In each stage, we use an alternating optimization (AO) framework to find the optimal power allocation, RIS phase shift matrix and analog precoders. We provide extensive numerical results to evaluate the performance of the proposed method, and demonstrate its performance superiority with respect to the state-of-the-art EE and fairness maximization techniques of [5] and [11].

Notations: Bold lowercase and uppercase letters denote vectors and matrices, respectively. |·| and arg(·) are the
magnitude and the angle of a complex number, respectively (for a complex vector, they are assumed to operate element-wise). $\| \cdot \|$ is the Euclidean norm. $(\cdot)^\top$ is matrix transpose. $I_a$ is an $a \times a$ identity matrix. $O_{a \times b}$ and $I_{a \times b}$ are $a \times b$ matrices all of whose elements are equal to zero and one, respectively. $\text{diag}(a_1, \ldots, a_N)$ is a diagonal matrix with the elements $a_1, \ldots, a_N$ on the main diagonal and zeros elsewhere. $\mathbb{C}$ and $\mathbb{R}^+$ indicate the set of the complex and non-negative real numbers, respectively. $j = \sqrt{-1}$ is the imaginary unit. $\mathbb{E}\{\cdot\}$ stands for the expectation operator. $\mathcal{CN}(0, b)$ represents a complex Gaussian random distribution with a mean of 0 and a variance of $b$, and $\mathcal{U}(a, b)$ represents a uniform distribution between $a$ and $b$. $\nabla_a f(\cdot)$ represents the gradient of the real-valued function $f(\cdot)$ with respect to $a$.

II. SYSTEM MODEL

We consider a downlink mmWave system in which a base station (BS) equipped with $M$ antennas communicates with $K$ single-antenna users as shown in Fig. 1. The direct links between the BS and the users are assumed to be blocked and the communication takes place via a frequency-flat RIS with $N$ reflecting elements. In the following subsections, we describe the received signal model and channel model.

We assume that the users are served using frequency-division multiple access (FDMA).\(^1\) The signal received by user $k$ is

$$y_k = h_{2,k} \Theta H_{1,k} v_k \sqrt{p_k s_k} + n_k, \tag{1}$$

where $h_{2,k} \in \mathbb{C}^{1 \times N}$ is the channel between the $k$-th user and the RIS, $\Theta = \text{diag}(\theta_1, \ldots, \theta_N) \in \mathbb{C}^{N \times N}$ is the RIS phase shift matrix with $\theta_n = e^{j\theta_n}$ and $\theta_n \in [0, 2\pi)$, $H_{1,k} \in \mathbb{C}^{N \times M}$ is the BS-RIS channel corresponding to the $k$-th user, $v_k \in \mathbb{C}^{M \times 1}$ is the analog precoder for user $k$ with each element having a magnitude of $1/\sqrt{M}$, $p_k \in \mathbb{R}^+$ is the power allocated to user $k$ with $\sum_{k=1}^K p_k \leq P_{\text{max}}$ where $P_{\text{max}}$ is the total power budget, $s_k$ is the symbol to be transmitted to the $k$-th user satisfying $\mathbb{E}\{|s_k|^2\} = 1$, and $n_k \sim \mathcal{CN}(0, \sigma^2)$ is the complex additive white Gaussian noise (AWGN).

III. PROBLEM FORMULATION

In this section, we formulate the multi-objective EE and fairness optimization problem. We assume that channel state information is available at the transmitter.\(^2\) The rate of the $k$-th user can be expressed as

$$R_k(p_k, \Theta, v_k) = B_k \log_2 \left( 1 + \frac{1}{\sigma^2} p_k |h_{2,k} \Theta H_{1,k} v_k|^2 \right), \tag{2}$$

where $B_k$ is the bandwidth allocated to the $k$-th user. For simplicity, we assume $B = B_1 = \cdots = B_K$.

