Hybrid Precoding Design for SWIPT Joint Multicast-Unicast mmWave System with Subarray Structure

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Abstract—In this paper, we investigate the hybrid precoding design for joint multicast-unicast millimeter wave (mmWave) system, where the simultaneous wireless information and power transfer is considered at receivers. The subarray-based sparse radio frequency chain structure is considered at base station (BS). Then, we formulate a joint hybrid analog/digital precoding and power splitting ratio optimization problem to maximize the energy efficiency of the system, while the maximum transmit power at BS and minimum harvested energy at receivers are considered. Due to the difficulty in solving the formulated problem, we first design the codebook-based analog precoding approach and then, we only need to jointly optimize the digital precoding and power splitting ratio. Next, we equivalently transform the fractional objective function of the optimization problem into a subtractive form one and propose a two-loop iterative algorithm to solve it. For the outer loop, the classic Bi-section iterative algorithm is applied. For the inner loop, we transform the formulated problem into a convex one by successive convex approximation techniques, which is solved by a proposed iterative algorithm. Finally, simulation results are provided to show the performance of the proposed algorithm.

Index Terms—Hybrid precoding, mmWave, Multicast, Unicast, Energy efficiency, SWIPT.

I. INTRODUCTION

Millimeter wave (mmWave) (30-300 GHz), owning the wider bandwidth, has been considered as a promising technique to meet the requirement with an exponential data traffic growth in future wireless communications [1]. Furthermore, due to the short wavelengths in mmWave bands, more antennas can be packed with a small physical size [2]. However, the use of a large number of antennas will cause a huge energy consumption and hardware cost when fully digital signal processing is applied, in the sense that each antenna needs a dedicated radio frequency (RF) chain, and the power consumption of the RF chain is as high as 250 mW at mmWave frequencies [3]. To reduce the energy consumption, a hybrid analog/digital precoding scheme can be employed, where the required number of RF chains will be much less than that of antennas [4].

On the other hand, the simultaneous wireless information and power transfer (SWIPT) has also been identified a promising technique for future wireless communications [5]. With power splitting, the receivers split the received RF signals for information detection and energy harvesting at the same time [6]. In fact, SWIPT is a very effective solution for a multi-user system, where the interference power can be transformed into the energy at receivers. However, the interference channel

also causes the difficulty for information decoding. Therefore, how to trade off the information and harvested energy is a challenge in the SWIPT system. In addition, there is an increasing demand for video transmissions and TV broadcasting over cellular networks, where multiple users intend to receive the same content [7]. Meanwhile, each user still wishes to receive the private message, for example, in the object oriented broadcasting (OBB) scenario. As a result, the joint multicast and unicast transmission can be an effective scheme to satisfy the users for simultaneously receiving the private and common messages, and in the meantime, performance enhancement can be achieved in comparison with the conventional frequency/time division multiplexing [8].

Currently, some works have been conducted to address the above problem. For the SWIPT system, [9] studies the joint optimal power allocation and power splitting ratio to maximize the minimum signal to interference plus noise ratio (SINR) of all users. The authors in [10] apply the SWIPT to a multicast system, where multiple users share the same message. The authors propose an efficient subcarrier allocation and power allocation scheme to maximize the minimum SINR at each subcarrier. Similarly, they later formulate a nonconvex optimization problem as maximizing the minimum SINR among users in [11], and two successive convex approximation (SCA)-based iterative algorithms are proposed to solve the formulated problem. Meanwhile, they extend the system to the sparse RF chain structure at BS in [12]. For the above system, they develop an efficient antenna selection and hybrid beamforming design algorithm to minimize the transmit power. In addition, [13] investigates the spectrum and energy-efficient beamforming design problem in the mMIMO-NOMA mmWave with lens antenna array, and the ZF precoding scheme is used to reduce the inter-beam interference. Then, a dynamic power allocation algorithm is proposed to maximize the sum rate of the system. However, the existing works have not jointly investigated the multicast-unicast mmWave communication with SWIPT.

Different from the previous works, in this paper, we consider the joint multicast-unicast mmWave communication, where the SWIPT is applied at each receiver. To reduce the hardware cost and energy consumption, we consider the sparse RF chain structure at BS. Based on the above considered system, we formulate an energy efficiency (EE) maximization problem by jointly optimizing hybrid analog/digital precoding and power

Fig. 1: Multicast-unicast mmWave communications with SWIPT.

splitting ratio. Meanwhile, we consider the maximum transmit power constraint for the BS and the minimum harvested energy requirement for each receiver. The formulated problem is a nonconvex optimization problem, which is intractable in its original form. Based on this, we first propose a codebook-based analog precoding. Next, we still need to jointly optimize the digital precoding and power splitting ratio, and we equivalently transform the fractional objective function of the optimization problem into a subtractive form one and a two-loop iterative algorithm is developed to solve it. Specifically, the Bi-section iterative algorithm is applied at outer loop. However, for inner loop, we need to solve a nonconvex optimization problem. To this end, by introducing new variables and employing the SCA technique, we transform the original nonconvex optimization problem into a convex one and propose an iterative algorithm to solve it.

