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Wireless Information and Energy Transfer in MIMO Communication With Interference Channels

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ABSTRACT In this paper, we consider a wireless information and energy transfer (WIET) system, which consists of multiple information transmitter-receiver pairs, and multiple additional energy transmitters to improve the energy transfer. For such a new WIET system, we investigate the energy efficiency (EE) under two different setups, respectively: the information transmitters and energy transmitters use the same and different frequency bands. For each setup, we propose a novel centralized beamformer design method to solve the EE maximization problem, which can be transformed into a convex optimization problem using semidefinite relaxation (SDR) technique. Moreover, we develop a distributed optimization algorithm to solve the SDR approximation formulation for each setup. Simulation results show that the same frequency setup can achieve larger EE value and less computational complexity, however, suffering from lower sum rate. For each setup, the distributed scheme has slightly worse performance than the centralized one, while enjoys less computational complexity, especially when the number of the additional energy transmitters is large.

INDEX TERMS Wireless information and energy transfer, semidefinite relaxation, distributed scheme, alternating direction method of multipliers.

I. INTRODUCTION

Wireless information and energy transfer (WIET) utilizes electromagnetic waves as the information and energy carrier, which has drawn an upsurge of research interests in recent years. WIET can conveniently and perpetually provide wireless information and energy to the mobile users using the same or different frequency bands.

In general, there exist two crucial issues for realizing WIET systems in practice. One major practical issue for implementing WIET is the fact that the circuits of the receivers for harvesting energy are not able to directly decode the carried information [1]. As a result, the receiver architecture design plays a significant role in determining the trade-offs between the end-to-end information versus energy transfer. In [2], Zhang and Ho proposed time switching (TS) and power splitting (PS) receiver designs for WIET. The rate-energy tradeoff for these two architectures are characterized of their regions may be much smaller than those in the theoretically ideal case [2, Fig. 8]. In [3], Zhou *et al*. investigated various practical receiver architectures for WIET, where a new PS based integrated information and energy receiver design was proposed.

The other major issue for implementing WIET is the significant decay of energy transfer efficiency due to the propagation pass loss. Compared to the techniques based on induction and magnetic resonance coupling, radio frequency (RF) signals can achieve long-distance WET. However, the energy transferring efficiency is in general low, thus not catering for the broad practical scenarios. To tackle this problem, advanced signal processing techniques such as multiple antennas are employed in order to improve the power transfer efficiency while still achieving high spectral efficiency for information transmission. The performance limits of a three-node MIMO broadcasting system has been studied in [2], which consists of a transmitter and two separated or co-located receivers: one for harvesting energy and the other for decoding information from the same transmitted signals. The works [4], [5] respectively considered the transmission strategy for WIET in a two-user and a general K-user MIMO interference channel (IFC) under the assumption that the receivers perform either energy harvesting or information decoding.

Most current researches about MIMO based beamformers focus on beamforming design under different channel setups [6]–[8]. One general design problem is to maximize information rate under certain power constraints [9]–[11]. However, the harvested energy cannot be maximized simultaneously under this design criterion because the harvested energy will decrease with the increase of information rate and vice versa [2], [11]–[13]. In addition, most existing works provide only centralized schemes [11], [14]–[16].

Since WIET is not as efficient as expected at this stage, people propose to build up power stations that are purely used for charging purpose. Bi *et al.* [17] overviewed the applications of RF-enabled wireless energy transfer (WET) technologies in wireless power communication networks (WPCN). Lu *et. al.* [18] provided a survey about RF energy harvesting networks, where dedicated RF sources are reviewed. The works [19]–[21] proposed different energy transfer schemes for WET in order to harvest more energy. However, the efficiency for transferring energy is not satisfying [20, simulation therein]. Dedicated RF-based power transfer which may be implemented by the *Powercast company* is suitable for the scenarios where substantial power consumptions are required [22]. The current WET technology can already deliver tens of microwatts RF power to wireless devices from a distance of more than 10 meters, which implies that WPCN has great potential for low-power applications.

In order to provide more reliable and more substantial power in practice, we aim to propose novel system structure and beamforming scheme for information and energy transmission in this paper. To be more specific, the new structure includes several transmitters, of which more than one transmitter are dedicated to transmitting the energy. Moreover, the joint transmission of information and energy can been focused on by using the same or different frequency bands based on PS scheme. The beamformer design algorithms are respectively proposed in the centralized and distributed fashions to maximize the energy efficiency of the system.

The main contributions of our paper are summarized as follows.

Firstly, we propose a new WIET structure. Although there are existing many WIET structures, the amount of harvested energy is not as much as expected, as discussed above. Therefore, we introduce a novel WIET system with multiple energy transmitters (e.g., wireless charging stations) to efficiently realize information and energy transfer. The proposed novel architectures are further considered in the two setups, where the additional energy transmitters (ETs) use the same frequency bands as those of the original system, and followed by using different frequency bands.

Secondly, we propose a novel beamformer design method for the WIET system by maximizing the energy efficiency (EE), which is defined as the ratio of the information rate at the information decoder and the total transmitted energy at the transmitter side subject to the harvested energy constraint. The original formulation is nonconvex which is hard to solve, and we transform it into a convex optimization one by some equivalent transforms and semidefinite relaxation (SDR) techniques [23]. The resultant approximation formulation is convex, which can be efficiently solved by interior-point methods [24].

Thirdly, we further develop the distributed optimization algorithms that can solve the proposed SDR approximation formulation for both setups (same and different frequency bands). We consider the so called *alternating direction method of multipliers (ADMM)* [25], [26] to tackle this problem. ADMM was first introduced in [27] and [28] and has been widely introduced to various research fields [29], [30]. By introducing Gauss-Seidel iteration scheme [25] into ADMM, the original optimization problem can be decoupled into a series of separate sub-optimization problems, which leads to the original problem much easier and faster to solve [26]. Furthermore, under the augmented Lagrangian framework, ADMM is derived from the idea of the combination of dual decomposition and the augmented Lagrangian method [31]. Thus, ADMM is also more numerically stable than the conventional dual decomposition method [26], [32] because the augmented Lagrangian method makes the original problem strictly convex by adding the penalty term.

The rest of this paper is organized as follows. We describe the WIET system model under the setups of both the same frequency bands and the different frequency bands in Section II. The beamformer designs for the two setups are investigated in Sections III and IV, respectively. Then, in Section V, we illustrate the effect and efficiency of our designed algorithms. Finally, Section VI concludes the paper.