On the other hand, the total power consumption of the system can be written as [5]

$$P_{\text{tot}}(p) = P_{\text{BS}} + \xi \sum_{k=1}^K p_k + N P_{\theta} + \sum_{k=1}^K P_{\text{RIS}}, \tag{3}$$

where $p = [p_1, \ldots, p_K]^T$, $P_{\text{BS}}$ is the total hardware static power consumption at the BS, $\xi$ is the power amplifier efficiency at the BS, $P_{\theta}$ is the power consumption of each phase shifter at the RIS, and $P_{\text{RIS}}$ is the hardware static power dissipated by user $k$.

The energy efficiency (EE) is then defined as

$$\eta_{\text{EE}}(p, \Theta, V) = \frac{R_{\text{sum}}(p, \Theta, V)}{P_{\text{tot}}(p)}, \tag{4}$$

where $R_{\text{sum}}(p, \Theta, V) = \sum_{k=1}^K R_k(p_k, \Theta, v_k)$, and $V = [v_1, \ldots, v_K]$.

Because of the high path loss in mmWave systems, some users may have significantly lower channel gains than others. For such a situation, maximizing (4) leads to allocating most of the resources in favor of the dominant users and ignoring those with small channel gains. As a result, achieving fairness among users in the system is also of high importance. This can be done by maximizing the following objective function:

$$F(p, \Theta, V) = \min_{k \in \{1, \ldots, K\}} \frac{R_k(p_k, \Theta, v_k)}{w_k}, \tag{5}$$

where $w_k$ is a weight assigned to the $k$-th user by the service provider and represents the relative QoS of that user.

The general EE and fairness optimization problem can then be formulated as a multi-objective optimization problem as follows:

$$\max_{p, \Theta, V} \left[ \eta_{\text{EE}}(p, \Theta, V), F(p, \Theta, V) \right] \tag{6a}$$

s.t. $|\theta_n| = 1, \quad \forall n = 1, \ldots, N,$ \hspace{1cm} (6b)

$$\sum_{k=1}^K p_k \leq P_{\text{max}}, \hspace{1cm} (6c)$$

$$p_k \geq 0, \quad \forall k = 1, \ldots, K,$$ \hspace{1cm} (6d)

$$|v_{k,m}| = \frac{1}{\sqrt{M}}, \quad \forall k = 1, \ldots, K, \forall m = 1, \ldots, M, \hspace{1cm} (6e)$$

\(^2\)A similar assumption regarding the perfect CSI availability in different RIS-assisted systems was considered in [5]–[11]. The results in this paper serve as theoretical performance bounds for the corresponding system with imperfect CSI.
where \( v_{k,m} \) is the \( m \)-th element of \( v_k \). This multi-objective optimization problem is challenging to solve due to the presence of two objective functions that can have positive or negative correlation trends. To address this issue, we adopt a lexicographic approach [13], which divides (6) into two stages.

In the first stage, EE maximization is targeted by solving the following optimization problem:

\[
\eta_{\text{EE}}^* = \max_{p, \Theta, V} \eta_{\text{EE}}(p, \Theta, V) \quad \text{s.t.} \quad (6b), (6c), (6d), (6e).
\]  
\( \eta_{\text{EE}}^* \)

Once \( \eta_{\text{EE}}^* \) is obtained, the fairness can be maximized subject to an EE constraint in the second stage via

\[
\max_{p, \Theta, V} F(p, \Theta, V) \quad \text{s.t.} \quad (6b), (6c), (6d), (6e),
\]

\( \eta_{\text{EE}}(p, \Theta, V) \geq \rho \eta_{\text{EE}}^*, \)

where \( \rho \in (0, 1) \) is a design parameter. This optimization problem indicates that the fairness should be maximized at the expense of reducing the EE by a factor not greater than \((1 - \rho)\).

The optimal solutions to the optimization problems (7) and (8) are difficult to obtain directly due to the non-convexity of these problems with respect to the optimization variables and the coupling of the optimization variables in the objective functions. In the next section, we propose an alternating optimization framework to solve (7) and (8).

IV. PROPOSED SOLUTION

In this section, we present the method of solving (7) and (8) using an AO method for solving each optimization problem.