Notations: We use the following notations throughout this paper: $(\cdot)^*$, $(\cdot)^T$ and $(\cdot)^H$ denote the conjugate, transpose and Hermitian transpose, respectively, $\|\cdot\|$ is the Frobenius norm, $\mathbb{C}^{x \times y}$ means the space of $x \times y$ complex matrix, $\text{Re}(\cdot)$ denotes real number operation.

II. SYSTEM DESCRIPTION AND PROBLEM FORMULATION

We consider a downlink mmWave communication system as shown in Fig. 1, where the BS is equipped with N_{TX} antennas. To reduce the hardware cost and power consumption, we assume that the BS is equipped with N_{RF} RF chains ($N_{\text{RF}} \leq N_{\text{TX}}$). In addition, K ($K \leq N_{\text{RF}}$) single-antenna users are served simultaneously with multicast and unicast, and $\mathcal{K} = \{1, \dots, K\}$ denotes the set of all users. In this paper, we focus on a scenario that all users receive a common information stream by broadcast, meanwhile each user obtains a private information stream by unicast. For the subarray structure at BS, each RF chain is connected to a disjoint subset of antennas with several phase shifters as shown in Fig. 2.

The received signal by the k th user can be represented as

$$y_k = \mathbf{h}_k \mathbf{F} \mathbf{v}_k x_k + \mathbf{h}_k \mathbf{F} \mathbf{v}_0 x_0 + \mathbf{h}_k \mathbf{F} \sum_{i \neq k}^K \mathbf{v}_i x_i + n_k, \quad (1)$$

where $\mathbf{h}_k \in \mathbb{C}^{1 \times N_{\text{TX}}}$, $\mathbf{v}_k \in \mathbb{C}^{N_{\text{RF}} \times 1}$ and x_k , respectively, denote the downlink channel, digital precoding and private signal for the k th user. $\mathbf{v}_0 \in \mathbb{C}^{N_{\text{RF}} \times 1}$ and x_0 are the digital precoding and common signal for the k th user, respectively. n_k is an independent and identically distributed (i.i.d.) additive white Gaussian noise (AWGN) defined as $\mathcal{CN}(0, \delta_0^2)$. $\mathbf{F} \in \mathbb{C}^{N_{\text{TX}} \times N_{\text{RF}}}$ means the analog

Fig. 2: Subarray structure antenna

precoding matrix implemented by the equal power splitter and phase shifters [14], which can be represented as

$$\mathbf{F} = \begin{bmatrix} \mathbf{f}_1 & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{f}_2 & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{f}_{N_{\text{RF}}} \end{bmatrix}, \quad (2)$$

where $\mathbf{f}_k \in \mathbb{C}^{N_{\text{SUB}} \times 1}$ denotes the precoding vector associated with the k -th RF chain with $|(\mathbf{f}_k)_i| = 1/\sqrt{N_{\text{SUB}}}$ ($i = 1, \dots, N_{\text{SUB}}$). Here, N_{SUB} denotes the number of antennas connected to each RF chain, and we assume that N_{SUB} is the same for all RF chains with $N_{\text{SUB}} = N_{\text{TX}}/N_{\text{RF}}$ ¹.

In addition, each user splits the received signal into information decoder (ID) and energy harvester (EH). We assume that the β_k portion of received signal power is divided into the ID, while the remaining $1 - \beta_k$ portion of the received signal power is transformed into the EH. Accordingly, the received signal used for EH by the k th user can be written as

$$y_k^{\text{EH}} = \sqrt{1 - \beta_k} y_k, \quad (3)$$

and the harvested energy is

$$E_k = \varepsilon(1 - \beta_k) \left(\sum_{i=0}^K |\mathbf{h}_k \mathbf{F} \mathbf{v}_i|^2 + \delta_0^2 \right), \quad (4)$$

where $\varepsilon \in (0, 1]$ denotes the energy conversion efficiency. The received signal used for ID can be represented as

$$y_k^{\text{ID}} = \sqrt{\beta_k} y_k + n'_k, \quad (5)$$

where $n'_k \sim \mathcal{CN}(0, \delta_1^2)$ is the addition noise caused by the ID.