II. SYSTEM MODEL

Consider a wireless information and energy transmission (WIET) system where each receiver obtains information and power using power splitting scheme. Assume that there are N_1 transmitter-receiver pairs in the considered system, and each transmitter has M_1 antennas, while each receiver has only 1 antenna. We use the vector $\boldsymbol{h}_{ij} \in \mathbb{C}^{M_1\times 1}$ to denote the channel coefficient from the transmitter j to the receiver i. Thus, the received signal at the front end of receiver i for $i = 1, \cdots, N_1$ is denoted by

$$y_i = \boldsymbol{h}_{ii}^H \boldsymbol{v}_i s_i + \sum_{\substack{r=1,\\ r\neq i}}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{v}_r s_r + z_i,$$

where $(\cdot)^H$ denotes Hermitian transform, $s_i \in \mathbb{C}$ is a random transmitted signal with the normalized power ($\mathbb{E}[|s_i|^2] = 1$), $\boldsymbol{v}_i \in \mathbb{C}^{M_1\times 1}$ is the beamformer at the transmitter i, $y_i \in \mathbb{C}$ is the received signal at the receiver i, and $z_i \in \mathbb{C}$ is the complex Gaussian noise at the front end of the receiver i with distribution $\mathcal{CN}(0, \sigma_i^2)$.

The corresponding information signal $y_{Ii} \in \mathbb{C},\ i = 1, \cdots, N_1$, using the power splitting scheme is denoted by

$$y_{Ii} = \sqrt{\rho_i}\left(\boldsymbol{h}_{ii}^H \boldsymbol{v}_i s_i + \sum_{\substack{r=1,\\ r\neq i}}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{v}_r s_r + z_i\right) + z_{Ii},$$

where ρ_i denotes the portion of the power split to the information decoder at the receiver i, while $z_{Ii} \in \mathbb{C}$ is the complex Gaussian noise with distribution $\mathcal{CN}(0, \sigma_{Ii}^2)$.

The total harvested RF-band energy during a transmission interval Δ is assumed to be proportional to the power of the received baseband signal [2]. Note that the transmission interval Δ is inverse proportion to the bandwidth. Thus, the harvested energy $\mathcal{Q}_i,\ i = 1, \cdots, N_1$, can be represented by (ignoring the noise)

$$\mathcal{Q}_i = \gamma \Delta \mathbb{E}\left[y_{Ei} y_{Ei}^H\right] = \gamma \frac{(1-\rho_i) \sum_{r=1}^{N_1} \|\boldsymbol{v}_r^H \boldsymbol{h}_{ir}\|^2}{B},$$

where $0 \leq \gamma \leq 1$ is the power splitting factor, a constant accounting for the energy conversion loss in the transducer.

However, it may not be enough to harvest energy directly from the signal transmitted by the transmitters in practice [2]. Besides, the whole communication quality could be dramatically deteriorated by this approach as discussed in Section I. Therefore, we consider to add additional ETs to exclusively transmit the energy to the receivers in order to satisfy the quality of service (QoS) of the communication links. Assume there are additional N_2 ($N_2 < N_1$) ETs transferring energy to the receivers and the channel $\boldsymbol{f}_{ij} \in \mathbb{C}^{M_2 \times 1}$ denoting the channel from the ET j to the receiver i. The whole communication system is shown in Fig. 1.

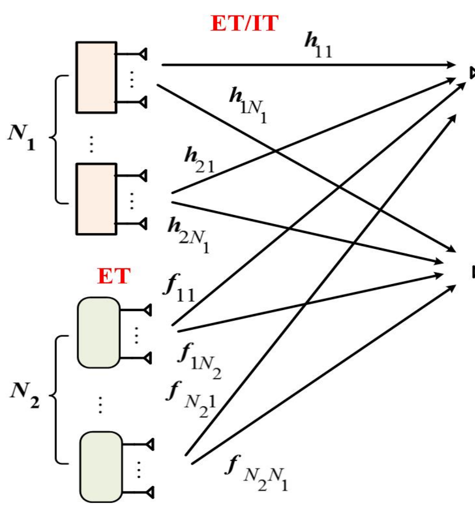

FIGURE 1. MIMO WIET system.

Consider the following two setups 1) the additional ETs use the same frequency bands as the transmitters; 2) the additional ETs use different frequency bands. In the sequel, we will establish the expressions of the received signals at each information decoder (ID) and energy harvester (EH) pair, along with the corresponding information rate and the harvested energy in these two setups.

A. SAME FREQUENCY BANDS

In this setup, each receiver uses 1 antenna to receive the signal and then split it to the ID-EH pair [2], which is shown in Fig. 2.

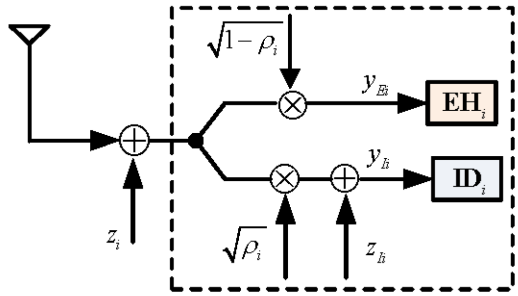

FIGURE 2. Receiver architecture I.

The received signal $y_{Ii} \in \mathbb{C}$ at the ID i, $i = 1, \cdots, N_1$, is

$$y_{Ii} = \sqrt{\rho_i}\left(\boldsymbol{h}_{ii}^H \boldsymbol{v}_i s_i + \sum_{\substack{r=1,\\ r\neq i}}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{v}_r s_r + \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \boldsymbol{u}_j s_{Ej} + z_i\right) + z_{Ii}.$$

Assume the total transmitted bandwidth is B Hz. The information rate in bits/second (bps) is achievable at the ID i, $i = 1, \cdots, N_1$ (ignoring the noise z_i),

$$\mathcal{R}_{1i} = B \log_2\left(1 + \frac{\rho_i \|\boldsymbol{v}_i^H \boldsymbol{h}_{ii}\|^2}{\rho_i \sum_{\substack{r=1,\\ r\neq i}}^{N_1} \|\boldsymbol{v}_r^H \boldsymbol{h}_{ir}\|^2 + \rho_i \sum_{j=1}^{N_2} \|\boldsymbol{u}_j^H \boldsymbol{f}_{ij}\|^2 + N_0 B}\right),$$

where N_0 is the single-band power spectral density.