A. Stage 1: EE Maximization

1. Power allocation: For fixed values of the RIS phase-shift matrix and analog precoders, we target maximizing (4) with respect to the power allocation vector \( p \) subject to the constraints (6c) and (6d). Dinkelbach’s algorithm [14] can be used to efficiently solve this fractional programming problem. Specifically, the objective function (4) can be transformed into a concave function as \(^3\)

\[
\mathcal{G}(p, \omega^{(t-1)}) = R_{\text{sum}}(p) - \omega^{(t-1)} P_{\text{ue}}(p),
\]

where \( \omega^{(t)} \triangleq \eta_{\text{EE}}(p^{(t)}) \) and \( p^{(t)} \) denotes the value of \( p \) in the \( t \)-th iteration. The optimal power allocation can be obtained by finding the optimal value of \( p \) that maximizes the concave function (9) subject to the constraints (6c) and (6d) (this can be achieved using a standard algorithm, such as the interior-point method or active-set method, via the CVX toolbox [15] with \( \omega^{(t)} \) updated in each iteration until convergence. A summary of the power allocation algorithm for EE maximization is given in Algorithm 1.

\( ^3 \)Having some arguments omitted in a multi-variable function indicates that their values are being held fixed.

| Algorithm 1: Power allocation based on Dinkelbach’s method for EE maximization. |
|---|
| **Input**: \( \Theta, V, \omega^{(1)} = 0, \tau = 1, \epsilon > 0 \) |
| **Output**: \( p^{(\tau)} \) |
| **repeat** |
| 1. Solve the concave optimization problem \( p^{(\tau+1)} = \arg \max_p \mathcal{G}(p, \omega^{(\tau)}) \quad \text{s.t.} \quad (6c), (6d), \) |
| 2. where \( \mathcal{G}(\cdot) \) is given by (9); |
| 3. \( \omega^{(\tau+1)} = \eta_{\text{EE}}(p^{(\tau+1)}, \Theta, V); \) |
| 4. \( \tau \leftarrow \tau + 1; \) |
| **until** \( |\omega^{(\tau)} - \omega^{(\tau-1)}| < \epsilon; \) |

2. Phase shift matrix: Since the phase shift matrix appears only in the numerator of (4), it is sufficient to maximize \( R_{\text{sum}} \) subject to the constraint (6b).

We use the following substitutions for clarity:

\[
H_{1,k} v_k = [b_{1,k} e^{j\gamma_{1,k}}, b_{2,k} e^{j\gamma_{2,k}}, \ldots, b_{N,k} e^{j\gamma_{N,k}}]^T, \quad (10)
\]

\[
h_{2,k} = [c_{1,k} e^{j\mu_{1,k}}, c_{2,k} e^{j\mu_{2,k}}, \ldots, c_{N,k} e^{j\mu_{N,k}}], \quad (11)
\]

where \( b_{n,k}, c_{n,k} \in \mathbb{R}^+, \) and \( \gamma_{n,k}, \mu_{n,k} \in [0, 2\pi] \). Using (10) and (11), we can express the effective channel gain as

\[
h_k = \|h_{2,k} \Theta H_{1,k} v_k\|^2 = \sum_{i=1}^{N} b_{i,k}^2 + 2 \sum_{m=1}^{N-1} \sum_{\ell=m+1}^{N} \left[ b_{m,k} c_{m,k} b_{\ell,k} c_{\ell,k} \cos(\theta_m - \theta_{\ell} + \psi_{m,k} - \psi_{\ell,k}) \right],
\]

where \( \psi_{i,k} = \gamma_{i,k} + \mu_{i,k} \).

Therefore

\[
\frac{\partial R_k}{\partial \theta_n} = -2 b_{n,k} c_{n,k} \sum_{i=1,i\neq n}^{N} \frac{b_{i,k} c_{i,k} \sin(\theta_i - \theta_n + \psi_{n,k} - \psi_{i,k})}{\sigma_n^2 + p_k h_k}.
\]

and

\[
\frac{\partial R_k}{\partial \theta_n} = \frac{B}{\ln 2} \left( \frac{p_k}{\sigma_n^2 + p_k h_k} \right) \frac{\partial h_k}{\partial \theta_n}. \quad (14)
\]