By using the layered division multiplexing, the common and private signal can be transmitted simultaneously [15]. At receiver, the user can decode the signals with successive interference cancellation. Based on this, each user first decodes the common signal by treating all private signals as noise², and then the private signal is decoded by subtracting the common signal from the received signal. To this end, the achievable SINR of the common signal at the k th user can be expressed as

$$\gamma_k^0 = \frac{\beta_k |\mathbf{h}_k \mathbf{F} \mathbf{v}_0|^2}{\beta_k \left(\sum_{i=1}^K |\mathbf{h}_k \mathbf{F} \mathbf{v}_i|^2 + \delta_0^2 \right) + \delta_1^2}, \quad (6)$$

and the achievable SINR of the private signal at the k th user

¹Here, N_{SUB} should be an integer. In fact, when N_{SUB} is not an integer, i.e. the number of antennas in different subarrays may be different, it is also suitable in our scheme.

²In general, the multicast message have a higher priority because it is sent to multiple users [15]. Therefore, we assume that the common signal is first decoded.

can be represented as

$$\gamma_k = \frac{\beta_k |\mathbf{h}_k \mathbf{F} \mathbf{v}_k|^2}{\beta_k \left(\sum_{i \neq k}^K |\mathbf{h}_k \mathbf{F} \mathbf{v}_i|^2 + \delta_0^2 \right) + \delta_1^2}. \quad (7)$$

For mmWave channel, we adopt a widely used geometric channel mode as follows [16],

$$\mathbf{h}_k = \sqrt{\frac{N_{\text{TX}}}{\rho_k}} \sum_{l=1}^L \alpha_k^l \mathbf{a}^H(\theta_k^l), \quad (8)$$

where ρ_k denotes the average path-loss from the BS to the k th user, and α_k represents the complex gain of the l th path. $\mathbf{a}(\theta_k^l)$ is the antenna array response vector at user k . When the uniform linear array is used, $\mathbf{a}(\theta_k^l)$ can be expressed as

$$\mathbf{a}(\theta_k^l) = \frac{1}{\sqrt{N_{\text{TX}}}} \left[1, e^{j(2\pi/\lambda)d \sin(\theta_k^l)}, \dots, e^{j(N_{\text{TX}}-1)(2\pi/\lambda)d \sin(\theta_k^l)} \right]^T, \quad (9)$$

where $\theta_k^l \in [0, 2\pi]$ is the azimuth angles of departure of the BS at the l th path, λ is the wavelength, and d is the distance between two adjacent antenna array elements.

In general, the power consumption includes two parts, namely transmit power and circuit power consumption. The circuit power consumption mainly includes baseband signal processing, RF chains and phase shifters [2]. The circuit power consumptions can be written as

$$P_C = P_{\text{BB}} + N_{\text{RF}} P_{\text{RF}} + N_{\text{TX}} P_{\text{PS}}, \quad (10)$$

where P_{BB} , P_{RF} , and P_{PS} , respectively, denote the power consumption of the baseband, the RF chain and the phase shifter. Finally, we give the total power consumption as follows

$$P_{\text{total}} = \sum_{k=0}^K \xi \|\mathbf{F} \mathbf{v}_k\|^2 + P_C. \quad (11)$$

where $\xi \geq 1$ is the inefficiency of the power amplifier.

Next, we define the EE of the system as [17]

$$\eta_{\text{EE}} = \frac{\min_{\forall k} \{\log_2(1 + \gamma_k^0)\} + \sum_{k=1}^K \log_2(1 + \gamma_k)}{P_{\text{total}}}. \quad (12)$$

In this paper, we aim to maximize the EE of the system by jointly optimizing the power splitting ratio $\beta_k (k \in \mathcal{K})$, analog precoding $\mathbf{F}$ and digital precoding $\mathbf{v}_k (k \in \{0, \mathcal{K}\})$, which is written as

$$\max_{\{\beta_k\}, \mathbf{F}, \{\mathbf{v}_k\}} \eta_{\text{EE}} \quad (13a)$$

$$\text{s.t. } E_k \geq E_k^{\min}, k \in \mathcal{K}, \quad (13b)$$

$$\sum_{k=0}^K \|\mathbf{F} \mathbf{v}_k\|^2 \leq P_{\text{max}}, \quad (13c)$$

where (13b) denotes the minimum requirement of the harvested energy for each user, and (13c) defines the maximum transmit power constraint for the BS.