The received signal $y_{Ei} \in \mathbb{C}$ at the EH i, $i = 1, \cdots, N_1$, is

$$y_{Ei} = \sqrt{1-\rho_i}\left(\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{v}_r s_r + \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \boldsymbol{u}_j s_{Ej} + z_i\right).$$

Thus, the harvested energy $\mathcal{Q}_i$ at the EH i, $i = 1, \cdots, N_1$, can be represented by (ignoring the noise z_i)

$$\mathcal{Q}_i = \gamma \frac{(1-\rho_i)\left(\sum_{r=1}^{N_1} \|\boldsymbol{v}_r^H \boldsymbol{h}_{ir}\|^2 + \sum_{j=1}^{N_2} \|\boldsymbol{u}_j^H \boldsymbol{f}_{ij}\|^2\right)}{B}.$$

B. DIFFERENT FREQUENCY BANDS

In this setup, owing to different band used for transmitting the additional energy, the channel for harvesting it is orthogonal to that for receiving the information, which leads to a different architecture used to receive the information and the harvested energy [18]. Specifically, each receiver uses 1 antenna to receive the signal mixed information with energy. Then, a band passing (BP) filter with half the total bandwidth and some center frequency f_1 ($f_1 \neq f_2$, f_2 is the center frequency used to transmit the additional energy signal) is used to extract the information signal. Each receiver architecture using different frequency bands is shown in Fig. 3.

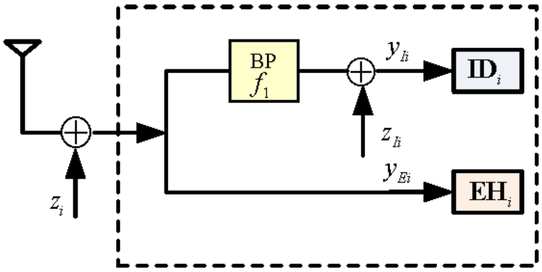

FIGURE 3. Receiver architecture II.

The received signal $y_{Ii} \in \mathbb{C}$ at the ID i, $i = 1, \cdots, N_1$, is

$$y_{Ii} = \left(\boldsymbol{h}_{ii}^H \boldsymbol{v}_i s_i + \sum_{\substack{r=1,\\ r \neq i}}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{v}_r s_r + z_i \right) + z_{Ii}.$$

Also, assume the total transmission bandwidth is B Hz. Because we use one half bandwidth to transmit the signal, the information rate in bits/second (bps) is achievable at the ID i (ignoring the noise z_i), $i = 1, \cdots, N_1$, is

$$\mathcal{R}_{2i} = \frac{B}{2} \log_2 \left(1 + \frac{\|\boldsymbol{v}_i^H \boldsymbol{h}_{ii}\|^2}{\sum_{\substack{r=1,\\ r \neq i}}^{N_1} \|\boldsymbol{v}_r^H \boldsymbol{h}_{ir}\|^2 + N_0\, B/2} \right).$$

The received signal $y_{Ei} \in \mathbb{C}$ at the EH i, $i = 1, \cdots, N_1$, is

$$y_{Ei} = \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \boldsymbol{u}_j s_{Ej} + \sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{v}_r s_r + z_i.$$

Thus, the harvested energy $\mathcal{Q}_i$ at the EH i, $i = 1, \cdots, N_1$, can be represented by (ignoring the noise z_i)

$$\mathcal{Q}_i = \gamma \frac{2 \left(\sum_{j=1}^{N_2} \|\boldsymbol{u}_j^H \boldsymbol{f}_{ij}\|^2 + \sum_{r=1}^{N_1} \|\boldsymbol{v}_r^H \boldsymbol{h}_{ir}\|^2 \right)}{B}.$$

III. BEAMFORMING DESIGN IN SAME FREQUENCY BANDS

In this section, we design the beamformers $\{\boldsymbol{v}_i, \boldsymbol{u}_j, i = 1, \cdots, N_1, j = 1, \cdots, N_2\}$ of the system for the proposed WIET architecture I using energy efficiency (EE) function as the performance metric which is defined as the ratio of the sum information rate to the transmitted power. Mathematically, it can be expressed by

$$\frac{\mathcal{R}}{\mathcal{E}} = \frac{\sum_{i=1}^{N_1} \mathcal{R}_{1i}}{\sum_{i=1}^{N_1} \|\boldsymbol{v}_i\|_2^2 + \sum_{j=1}^{N_2} \|\boldsymbol{u}_j\|_2^2},$$

Therefore, the beamformer design optimization problem in this setup is based on maximizing EE function subject to the whole harvested energy constraint at each receiver which can be formulated as

$$(\mathrm{P}_1) \quad \max_{\substack{\{\rho_i, \boldsymbol{v}_i, \boldsymbol{u}_j,\\ i=1,\cdots,N_1,\\ j=1,\cdots,N_2,\}}} \frac{\sum_{i=1}^{N_1} \mathcal{R}_{1i}}{\sum_{i=1}^{N_1} \|\boldsymbol{v}_i\|_2^2 + \sum_{j=1}^{N_2} \|\boldsymbol{u}_j\|_2^2},$$
$$\text{s.t. Eq. (1)} \geq \Gamma_i,$$
$$0 \leq \rho_i \leq 1.$$

where Γ_i is the harvested energy limit, the maximum value of the harvested energy.

Problem (P_1) is hard to solve due to the nonconcave objective function and the first nonconvex constraint [26]. However, by some mathematical manipulations, we can transform Problem (P_1) into a convex problem which is easy to tackle. In what follows, we will design the beamformer in centralized scheme, followed by that in distributed scheme.

A. CENTRALIZED DESIGN

Introducing two matrices $\boldsymbol{V}_i = \boldsymbol{v}_i \boldsymbol{v}_i^H$ and $\boldsymbol{U}_i = \boldsymbol{u}_i \boldsymbol{u}_i^H$, we can write the objective function in Problem (P_1) as

$$\frac{\sum_{i=1}^{N_1} \mathcal{R}_{1i}}{\sum_{i=1}^{N_1} tr(\boldsymbol{V}_i) + \sum_{j=1}^{N_2} tr(\boldsymbol{U}_j)},$$

where

$$\mathcal{R}_{1i} = B \log_2 \left(1 + \frac{\rho_i \boldsymbol{h}_{ii}^H \boldsymbol{V}_i \boldsymbol{h}_{ii}}{\rho_i \sum_{\substack{r=1,\\ r \neq i}}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{V}_r \boldsymbol{h}_{ir} + \rho_i \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \boldsymbol{U}_j \boldsymbol{f}_{ij} + N_0 B} \right). \tag{1}$$

The harvested energy $\mathcal{Q}_i$ at the EH i, $i = 1, \cdots, N_1$, can be rewritten as

$$\mathcal{Q}_i = \gamma \frac{(1-\rho_i) \left(\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{V}_r \boldsymbol{h}_{ir} + \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \boldsymbol{U}_j \boldsymbol{f}_{ij} \right)}{B}. \tag{2}$$