where \( \theta = [\theta_1, \ldots, \theta_n]^T \). Also, we can obtain

\[
\frac{\partial R_{\text{sum}}}{\partial \theta_n} = \sum_{k=1}^{K} \frac{\partial R_k}{\partial \theta_n},
\]

and the update of \( \theta \) should follow

\[
\theta^{(t+1)} = \theta^{(t)} + \alpha \nabla_\theta R_{\text{sum}}(\theta^{(t)}),
\]

where \( \theta^{(t)} \) denotes the value of \( \theta \) at the \( t \)-th iteration, \( \alpha > 0 \) is the step size, and \( \nabla_\theta R_{\text{sum}}(\theta) = \left[ \frac{\partial R_{\text{sum}}}{\partial \theta_1}, \ldots, \frac{\partial R_{\text{sum}}}{\partial \theta_n} \right]^T \).

3. Analog precoder: The \( k \)-th user’s analog precoder optimization problem is given by

\[
\max_{v_k} \|h_{2,k} \Theta H_{1,k} v_k\|^2 \quad \text{s.t.} \quad (6c).
\]
Let\[ h_{2,k}\Theta_{1,k} = [s_1 e^{j\beta_1}, \ldots, s_M e^{j\beta_M}], \quad (18) \]
and\[ v_k = 1/\sqrt{M} \left[ e^{j\varphi_1}, \ldots, e^{j\varphi_M} \right]^T, \quad (19) \]
where \( s_n \in \mathbb{R}^+ \) and \( \beta_n, \varphi_n \in [0, 2\pi) \). Then the objective function in (17) can be written as
\[ |h_{2,k}\Theta_{1,k}v_k|^2 = \frac{1}{\sqrt{M}} \left| \sum_{i=1}^M s_i e^{j(\varphi_i + \beta_i)} \right|^2 \leq \frac{1}{\sqrt{M}} \left( \sum_{i=1}^M |s_i|^2 \right)^2, \quad (20) \]
where the upper bound is obtained by using the triangle inequality and setting \( \varphi_i = -\beta_i \) \( \forall i = 1, \ldots, M \).

B. Stage 2: Fairness Maximization with an EE Constraint

1. Power allocation: Next, we target the optimization problem (8) with respect to the power allocation vector \( p \). Using a slack variable \( z \) and by dropping the constant terms, the problem in (8) can be reformulated as
\[
\begin{align*}
\max_{p,z} & \quad z \quad (21a) \\
\text{s.t.} & \quad (6c) \text{ and } (6d), \\
& \quad R_{\text{sum}}(p) \geq \rho_{\text{EE}} P_{\text{tot}}(p), \quad (21b) \\
& \quad 1/w_k R_k(p) \geq z, \quad \forall k = 1, \ldots, K, \quad (21c) \\
& \quad 1 - \delta R_k(p) \geq z, \quad \forall k = 1, \ldots, K, \quad (21d)
\end{align*}
\]
which is a concave optimization problem amenable to solution via standard solvers such as CVX.

2. Phase shift matrix: As the next step in the AO approach, we consider the optimization problem (8) with respect to the phase shift matrix. The derivative of the minimum function in (5) is non-smooth and has discontinuities at points where \( \frac{R_k}{w_k} = \frac{R_i}{w_i} \), where \( i, k \in \{1, \ldots, K\} \) and \( i \neq k \). Therefore, the gradient ascent method cannot be applied directly. To resolve this issue, we use the well-known log-sum-exp (LSE) approximation to approximate \( F \) as [16]
\[ F \approx \tilde{F} = -\frac{1}{\zeta} \ln \left( \sum_{k=1}^K e^{-\zeta R_k/w_k} \right), \quad (22) \]
where \( \zeta > 0 \) is a smoothing parameter. This approximation is accurate for sufficiently large values of \( \zeta \).

The partial derivative of \( \tilde{F} \) with respect to \( \theta_n \) can be written as
\[ \frac{\partial \tilde{F}}{\partial \theta_n}(\theta) = \sum_{k=1}^K \frac{1}{w_k} \frac{\partial R_k}{\partial \theta_n} e^{-\zeta R_k/w_k}, \quad (23) \]
which is a continuous function of \( \theta \). Therefore, the expression (23) can be used as an approximation to the partial derivative \( \partial F/\partial \theta_n \).