III. PROPOSED HYBRID PRECODING ALGORITHM

A. Analog Precoding Design

For the sparse RF chain structure, the design of the analog precoding depends on the phase shifters. Since only quantized angles are available for the phase shifters, the selection of the precoding angles should depend on the finite-size codebook, and we assume that the codebook have the same form as the array steering vectors in (9). Based on this, we can obtain the analog precoding by searching the codebook. We define the

Algorithm 1: The Analog precoding Selection Algorithm

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1 Initialize  $\mathcal{A}$ ,  $\mathbf{F} = \mathbf{0}_{N_{\text{TX}} \times N_{\text{RF}}}$ ,  $n = 1$ .
2 while  $n \leq N_{\text{RF}}$  do
3   for  $k = 1 : K$  do
4     Compute  $\mathbf{f}_n^* = \arg \max_{\mathbf{f}_n \in \mathcal{A}} |\mathbf{h}_{k,n} \mathbf{f}_n|^2$ ,
5      $\mathbf{F}((n-1)N_{\text{SUB}} + 1 : nN_{\text{SUB}}, n) = \mathbf{f}_n^*$ ,  $\mathcal{A} = \mathcal{A} - \{\mathbf{f}_n^*\}$ ,
6      $n = n + 1$ .
7   if  $n > N_{\text{RF}}$  then
8     Break;
9   end if
10 end for
11 end while

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codebook as $\mathcal{A} = \{\mathbf{a}(\theta_k^l), \forall k, l\}$. For the subarray structure, all RF chains are connected to the disjoint subset of antennas, and each of them has one beamforming direction. To this end, we divide the channel $\mathbf{h}_k$ as $\mathbf{h}_k = [\mathbf{h}_{k,1}, \mathbf{h}_{k,2}, \dots, \mathbf{h}_{k,N_{\text{RF}}}]$, where $\mathbf{h}_{k,i}$ denotes the channel gain from the i th subarray antennas to the k th user. The analog precoding for the subarray i at the k th user can be selected as

$$\mathbf{f}_k^* = \arg \max_{\mathbf{f}_k \in \mathcal{A}} |\mathbf{h}_{k,i} \mathbf{f}_k|^2. \quad (14)$$

We summarize the analog precoding selection scheme as Algorithm 1.

B. Optimizing Digital Precoding and Power Splitting Ratio

After obtaining the analog precoding $\mathbf{F}$, we define the equivalent channel as $\hat{\mathbf{h}}_k = \mathbf{h}_k \mathbf{F}$. By introducing auxiliary variables t_0 and t_k , the original EE maximization problem can be equivalently expressed as

$$\max_{\{\beta_k\}, \{\mathbf{v}_k\}, t_0, \{t_k\}} \frac{\sum_{k=0}^K \log_2(1 + t_k)}{P_{\text{total}}} \quad (15a)$$

$$\text{s.t. } \frac{\beta_k |\hat{\mathbf{h}}_k \mathbf{v}_0|^2}{\beta_k \left(\sum_{i=1}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 \right) + \delta_1^2} \geq t_0, k \in \mathcal{K}, \quad (15b)$$

$$\frac{\beta_k |\hat{\mathbf{h}}_k \mathbf{v}_k|^2}{\beta_k \left(\sum_{i \neq k}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 \right) + \delta_1^2} \geq t_k, k \in \mathcal{K}, \quad (15c)$$

$$\varepsilon(1 - \beta_k) \left(\sum_{i=0}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 \right) \geq E_k^{\min}, k \in \mathcal{K}, \quad (15d)$$

$$\sum_{k=0}^K \|\mathbf{F} \mathbf{v}_k\|^2 \leq P_{\text{max}}, \quad (15e)$$

It is evident that (15) is a nonconvex optimization problem due to the fractional objective function (15a) and nonconvex constraints (15b)-(15d). To solve the above problem, we first equivalently transform the fractional objection function into the subtractive form. We denote q^* as the obtained maximum EE of the system, namely

$$q^* = \frac{\sum_{k=0}^K \log_2(1 + t_k^*)}{\sum_{k=0}^K \xi \|\mathbf{F} \mathbf{v}_k^*\|^2 + P_C} = \max_{\{\beta_k\}, \{\mathbf{v}_k\}, t_0, \{t_k\}} \frac{\sum_{k=0}^K \log_2(1 + t_k)}{\sum_{k=0}^K \xi \|\mathbf{F} \mathbf{v}_k\|^2 + P_C}, \quad (16)$$

where $\{\beta_k\}, \{\mathbf{v}_k\}, t_0, \{t_k\}$ should satisfy constraints (15b)-(15e). Then, we apply the following Theorem.