Therefore, Problem (P_1) can be reformulated as

$$\max_{\substack{\{\rho_i, \boldsymbol{V}_i, \boldsymbol{U}_j,\\ i=1,\cdots,N_1,\\ j=1,\cdots,N_2,\}}} \frac{\sum_{i=1}^{N_1} \mathcal{R}_{1i}}{\sum_{i=1}^{N_1} tr(\boldsymbol{V}_i) + \sum_{j=1}^{N_2} tr(\boldsymbol{U}_j)},$$
$$\text{s.t. Eq. (2)} \geq \Gamma_i,$$
$$0 \leq \rho_i \leq 1,$$
$$\boldsymbol{V}_i \succeq \boldsymbol{0}, \quad \boldsymbol{U}_j \succeq \boldsymbol{0},$$
$$\mathrm{rank}(\boldsymbol{V}_i) = 1, \quad \mathrm{rank}(\boldsymbol{U}_j) = 1. \tag{3}$$

By discarding $\mathrm{rank}(\boldsymbol{V}_i) = 1$ and $\mathrm{rank}(\boldsymbol{U}_j) = 1$, $i = 1, \cdots, N_1$, $j = 1, \cdots, N_2$, we can relaxedly transform (3) as follows:

$$\max_{\substack{\{\rho_i,\boldsymbol{V}_i,\boldsymbol{U}_j,\\ i=1,\cdots,N_1,\\ j=1,\cdots,N_2,\}}} \frac{\sum_{i=1}^{N_1}\mathcal{R}_{1i}}{\sum_{i=1}^{N_1} tr(\boldsymbol{V}_i)+\sum_{j=1}^{N_2} tr(\boldsymbol{U}_j)},$$
$$\text{s.t. Eq. (2)} \geq \Gamma_i,\quad 0\leq\rho_i\leq 1,\quad \boldsymbol{V}_i \succeq \mathbf{0},\quad \boldsymbol{U}_j\succeq\mathbf{0}. \tag{4}$$

Problem (4) is nonconvex due to the noncave objective function, which leads it difficult to solve. In what follows, we will use some mathematical manipulations to further transform Problem (P_1) in order to make it easy to tackle.

Introducing a slack variable t, we can reformulate (4) as

$$\max_{\substack{\{t,\rho_i,\boldsymbol{v}_i,\boldsymbol{u}_j,\\ i=1,\cdots,N_1,\\ j=1,\cdots,N_2,\}}} t\sum_{i=1}^{N_1}\mathcal{R}_{1i},$$
$$\text{s.t.} \sum_{i=1}^{N_1}\text{tr}(\boldsymbol{V}_i)+\sum_{j=1}^{N_2}\text{tr}(\boldsymbol{U}_j)=\frac{1}{t},\quad \text{Eq. (2)}\geq\Gamma_i,\quad 0\leq\rho_i\leq 1,\quad \boldsymbol{V}_i\succeq\mathbf{0},\quad \boldsymbol{U}_j\succeq\mathbf{0}. \tag{5}$$

Assume that $\rho_i = \frac{1}{\theta_i}$, $i=1,\cdots,N_1$, the information rate (1) can be expressed by

$$\mathcal{R}_{1i} = B\log_2\left(1+\frac{\boldsymbol{h}_{ii}^H\boldsymbol{V}_i\boldsymbol{h}_{ii}}{\sum_{r=1,r\neq i}^{N_1}\boldsymbol{h}_{ir}^H\boldsymbol{V}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\boldsymbol{U}_j\boldsymbol{f}_{ij}+\theta_i N_0 B}\right),$$

which, similar to [11], can be lower bounded, i.e.,

$$\mathcal{R}_{1i}\geq B\log_2\frac{\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\boldsymbol{V}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\boldsymbol{U}_j\boldsymbol{f}_{ij}+\theta_i N_0 B}{r_i^{[n-1]}} - B\frac{\sum_{r=1,r\neq i}^{N_1}\boldsymbol{h}_{ir}^H(\boldsymbol{V}_r-\boldsymbol{V}_r^{[n-1]})\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H(\boldsymbol{U}_j-\boldsymbol{U}_j^{[n-1]})\boldsymbol{f}_{ij}}{r_i^{[n-1]}\ln 2} - B\frac{(\theta_i-\theta_i^{\star[n-1]})N_0 B}{r_i^{[n-1]}\ln 2}, \tag{6}$$

where

$$r_i^{[n-1]} = \sum_{r=1,r\neq i}^{N_1}\boldsymbol{h}_{ir}^H\boldsymbol{V}_r^{[n-1]}\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\boldsymbol{U}_j^{[n-1]}\boldsymbol{f}_{ij}+\theta_i^{\star[n-1]}N_0 B.$$

It is obvious that the approximation information rate (6) is a concave function in variables $\boldsymbol{U}_j,\ \boldsymbol{V}_r,\ \theta_i$.

Assume that

$$\bar{\boldsymbol{V}}_i = t\boldsymbol{V}_i,\quad i=1,\cdots,N_1,$$
$$\bar{\boldsymbol{U}}_j = t\boldsymbol{U}_j,\quad j=1,\cdots,N_2,$$
$$\bar{\theta}_i = \frac{t}{\rho_i} = t\theta_i.$$

Each term in the sum of (6) can be rewritten as

$$B\left[t\log_2\frac{\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}+\bar{\theta}_i N_0 B}{r_i^{[n-1]}t} - \frac{\sum_{r=1,r\neq i}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}+\bar{\theta}_i N_0 B}{r_i^{[n-1]}\ln 2}+\frac{t}{\ln 2}\right]. \tag{7}$$

The first term of (7) is concave with respect to t, $\bar{\boldsymbol{V}}_i$, $\bar{\boldsymbol{U}}_j$ and $\bar{\theta}_i$ because it is the perspective function of the concave function $B\log_2\frac{\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}+\bar{\theta}_i N_0 B}{r_i^{[n-1]}}$, while the second term of (7) is linear with respect to $\bar{\boldsymbol{V}}_i$, $\bar{\boldsymbol{U}}_j$ and $\bar{\theta}_i$. Thus, the objective function of (7) is a concave function.

The first constraint of (5) can be rewritten as

$$\sum_{i=1}^{N_1}tr(\bar{\boldsymbol{V}}_i)+\sum_{j=1}^{N_2}tr(\bar{\boldsymbol{U}}_j)=1.$$

Obviously, it is convex.