The update of \( \theta \) should then follow
\[ \theta^{(t+1)} = \theta^{(t)} + \alpha \nabla_\theta \tilde{F}(\theta^{(t)}), \quad (24) \]
where \( \nabla_\theta \tilde{F}(\theta) = [\frac{\partial \tilde{F}}{\partial \theta_1}(\theta), \ldots, \frac{\partial \tilde{F}}{\partial \theta_N}(\theta)]^T \). However, the constraint (21c) should be checked after each update of \( \theta \); if it is violated by the new value of \( \theta \), the update is not accepted by the algorithm.

3. Analog precoder: Since it is required to maximize the effective channel gain of the user with the minimum weighted rate, we can follow the same procedure as in the EE maximization (Stage 1) to obtain the analog precoder.

The two-stage optimization procedure is summarized in Algorithm 2.

V. Numerical Results

In this section, the performance of the proposed method is demonstrated and compared with that of two benchmark schemes, the pure EE maximization scheme of [5], and the EE-aware fairness maximization scheme of [11].

A cubic cell with a side of 150 m is considered in simulations with the BS located at the point \((0, 0, 0) \) m having \( M = 16 \) antennas that serve four users with \( w_k \sim U(1, 4) \). FDMA transmission is used with a center frequency for the k-th user of \( f_k = 27.75 + (2k - 1)0.0625 \) GHz (each user has a bandwidth of 125 MHz). A spacing of \( \lambda_c/2 \) is assumed between two adjacent antennas at the BS, where \( \lambda_c \) is the carrier wavelength for the system center frequency \( f_c = 28 \) GHz. The number of RIS elements is assumed to be \( N = 64 \) (unless stated otherwise) with both vertical and horizontal spacings of \( \lambda_c/2 \) between adjacent elements.

We assume that the locations of the users are uniformly distributed in the cuboidal region with opposite corners at \((30, -75, 0) \) m and \((150, 75, 2) \) m. The total hardware static power at the BS is \( P_B = 9 \) dBW, while that of the k-th UE is \( P_{U,k} = 10 \) dBm. The power consumption of each RIS phase shifter is assumed to be \( P_S = 1 \) dBm and the circuit dissipated power coefficient at the BS \( \xi \) is set to 1.2 [5]. The minimum function approximation parameter \( \zeta \) is set to 50 and the algorithmic convergence threshold is selected to be \( \epsilon = 1 \times 10^{-3} \).

Monte Carlo simulation is performed to obtain the results by averaging the performance metric over 1000 independent realizations of small-scale fading and user locations. The widely used Saleh-Valenzuela (SV) channel model [17] is adopted, where the number of paths is assumed to be \( L = 4 \) [5], [6]. The path gain of the LoS component is calculated using the free space path loss formula, and a difference of 15 dBm is assumed between the LoS and NLoS path gains [18]. The small-scale fading is modeled as a Gaussian random variable with zero mean and unit variance.

Two metrics are used to compare the performance of the different methods; the EE (defined in (4)) and Jain’s fairness index for weighted rates, which is defined as [19]
\[ F_J = \frac{\sum_{k=1}^K R_k/w_k}{K \sum_{k=1}^K (R_k/w_k)^2} \in [1/K, 1], \quad (25) \]
where \( F_J = 1 \) indicates that all users have the same weighted rate \( R_k/w_k \).

To examine the convergence of the objective functions (4) and (5) during Algorithm 2, we plot the EE and the minimum
respectively, for EE maximization (Stage 1) and fairness maximization (Stage 2) at $P_{\text{max}} = 25$ dBm.

Fig. 5. Average Jain’s fairness index as the power budget varies for EE maximization [5], EE-aware fairness maximization [11], and the proposed approach.

Figs. 6 and 7 depict the EE and Jain’s fairness index as a function of the number of RIS elements increases for both EE maximization [5], EE-aware fairness maximization [11], and the proposed approach.