Theorem 1: The maximum EE q^* is obtained if and only if

$$\begin{aligned} \max_{\{\{\beta_k\}, \{\mathbf{v}_k\}, t_0, \{t_k\}\}} \sum_{k=0}^K \log_2(1+t_k) - q^* \left(\sum_{k=0}^K \xi \|\mathbf{F}\mathbf{v}_k\|^2 + P_C \right) \\ = \sum_{k=0}^K \log_2(1+t_k^*) - q^* \left(\sum_{k=0}^K \xi \|\mathbf{F}\mathbf{v}_k^*\|^2 + P_C \right) = 0, \end{aligned} \quad (17)$$

where $\sum_{k=0}^K \log_2(1+t_k) \geq 0$ and $\sum_{k=0}^K \xi \|\mathbf{F}\mathbf{v}_k\|^2 + P_C > 0$.

Proof The proof of Theorem 1 can follow the similar approach to the one in [18].

As a result, we need to solve the following optimization problem for a given q

$$\max_{\{\{\beta_k\}, \{\mathbf{v}_k\}, t_0, \{t_k\}\}} \sum_{k=0}^K \log_2(1+t_k) - q \sum_{k=0}^K \xi \|\mathbf{F}\mathbf{v}_k\|^2 \quad (18a)$$

s.t. (15b) – (15e), (18b)

where q can be regarded as a parameter and we can denote the optimal value of (18a) as $T(q)$. To this end, we have the following according to Theorem 1

$$q = q^* \Leftrightarrow T(q) = 0, \quad (19)$$

which means that searching the root for the nonlinear equation $T(q) = 0$ is equivalent to solve (15). It can be found that $T(q)$ is a strictly decreasing and convex function with respect to q , where $T(q) > 0$ with $q \rightarrow -\infty$ and $T(q) < 0$ with $q \rightarrow \infty$. Therefore, we can use the classical Bi-section method to find $T(q) = 0$, which is summarized as Algorithm 2.

Apparently, (18) is a nonconvex optimization problem due to the nonconvex constraints (15b)-(15d). Next, we define two new variables $\mu_k = 1/\beta_k$ and $\omega_k = 1/(1 - \beta_k)$, and then we reformulate the following optimization problem

$$\max_{\{\{\mu_k\}, \{\omega_k\}, \{\mathbf{v}_k\}, t_0, \{t_k\}\}} \sum_{k=0}^K \log_2(1+t_k) - q \sum_{k=0}^K \xi \|\mathbf{F}\mathbf{v}_k\|^2 \quad (20a)$$

$$\text{s.t. } |\hat{\mathbf{h}}_k \mathbf{v}_0|^2 \geq t_0 \left(\sum_{i=1}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 + \mu_k \delta_1^2 \right), k \in \mathcal{K}, \quad (20b)$$

$$|\hat{\mathbf{h}}_k \mathbf{v}_k|^2 \geq t_k \left(\sum_{i \neq k}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 + \mu_k \delta_1^2 \right), k \in \mathcal{K}, \quad (20c)$$

$$\sum_{i=0}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 \geq \frac{E_k^{\min}}{\varepsilon} \omega_k, k \in \mathcal{K}, \quad (20d)$$

$$\left\| \frac{\mu_k - \omega_k}{2} \right\|_2 \leq \mu_k + \omega_k - 2, k \in \mathcal{K}, \quad (20e)$$

$$(15e). \quad (20f)$$

Meanwhile, we have the following theorem.

Theorem 2: The optimal solution of (20) is also the optimal solution of (18).

Proof From (20e), we have $\mu_k + \omega_k \leq \mu_k \omega_k$ and $\frac{1}{\mu_k} + \frac{1}{\omega_k} \leq 1$. Assume $\{\{\mu_k^*\}, \{\omega_k^*\}, \{\mathbf{v}_k^*\}, t_0^*, \{t_k^*\}\}$ represents a global optimization solution of (20). If (20e) is satisfied with equality, namely $1/\mu_k^* + 1/\omega_k^* = 1$, it is clear that problems (18) and (20) are equivalent and we only need to replace $1/\mu_k^*$ with β_k^* for $k \in \mathcal{K}$. Otherwise, if $1/\mu_k^* + 1/\omega_k^* < 1$, we scale $\{\{\mu_k^*\}, \{\omega_k^*\}\}$