The second constraint of (5) can be rewritten as

$$(1-\rho_i)\left[\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}\right]\geq\frac{B\Gamma_i t}{\gamma}.$$

Therefore, problem (5) can be reformulated as

$$(\mathrm{P}_2)\quad \max_{\substack{\{t,\rho_i,\bar{\theta}_i,\\ \boldsymbol{V}_i,\boldsymbol{U}_j,\}}} B\sum_{i=1}^{N_1}\left[t\log_2\frac{\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}+\bar{\theta}_i N_0 B}{r_i^{[n-1]}t} - \frac{\sum_{r=1,r\neq i}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}+\bar{\theta}_i N_0 B}{r_i^{[n-1]}\ln 2}+\frac{t}{\ln 2}\right],$$
$$\text{s.t.} \sum_{i=1}^{N_1}tr(\bar{\boldsymbol{V}}_i)+\sum_{j=1}^{N_2}tr(\bar{\boldsymbol{U}}_j)=1,$$
$$(1-\rho_i)\left[\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}\right]\geq\frac{B\Gamma_i t}{\gamma},$$
$$\bar{\theta}_i=\frac{t}{\rho_i},$$
$$\bar{\boldsymbol{V}}_i\succeq\mathbf{0},\quad \bar{\boldsymbol{U}}_j\succeq\mathbf{0},$$
$$0\leq\rho_i\leq 1,\quad i=1,\cdots,N_1,\ j=1,\cdots,N_2.$$

Problem (P_2) is nonconvex due to the nonconvexity of both the second and third constraints.

However, after some mathematical manipulations, the second constraint can be approximately convex. Taking logarithm operation on both sides of the second constraint, it can be transformed as follows:

$$\log(1-\rho_i)+\log\left[\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}\right] \geq \log t+\log\frac{B\Gamma_i}{\gamma}. \quad (8)$$

Using the first-order Taylor expansion, $\log t$ can be upper bounded by

$$\log t \leq \log t^{k-1}+\frac{1}{t^{k-1}}(t-t^{k-1}),$$

which makes (8) further approximated as

$$\log(1-\rho_i)+\log\left[\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}\right] \geq \log\frac{B\Gamma_i}{\gamma}+\log t^{k-1}+\frac{1}{t^{k-1}}(t-t^{k-1}).$$

Obviously, this constraint is convex.

Using similar mathematical manipulations to the third constraint of (P_2), we can approximate it by

$$\log\bar{\theta}_i+\log\rho_i \geq \log t^{k-1}+\frac{1}{t^{k-1}}(t-t^{k-1}).$$

Therefore, problem (5) can be reformulated as

$$(\mathrm{P}_3)\quad \max_{\substack{\{t,\rho_i,\bar{\theta}_i,\\ \bar{\boldsymbol{V}}_i,\bar{\boldsymbol{U}}_j,\}}} B\sum_{i=1}^{N_1}\left[t\log_2\frac{\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}+\bar{\theta}_iN_0B}{r_i^{[n-1]}t} - \frac{\sum_{r=1,r\neq i}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}+\bar{\theta}_iN_0B}{r_i^{[n-1]}\ln 2}+\frac{t}{\ln 2}\right],$$

$$\text{s.t.}\ \sum_{i=1}^{N_1}tr(\bar{\boldsymbol{V}}_i)+\sum_{j=1}^{N_2}tr(\bar{\boldsymbol{U}}_j)=1,$$

$$\log(1-\rho_i)+\log\left[\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}\right]$$
$$\geq\log\frac{B\Gamma_i}{\gamma}+\log t^{k-1}+\frac{1}{t^{k-1}}(t-t^{k-1}),$$
$$\log\bar{\theta}_i+\log\rho_i\geq\log t^{k-1}+\frac{1}{t^{k-1}}(t-t^{k-1}),$$
$$\bar{\boldsymbol{V}}_i\succeq\boldsymbol{0},\quad \bar{\boldsymbol{U}}_j\succeq\boldsymbol{0},$$
$$0\leq\rho_i\leq 1,\quad i=1,\cdots,N_1,\ j=1,\cdots,N_2.$$

Owing to the concave objective function and the convex constraints, Problem (P_3) is convex. It can attain the global optimization solution by directly solving it using off-the-shelf software CVX [34].

In what follows, we analyze the rank property of the solution of Problem (P_3).

Proposition 1: Denote the optimal solution of Problem (P_3) is $\bar{\boldsymbol{V}}_m^\star$, $\bar{\boldsymbol{U}}_n^\star$, $m=1,\cdots,N_1$, $n=1,\cdots,N_2$. Both $\bar{\boldsymbol{V}}_m^\star$ and $\bar{\boldsymbol{U}}_n^\star$ have rank greater than or equal to 1.

The proof is relegated in Appendix I.

According to *Proposition 1*, if $\text{rank}(\bar{\boldsymbol{V}}_m^\star)=1$, we can obtain the optimal information beamformer by using the eigenvalue decomposition method. Otherwise, we can run *rank reduction procedure* [36] to $\bar{\boldsymbol{V}}_m^\star$ to get a rank-one solution to Problem (P_3) and then perform eigen-decomposition on it to obtain the optimal solution to Problem (P_1). Similar process can be applied to $\bar{\boldsymbol{U}}_n^\star$.

B. DISTRIBUTED DESIGN

For the purpose of distributed implementation, we assume that the local channel state information is available for each receiver [33]. Furthermore, in order to use the ADMM to efficiently obtain the beamformers in this setup, we design the algorithm in distribution to solve (P_2).

As stated in previous subsection, Problem (P_2) is nonconcave. Furthermore, when the size of $\boldsymbol{V}_i$, $\boldsymbol{U}_j$, $i=1,\cdots,N_1$, $j=1,\cdots,N_2$ is large, that is, Problem (P_2) is in large scale, it is very time-consuming to solve Problem (P_3) directly. In what follows, we will design an algorithm based on ADMM for Problem (P_2).

Assume that

$$x_i=\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir},\quad y_i=\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij},$$
$$z_i=\boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i\boldsymbol{h}_{ii},\quad \breve{x}_i=\rho_ix_i,\ \breve{y}_i=\rho_iy_i,$$
$$\boldsymbol{\mathcal{X}}=\{t,t_i,\rho_i,x_i,y_i,\breve{x}_i,\breve{y}_i,z_i,\bar{\boldsymbol{U}}_j,\bar{\boldsymbol{V}}_i,\bar{\theta}_i,p_i,\ i=1,\cdots,N_1,\ j=1,\cdots,N_2\}.$$