VI. CONCLUSION

This paper presents a two-stage lexicographic approach to find the optimal power allocation, RIS phase shift matrix, and analog precoders that maximize both EE and fairness in an RIS-assisted mmWave MU-MISO system. First, the EE is maximized by ignoring the fairness, and then the minimum weighted rate is maximized subject to a constraint on the allowable reduction in the optimal EE. The optimization
Algorithm 2: Lexicographic approach for EE and fairness maximization.

Input: $\zeta \geq 0$, $\rho \in [0, 1]$, $\alpha > 0$, $\Theta^{(1)} = I_N$, $V^{(1)} = \frac{1}{\sqrt{M}} M_{K} X_{K}$, $\eta^{(1)} = 0$, $t = 1$, $\epsilon > 0$

Output: $p = p^{(t)}$, $\Theta = \Theta^{(t)}$, $V = V^{(t)}$

/* Stage 1: EE maximization */
repeat
\[ \text{Compute } p^{(t+1)} \text{ using Algorithm 1;} \]
\[ \theta^{(t)} \leftarrow 0_{N \times 1}, i = 1; \]
repeat
\[ \theta^{(i+1)} = \theta^{(i)} + \alpha \nabla_{\theta} R_{\text{sum}}(\theta^{(i)}); \]
\[ i \leftarrow i + 1; \]
until $\|\theta^{(i)} - \theta^{(i-1)}\|_\sigma < \epsilon$;
\[ \Theta^{(t+1)} = \text{diag}(\exp(\theta^{(i)})); \]
for $k = 1, 2, \ldots, K$ do
\[ \beta_k = \text{arg}(1_{2K} \Theta_{h,k}); \]
\[ v^{(t+1)} = \frac{1}{\sqrt{M}} e_j \beta_k; \]
end
\[ V^{(t+1)} = [v^{(t+1)}, \ldots, v_K^{(t+1)}]; \]
Compute $F_{\text{EE}}^{(t+1)}(p^{(t+1)}, \Theta^{(t+1)}, V^{(t+1)})$ using (4);
\[ t \leftarrow t + 1; \]
until $|\eta^{(t)} - \eta^{(t-1)}| < \epsilon$;
\[ \eta^{(t)} = \eta^{(t)}; \]
/* Stage 2: Fairness maximization with EE constraint */
\[ F^{(t)} = F(p^{(t)}, \Theta^{(t)}, V^{(t)}); \]
repeat
Solve the concave optimization problem
\[ (p^{(t+1)}, z^{(t+1)}) = \arg \max_z z \text{ s.t. (6c),(6d),(21c),(21d);} \]
\[ \theta^{(t)} = \theta^{(t)}; \]
repeat
\[ \theta^{(i+1)} = \theta^{(i)} + \alpha \nabla_{\theta} F(\theta^{(i)}); \]
Compute $\eta_{\text{EE}}(\theta^{(i+1)})$ using (4);
if $\eta_{\text{EE}}(\theta^{(i+1)}) \geq \rho \eta_{\text{EE}}^*$ then
\[ \theta^{(i+1)} = \theta^{(i)} - \alpha \nabla_{\theta} F(\theta^{(i)}); \]
break out of the loop;
end
\[ i \leftarrow i + 1; \]
until $\|\theta^{(i)} - \theta^{(i-1)}\|_\sigma < \epsilon$;
\[ \Theta^{(t+1)} = \text{diag}(\epsilon \theta^{(i)}); \]
Compute $V^{(t+1)}$ as per lines 9-13;
Compute $F^{(t+1)}(p^{(t+1)}, \Theta^{(t+1)}, V^{(t+1)})$ using (5);
\[ t \leftarrow t + 1; \]
until $|F^{(t)} - F^{(t-1)}| < \epsilon$;

problems in both stages are solved via an AO procedure that uses Dinkelbach’s method for power allocation, gradient ascent for RIS phase shift matrix optimization, and beam alignment for analog precoder design. The results show that the proposed method can achieve a better trade-off between EE and fairness compared to benchmark methods that optimize only one of these metrics.

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