Algorithm 2: The Bi-section-Based EE Resource Allocation Algorithm

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1 Initialize  $q_s = 0, q_b \gg 0$  with  $T(q_s) > 0$  and  $T(q_b) < 0$ , a small
   constant  $\epsilon$ .
2 repeat
3   Update  $q_m \leftarrow (q_s + q_b)/2$ ,
4   Solve problem (18) and obtain  $T(q_m)$ ,
5    $q_s \leftarrow q_m$  if  $T(q_m) > 0$ , else  $q_b \leftarrow q_m$ .
6 until  $|T(q_m)| < \epsilon$ ;

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by $(1/\mu_k^* + 1/\omega_k^*)$ and have

$$\frac{1}{\mu_k^*(1/\mu_k^* + 1/\omega_k^*)} + \frac{1}{\omega_k^*(1/\mu_k^* + 1/\omega_k^*)} = 1. \quad (21)$$

It means that (20e) can satisfy the equality and the harvested power does not violate the constraint (20d) due to $1/\mu_k^* + 1/\omega_k^* < 1$. As a result, the values of $\sum_{i=1}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 + \mu_k \delta_1^2$ and $\sum_{i \neq k}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 + \mu_k \delta_1^2$ in (20b) and (20c) will become smaller. Meanwhile, we can obtain a large $\{t_0, t_k\}$ than the optimal $\{t_0^*, t_k^*\}$, which means a greater rate can be obtained for the same $\mathbf{v}_k$. It is contradictory with our original assumption, and we finish the proof.

Next, we need to solve (20), which is still a nonconvex optimization problem due to the nonconvex constraints (20b)-(20d). Let $\{\hat{\mathbf{v}}_k\} (k \in \mathcal{K})$ is a feasible solution and then, we define $\mathbf{v}_k \triangleq \hat{\mathbf{v}}_k + \Delta \mathbf{v}_k$ and have

$$\begin{aligned} |\hat{\mathbf{h}}_k \mathbf{v}_k|^2 &= (\hat{\mathbf{v}}_k + \Delta \mathbf{v}_k)^H \hat{\mathbf{H}}_k (\hat{\mathbf{v}}_k + \Delta \mathbf{v}_k) \\ &\geq 2\text{Re}\{(\hat{\mathbf{v}}_k)^H \hat{\mathbf{H}}_k \Delta \mathbf{v}_k\} + (\hat{\mathbf{v}}_k)^H \hat{\mathbf{H}}_k \hat{\mathbf{v}}_k, \end{aligned} \quad (22)$$

where $\hat{\mathbf{H}}_k = \hat{\mathbf{h}}_k^H \hat{\mathbf{h}}_k$. In this case, $|\hat{\mathbf{h}}_k \mathbf{v}_k|^2$ can be replaced by its convex approximations and the formulated problem can be solved iteratively. Accordingly, (20b)-(20d) can transform as

$$2\text{Re}\{(\hat{\mathbf{v}}_0)^H \hat{\mathbf{H}}_k \Delta \mathbf{v}_0\} + (\hat{\mathbf{v}}_0)^H \hat{\mathbf{H}}_k \hat{\mathbf{v}}_0 \geq t_0 \left(\sum_{i=1}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 + \mu_k \delta_1^2 \right) \quad (23)$$

$$2\text{Re}\{(\hat{\mathbf{v}}_k)^H \hat{\mathbf{H}}_k \Delta \mathbf{v}_k\} + (\hat{\mathbf{v}}_k)^H \hat{\mathbf{H}}_k \hat{\mathbf{v}}_k \geq t_k \left(\sum_{i \neq k}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 + \mu_k \delta_1^2 \right) \quad (24)$$

$$\sum_{i=0}^K 2\text{Re}\{(\hat{\mathbf{v}}_i)^H \hat{\mathbf{H}}_k \Delta \mathbf{v}_i\} + (\hat{\mathbf{v}}_i)^H \hat{\mathbf{H}}_k \hat{\mathbf{v}}_i + \delta_0^2 \geq E_k^{\min} \omega_k / \varepsilon. \quad (25)$$