Problem (P_2) can be reformulated as

$$\min_{\boldsymbol{\mathcal{X}}} -B\sum_{i=1}^{N_1}\left[t_i\log_2\frac{x_i+y_i+\bar{\theta}_iN_0B}{r_i^{[n-1]}t_i}+\frac{t_i}{\ln 2}\right] -B\sum_{i=1}^{N_1}\left[-\frac{x_i+y_i+\bar{\theta}_iN_0B}{r_i^{[n-1]}\ln 2}+\frac{z_i}{r_i^{[n-1]}\ln 2}\right],$$

$$\text{s.t.}\ \sum_{i=1}^{N_1}tr(\bar{\boldsymbol{V}}_i)+\sum_{j=1}^{N_2}tr(\bar{\boldsymbol{U}}_j)=1,$$
$$(x_i+y_i)-(\breve{x}_i+\breve{y}_i)-p_i=\frac{B\Gamma_it_i}{\gamma},$$
$$\bar{\theta}_i\rho_i=t_i,\quad t=t_i,\ z_i=\boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i\boldsymbol{h}_{ii},$$
$$x_i=\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir},\quad y_i=\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij},$$

$$\bar{\boldsymbol{V}}_i \succeq \boldsymbol{0}, \quad \bar{\boldsymbol{U}}_j \succeq \boldsymbol{0},$$
$$0 \le \breve{x}_i \le x_i, \quad 0 \le \breve{y}_i \le y_i,$$
$$0 \le \rho_i \le 1, \quad p_i \ge 0,$$

which can be further simplified as

$$(\mathrm{P}_4) \quad \min_{\boldsymbol{\mathcal{X}}} -B\sum_{i=1}^{N_1}\left[t_i \log_2 \frac{x_i+y_i+\bar{\theta}_i N_0 B}{r_i^{[n-1]} t_i} + \frac{t_i}{\ln 2}\right] -B\sum_{i=1}^{N_1}\left[-\frac{x_i+y_i+\bar{\theta}_i N_0 B}{r_i^{[n-1]}\ln 2} + \frac{z_i}{r_i^{[n-1]}\ln 2}\right],$$
$$\text{s.t.} \sum_{i=1}^{N_1} tr(\bar{\boldsymbol{V}}_i) + \sum_{j=1}^{N_2} tr(\bar{\boldsymbol{U}}_j) = 1,$$
$$\boldsymbol{A}_1\begin{bmatrix} x_i \\ y_i\end{bmatrix} - \boldsymbol{A}_2\begin{bmatrix} \breve{x}_i \\ \breve{y}_i\end{bmatrix} - \boldsymbol{a}_3 p_i = \boldsymbol{c}_i,$$
$$z_i = \boldsymbol{h}_{ii}^H \bar{\boldsymbol{V}}_i \boldsymbol{h}_{ii}, \quad \bar{\theta}_i\rho_i = t_i, \ t = t_i,$$
$$\bar{\boldsymbol{V}}_i \succeq \boldsymbol{0}, \quad \bar{\boldsymbol{U}}_j \succeq \boldsymbol{0},$$
$$0 \le \breve{x}_i \le x_i, \quad 0 \le \breve{y}_i \le y_i,$$
$$0 \le \rho_i \le 1, \quad p_i \ge 0,$$

where

$$\boldsymbol{A}_1 = \begin{bmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}^T, \quad \boldsymbol{A}_2 = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}^T,$$
$$\boldsymbol{a}_3 = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}^T, \quad \boldsymbol{c}_i = \begin{bmatrix} \frac{B\Gamma_i t_i}{\gamma} \\ \sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} \\ \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \bar{\boldsymbol{U}}_j \boldsymbol{f}_{ij} \end{bmatrix}.$$

The partial augmented Lagrangian function of (P_4) can be written as follows:

$$\begin{aligned}\mathcal{L}(\boldsymbol{\mathcal{X}}) = & -B\sum_{i=1}^{N_1}\left[t_i \log_2 \frac{x_i+y_i+\bar{\theta}_i N_0 B}{r_i^{[n-1]} t_i} + \frac{t_i}{\ln 2}\right] \\ & - B\sum_{i=1}^{N_1}\left[-\frac{x_i+y_i+\bar{\theta}_i N_0 B}{r_i^{[n-1]}\ln 2} + \frac{z_i}{r_i^{[n-1]}\ln 2}\right] \\ & + \sum_{i=1}^{N_1} \boldsymbol{\eta}_{1\,i}^H\left(\boldsymbol{A}_1\begin{bmatrix} x_i \\ y_i\end{bmatrix} - \boldsymbol{A}_2\begin{bmatrix} \breve{x}_i \\ \breve{y}_i\end{bmatrix} - \boldsymbol{a}_3 p_i - \boldsymbol{c}_i\right) \\ & + \sum_{i=1}^{N_1} \xi_i(\bar{\theta}_i\rho_i - t_i) + \sum_{i=1}^{N_1}\lambda_i(t-t_i) \\ & + \mu\left(\sum_{i=1}^{N_1} tr(\bar{\boldsymbol{V}}_i) + \sum_{j=1}^{N_2} tr(\bar{\boldsymbol{U}}_j) - 1\right) \\ & + \sum_{i=1}^{N_1}\eta_{2i}(z_i - \boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i\boldsymbol{h}_{ii}) + \sum_{i=1}^{N_1}\frac{\beta}{2}\left[\bar{\theta}_i\rho_i - t_i\right]^2 \\ & + \frac{\beta}{2}\left[\sum_{i=1}^{N_1} tr(\bar{\boldsymbol{V}}_i) + \sum_{j=1}^{N_2} tr(\bar{\boldsymbol{U}}_j) - 1\right]^2 \\ & + \sum_{i=1}^{N_1}\frac{\beta}{2}\left[z_i - \boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i\boldsymbol{h}_{ii}\right]^2 + \sum_{i=1}^{N_1}\frac{\beta}{2}(t-t_i)^2 \\ & + \sum_{i=1}^{N_1}\frac{\beta}{2}\left\|\boldsymbol{A}_1\begin{bmatrix} x_i \\ y_i\end{bmatrix} - \boldsymbol{A}_2\begin{bmatrix} \breve{x}_i \\ \breve{y}_i\end{bmatrix} - \boldsymbol{a}_3 p_i - \boldsymbol{c}_i\right\|^2 \end{aligned}$$
$$\text{s.t. } \bar{\boldsymbol{V}}_i \succeq \boldsymbol{0}, \quad \bar{\boldsymbol{U}}_j \succeq \boldsymbol{0},$$
$$0 \le \breve{x}_i \le x_i, \quad 0 \le \breve{y}_i \le y_i, \ 0 \le \rho_i \le 1,$$
$$p_i \ge 0, \quad i = 1, \cdots, N_1, \ j = 1, \cdots, N_2.$$

Dividing the set $\boldsymbol{\mathcal{X}}$ into four subsets $\boldsymbol{\mathcal{X}}_1 = \{\bar{\boldsymbol{U}}_j, \bar{\boldsymbol{V}}_i, i = 1, \cdots, N_1, j = 1, \cdots, N_2\}$, $\boldsymbol{\mathcal{X}}_2 = \{t_i, x_i, y_i, \breve{x}_i, \breve{y}_i, z_i, \bar{\theta}_i, p_i, i = 1, \cdots, N_1\}$, $\boldsymbol{\mathcal{X}}_3 = \{t\}$ and $\boldsymbol{\mathcal{X}}_4 = \{\rho_i, i = 1, \cdots, N_1\}$, we can solve the original problem (P_1) by solving the following four subproblems.