Then, we set the new variables $\tau_k \geq \sum_{i=1}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 + \mu_k \delta_1^2$ and $\lambda_k \geq \sum_{i \neq k}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 + \mu_k \delta_1^2$, and reformulate the following optimization as

$$\max_{\{\{\mu_k\}, \{\omega_k\}, \{\tau_k\}, \{\lambda_k\}, \{\mathbf{v}_k\}, t_0, \{t_k\}\}} \sum_{k=0}^K \log_2(1+t_k) - q \sum_{k=0}^K \xi \|\mathbf{F}\mathbf{v}_k\|^2 \quad (26a)$$

$$\text{s.t. } 2\text{Re}\{(\hat{\mathbf{v}}_0)^H \hat{\mathbf{H}}_k \Delta \mathbf{v}_0\} + (\hat{\mathbf{v}}_0)^H \hat{\mathbf{H}}_k \hat{\mathbf{v}}_0 \geq t_0 \tau_k, k \in \mathcal{K}, \quad (26b)$$

$$\sum_{i=1}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 + \mu_k \delta_1^2 \leq \tau_k, k \in \mathcal{K}, \quad (26c)$$

$$2\text{Re}\{(\hat{\mathbf{v}}_k)^H \hat{\mathbf{H}}_k \Delta \mathbf{v}_k\} + (\hat{\mathbf{v}}_k)^H \hat{\mathbf{H}}_k \hat{\mathbf{v}}_k \geq t_k \lambda_k, k \in \mathcal{K}, \quad (26d)$$

$$\sum_{i \neq k}^K |\hat{\mathbf{h}}_k \mathbf{v}_i|^2 + \delta_0^2 + \mu_k \delta_1^2 \leq \lambda_k, k \in \mathcal{K}, \quad (26e)$$

$$(15e), (20e), (25). \quad (26f)$$

Algorithm 3: The Joint Digital Precoding and Power Splitting Ratio Iterative Algorithm

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1 Initialize  $\{\tau_k^{[i-1]}\}, \{\lambda_k^{[i-1]}\}, \{\mathbf{v}_k^{[i-1]}\}, t_0^{[i-1]}, \{t_k^{[i-1]}\}, i = 1$ , the maximum
   iteration times  $T_{\max}$ .
2 repeat
3   Solve the optimization problem (28) and obtain the optimal
      $\{\mu_k^{[i]}\}, \{\omega_k^{[i]}\}, \{\tau_k^{[i]}\}, \{\lambda_k^{[i]}\}, \{\mathbf{v}_k^{[i]}\}, t_0, \{t_k^{[i]}\}$ .
4   Update  $i \leftarrow i + 1$ .
5 until  $i = T_{\max}$ ;

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So far, the only nonconvex constraints are (26b) and (26d) in (26). Similar to [19], the upper of $t_0\tau_k$ and $t_k\lambda_k$ can be written as

$$\frac{t_0^{[i-1]}}{2\tau_k^{[i-1]}}\tau_k^2 + \frac{\tau_k^{[i-1]}}{2t_0^{[i-1]}}t_0^2 \geq t_0\tau_k, \quad \frac{t_k^{[i-1]}}{2\lambda_k^{[i-1]}}\lambda_k^2 + \frac{\lambda_k^{[i-1]}}{2t_k^{[i-1]}}t_k^2 \geq t_k\lambda_k, \quad (27)$$

where $\{t_0^{[i-1]}, \{\tau_k^{[i-1]}\}, \{t_k^{[i-1]}\}, \{\lambda_k^{[i-1]}\}\}$ are the value of $\{t_0, \{\tau_k\}, \{t_k\}, \{\lambda_k\}\}$ at the $(i-1)$ th iteration. Finally, we formulate the following optimization problem

$$\max_{\{\mu_k\}, \{\omega_k\}, \{\tau_k\}, \{\lambda_k\}, \{\mathbf{v}_k\}, t_0, \{t_k\}} \sum_{k=0}^K \log_2(1+t_k) - q \sum_{k=0}^K \xi \|\mathbf{F}\mathbf{v}_k\|^2 \quad (28a)$$

$$\text{s.t. } 2\text{Re}\{(\hat{\mathbf{v}}_0)^H \hat{\mathbf{H}}_k \Delta \mathbf{v}_0\} + (\hat{\mathbf{v}}_0)^H \hat{\mathbf{H}}_k \hat{\mathbf{v}}_0 \geq \frac{t_0^{[i-1]}}{2\tau_k^{[i-1]}}\tau_k^2 + \frac{\tau_k^{[i-1]}}{2t_0^{[i-1]}}t_0^2, \quad (28b)$$

$$2\text{Re}\{(\hat{\mathbf{v}}_k)^H \hat{\mathbf{H}}_k \Delta \mathbf{v}_k\} + (\hat{\mathbf{v}}_k)^H \hat{\mathbf{H}}_k \hat{\mathbf{v}}_k \geq \frac{t_k^{[i-1]}}{2\lambda_k^{[i-1]}}\lambda_k^2 + \frac{\lambda_k^{[i-1]}}{2t_k^{[i-1]}}t_k^2, \quad (28c)$$