Firstly, the subproblem for $\boldsymbol{\mathcal{X}}_1 = \{\bar{\boldsymbol{U}}_i, \bar{\boldsymbol{V}}_j, i = 1, \cdots, N_1, j = 1, \cdots, N_2\}$ is

$(\mathrm{P}_4 - 1)$

$$\begin{aligned}\min_{\boldsymbol{\mathcal{X}}_1} & \frac{\beta}{2}\left[\sum_{i=1}^{N_1} tr(\bar{\boldsymbol{V}}_i) + \sum_{j=1}^{N_2} tr(\bar{\boldsymbol{U}}_j) - 1 + \frac{\mu^k}{\beta}\right]^2 \\ & + \sum_{i=1}^{N_1}\frac{\beta}{2}\left[z_i^k - \boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i\boldsymbol{h}_{ii} + \frac{\eta_{2i}^k}{\beta}\right]^2 \\ & + \sum_{i=1}^{N_1}\frac{\beta}{2}\left\|\boldsymbol{A}_1\begin{bmatrix} x_i^k \\ y_i^k\end{bmatrix} - \boldsymbol{A}_2\begin{bmatrix} \breve{x}_i^k \\ \breve{y}_i^k\end{bmatrix} - \boldsymbol{a}_3 p_i^k - \boldsymbol{c}_i^k + \frac{\boldsymbol{\eta}_{1i}^k}{\beta}\right\|^2 \end{aligned}$$
$$\text{s.t. } \bar{\boldsymbol{V}}_i \succeq \boldsymbol{0}, \quad \bar{\boldsymbol{U}}_j \succeq \boldsymbol{0},$$

where

$$\boldsymbol{c}_i^k = \begin{bmatrix} \frac{B\Gamma_i t_i^k}{\gamma} \\ \sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} \\ \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \bar{\boldsymbol{U}}_j \boldsymbol{f}_{ij} \end{bmatrix}.$$

We can update each $\bar{\boldsymbol{V}}_m$ in order assuming other $\bar{\boldsymbol{V}}_i$, $i \neq m$ and $\bar{\boldsymbol{U}}_n$ are fixed and then update each $\bar{\boldsymbol{U}}_n$ in order assuming other $\bar{\boldsymbol{V}}_i$ and $\bar{\boldsymbol{U}}_j$, $j \neq n$ are fixed.

Secondly, the subproblem for $\boldsymbol{\mathcal{X}}_2 = \{t_i, x_i, y_i, \breve{x}_i, \breve{y}_i, z_i, \bar{\theta}_i, p_i, i = 1, \cdots, N_1\}$ is

$(\mathrm{P}_4 - 2)$

$$\begin{aligned}\min_{\boldsymbol{\mathcal{X}}_2} & -B\sum_{i=1}^{N_1}\left[t_i \log_2 \frac{x_i+y_i+\bar{\theta}_i N_0 B}{r_i^{[n-1]} t_i} + \frac{t_i}{\ln 2}\right] \\ & -B\sum_{i=1}^{N_1}\left[-\frac{x_i+y_i+\bar{\theta}_i N_0 B}{r_i^{[n-1]}\ln 2} + \frac{z_i}{r_i^{[n-1]}\ln 2}\right] \\ & + \sum_{i=1}^{N_1}\frac{\beta}{2}\left\|\boldsymbol{A}_1\begin{bmatrix} x_i \\ y_i\end{bmatrix} - \boldsymbol{A}_2\begin{bmatrix} \breve{x}_i \\ \breve{y}_i\end{bmatrix} - \boldsymbol{a}_3 p_i - \boldsymbol{c}_i^{k+1} + \frac{\boldsymbol{\eta}_{1i}^k}{\beta}\right\|^2 \\ & + \sum_{i=1}^{N_1}\frac{\beta}{2}\left[z_i - \boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i^{k+1}\boldsymbol{h}_{ii} + \frac{\eta_{2i}^k}{\beta}\right]^2 \end{aligned}$$

$$+\sum_{i=1}^{N_1}\frac{\beta}{2}\left[t^k-t_i+\frac{\lambda_i^k}{\beta}\right]^2$$
$$+\sum_{i=1}^{N_1}\frac{\beta}{2}\left[\bar{\theta}_i\rho_i^k-t_i+\frac{\xi_i^k}{\beta}\right]^2,$$
$$\text{s.t. } 0\le\breve{x}_i\le x_i,\quad 0\le\breve{y}_i\le y_i,\quad p_i\ge 0,$$

where

$$\boldsymbol{c}_i^{k+1}=\begin{bmatrix}\frac{B\Gamma_i t_i}{\gamma}\\ \sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r^{k+1}\boldsymbol{h}_{ir}\\ \sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j^{k+1}\boldsymbol{f}_{ij}\end{bmatrix}.$$

Problem (P_4-2) can be further decoupled into N_1 subproblems

$$\min_{\boldsymbol{\mathcal{X}}_{2i}} -B\left[t_i\log_2\frac{x_i+y_i+\bar{\theta}_i N_0 B}{r_i^{[n-1]}t_i}+\frac{t_i}{\ln 2}\right]$$
$$-B\left[-\frac{x_i+y_i+\bar{\theta}_i N_0 B}{r_i^{[n-1]}\ln 2}+\frac{z_i}{r_i^{[n-1]}\ln 2}\right]$$
$$+\frac{\beta}{2}\left[\bar{\theta}_i\rho_i^k-t_i+\frac{\xi_i^k}{\beta}\right]^2$$
$$+\frac{\beta}{2}\left\|\boldsymbol{A}_1\begin{bmatrix}x_i\\y_i\end{bmatrix}-\boldsymbol{A}_2\begin{bmatrix}\breve{x}_i\\\breve{y}_i\end{bmatrix}-\boldsymbol{a}_3 p_i-\boldsymbol{c}_i^{k+1}+\frac{\boldsymbol{\eta}_{1i}^k}{\beta}\right\|^2$$
$$+\frac{\beta}{2}\left[z_i-\boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i^{k+1}\boldsymbol{h}_{ii}+\frac{\eta_{2i}^k}{\beta}\right]^2+\frac{\beta}{2}\left[t^k-t_i+\frac{\lambda_i^k}{\beta}\right]^2,$$
$$\text{s.t. } 0\le\breve{x}_i\le x_i,\quad 0\le\breve{y}_i\le y_i,\quad p_i\ge 0,\quad i=1,\cdots,N_1.$$

We can update each $\{t_i,x_i,y_i,\breve{x}_i,\breve{y}_i,z_i,\bar{\theta}_i\}$, followed by updating p_i.