$$(15e), (20e), (25), (26c), (26e). \quad (28d)$$

It is clear that (28) is convex optimization problem due to the concave objection function (28a) and convex constraints (28b)-(28d), which can be solve by existing convex solvers (e.g., CVX). Summarily, solving the original problem (18), we need to iteratively solve the optimal values of $\{\{\mu_k\}, \{\omega_k\}, \{\tau_k\}, \{\lambda_k\}, \{\mathbf{v}_k\}, t_0, \{t_k\}\}$ via (28). In addition, since obtained $\{\{\mu_k^{[i]}\}, \{\omega_k^{[i]}\}, \{\tau_k^{[i]}\}, \{\lambda_k^{[i]}\}, \{\mathbf{v}_k^{[i]}\}, t_0^{[i]}, \{t_k^{[i]}\}\}$ are the optimal solutions at the i th iteration, iteratively updating these variables will increase or maintain the value of the objective function (28a). To this end, the proposed iterative algorithm will converge to at least a local optimal solution, which is summarized in Algorithm 3.

IV. SIMULATION RESULTS

In this section, simulation results are provided to illustrate the effectiveness of the proposed algorithms. We assume that the BS has a coverage of 30 meters, and the path loss is modeled as $69.4 + 24 \log_{10}(d)$ dB, where d denotes the distance in meter. We assume that there are 8 paths for the mmWave channel, and the azimuth angle of departure at BS is uniformly distributed over $[0, 2\pi]$. The BS is equipped with $N_{\text{TX}} = 256$ antennas and $N_{\text{RF}} = 4$ RF chains. The noise power, δ_0^2 and δ_1^2 , are set -80 dBm and -60 dBm, respectively. The energy conversion efficiency ε and the inefficiency of the power amplifier ξ are set as 0.5 and 1/0.38, respectively. In addition, we set $P_{\text{BB}} = 200$ mW, $P_{\text{RF}} = 300$ mW, $P_{\text{PS}} = 40$ mW. Meanwhile, the minimum harvested energy is $E_k^{\min} = 100 \mu\text{W}$ for all users, the number of users is set as $K = 2$.

Fig. 3: Spectrum efficiency versus number of iterations.

Fig. 4: Energy efficiency versus number of iterations.

Fig. 3 shows the performance of convergence for the proposed Algorithms 3 under different number of RF chains, where digital structure means that each antenna is connected to one dedicated RF chain. We set $q = 0$ and the maximum transmit power $P_{\max} = 30$ dBm. It is clear that the proposed algorithm will converge after multiple iterations. In addition, one can observe that the SE under digital structure is the highest in comparison with that under subarray structure.

Fig. 4 shows the convergence property for the Algorithm 2, where we set the maximum transmit power $P_{\max} = 40$ dBm. Meanwhile, we compare the EE under different number of RF chains. It can be observed that the proposed algorithm will converge about 8 iterations. In addition, one can see that the EE with subarray structure is higher than that with digital structure. This is because although the SE with digital structure is higher as shown in Fig. 3, the circuit's power consumption is huge.

Fig. 5 shows the EE versus maximum transmit power at BS. We can observe that the EE first increases and then remains stable with $P_{\max}$. Understandably, larger transmit power can improve the SE of the system, but the rate of the SE will be lower. Therefore, the EE will reach the point of diminishing returns when the transmit power continues to increase. In addition, it is clear that the EE with sparse RF chains is higher just as explained earlier, and the digital structure still has a huge circuit's power consumption.

We examine the EE of the system under different optimiza-

Fig. 5: Energy efficiency versus max transmit power.

Fig. 6: Energy efficiency versus max transmit power.

tion schemes in Fig. 6. “Max_EE” stands that the EE of the system when the EE is maximized, while “Max_SE” represents the EE of the system when the SE is maximized. As the maximum transmit power increases, the EE reaches maximum and remains constant under “Max_EE” scheme, while the EE decreases under “Max_SE” scheme. In fact, the objection of “Max_SE” scheme is to maximize the SE without considering the power consumption. As a result, the EE may decrease for larger transmit power.

V. CONCLUSIONS

In this paper, we investigated the EE maximization problem in a joint multicast-unicast mmWave communication system with SWIPT. We first designed the analog precoding for the sparse RF chain structure. Next, we proposed a two-loop algorithm to solve the formulated EE optimization problem. The Bi-section algorithm is adopted in outer loop. Subsequently, we developed an iterative algorithm for the inner loop. Simulation

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results showed the effectiveness of the proposed algorithm, and there still a tradeoff between EE and SE.

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