Thirdly, the subproblem $\boldsymbol{\mathcal{X}}_3=\{t\}$ is

$$(\mathrm{P}_4-3)\quad\min_{\boldsymbol{\mathcal{X}}_3}\sum_{i=1}^{N_1}\frac{\beta}{2}\left[t-t_i^{k+1}+\frac{\lambda_i^k}{\beta}\right]^2.$$

The close-form solution of (P_4-3) is

$$t=\frac{1}{N_1}\sum_{i=1}^{N_1}\left(t_i^{k+1}-\frac{\lambda_i^k}{\beta}\right).\tag{9}$$

Fourthly, the subproblem for $\boldsymbol{\mathcal{X}}_4=\{\rho_i,\ i=1,\cdots,N_1\}$ is

$$(\mathrm{P}_4-4)\quad\min_{\boldsymbol{\mathcal{X}}_4}\sum_{i=1}^{N_1}\frac{\beta}{2}\left[\bar{\theta}_i^{k+1}\rho_i-t_i^{k+1}+\frac{\xi_i^k}{\beta}\right]^2,\quad\text{s.t. } 0\le\rho_i\le 1,$$

which can be further decoupled into N_1 subproblems for $i=1,\cdots,N_1$

$$\min_{\boldsymbol{\mathcal{X}}_{4i}}\frac{\beta}{2}\left[\bar{\theta}_i^{k+1}\rho_i-t_i^{k+1}+\frac{\xi_i^k}{\beta}\right]^2,\quad\text{s.t. } 0\le\rho_i\le 1.$$

Finally, the dual variables $\boldsymbol{\eta}_{1i},\eta_{2i},\lambda_i,\xi_i,\mu$ are updated as follows:

$$\boldsymbol{\eta}_{1i}^{k+1}=\boldsymbol{\eta}_{1i}^k+\beta\left(\boldsymbol{A}_1\begin{bmatrix}x_i^{k+1}\\y_i^{k+1}\end{bmatrix}-\boldsymbol{A}_2\begin{bmatrix}\breve{x}_i^{k+1}\\\breve{y}_i^{k+1}\end{bmatrix}-\boldsymbol{a}_3 p_i^{k+1}-\boldsymbol{c}_i^{k+1}\right),$$
$$\eta_{2i}^{k+1}=\eta_{2i}^k+\beta\left(z_i^{k+1}-\boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i^{k+1}\boldsymbol{h}_{ii}\right),$$
$$\lambda_i^{k+1}=\lambda_i^k+\beta\left(t^{k+1}-t_i^{k+1}\right),$$
$$\xi_i^{k+1}=\xi_i^k+\beta\left(\bar{\theta}_i^{k+1}\rho_i^{k+1}-t_i^{k+1}\right),$$
$$\mu^{k+1}=\mu^k+\beta\left(\sum_{i=1}^{N_1}tr(\bar{\boldsymbol{V}}_i^{k+1})+\sum_{i=1}^{N_2}tr(\bar{\boldsymbol{U}}_i^{k+1})-1\right).\tag{10}$$

In short, the new algorithm for solving Problem (P_2) based on ADMM is summarized in **Algorithm** 1 in Table 1.

TABLE 1.

The Proposed **Algorithm** 1 for (P_2)
1: **Initialization**: set the initial values of x_i^0, y_i^0, $\breve{x}_i^0, \breve{y}_i^0, z_i^0, \rho_i^0, \lambda_i^0, \xi_i^0, \boldsymbol{\eta}_{1i}^0, \eta_{2i}^0$ and μ^0.
2: **Repeat**:
3: $k=k+1$,
4: obtain the solution $\boldsymbol{\mathcal{X}}_1=\{\bar{\boldsymbol{U}}_j^k,\ \bar{\boldsymbol{V}}_i^k,\ i=1,\cdots,N_1,\ j=1,\cdots,N_2\}$ by solving (P_4-1).
5: obtain the solution $\boldsymbol{\mathcal{X}}_2=\{t_i^k,x_i^k,y_i^k,\breve{x}_i^k,\breve{y}_i^k,z_i^k,\bar{\theta}_i^k,p_i^k,\ i=1,\cdots,N_1\}$ by solving (P_4-2).
6: obtain the solution $\boldsymbol{\mathcal{X}}_3=\{t^k\}$ using Eq. (9).
7: obtain the solution $\boldsymbol{\mathcal{X}}_4=\{\rho_i^k,\ i=1,\cdots,N_1\}$ by solving (P_4-4).
8: updating $\boldsymbol{\eta}_{1i}^k,\ \eta_{2i}^k,\ \lambda_i^k,\ \xi_i^k,\ i=1,\cdots,N_1$ and μ^k using (10) respectively.
9: **until** the stopping criterion is met.
10: **Output** $\boldsymbol{\mathcal{X}}_1=\{\bar{\boldsymbol{U}}_j^k,\ \bar{\boldsymbol{V}}_i^k,\ i=1,\cdots,N_1,\ j=1,\cdots,N_2\}$ as an approximate solution.

Recently, Hong and Luo [37] have pointed out that for any finite $K>0$ (K is the number of optimization variable sets of suboptimization problems), the ADMM algorithm linearly converges provided some regularity conditions are satisfied and the dual step size is small enough. However, there exist two important open problems for ADMM. One is that no convergence is guaranteed in general when $K>2$, and the other is that how fast the algorithm converges in general for any $K>1$ is still unknown. Therefore, to our best knowledge, the general convergence and iteration complexity of our proposed Algorithm 1 which is based on ADMM are not known, which could be our further study.

IV. BEAMFORMING DESIGN IN DIFFERENT FREQUENCY BANDS

In this section, we design the beamformers $\{\boldsymbol{v}_i,\boldsymbol{u}_j,i=1,\cdots,N_1,j=1,\cdots,N_2\}$ of the system for the proposed WIET architecture II, as described in Section II.B.

Then, the EE expression can be expressed by

$$\frac{\mathcal{R}}{\mathcal{E}} = \frac{\sum_{i=1}^{N_1} \mathcal{R}_{2i}}{\sum_{i=1}^{N_1} \|\boldsymbol{v}_i\|_2^2 + \sum_{j=1}^{N_2} \|\boldsymbol{u}_j\|_2^2}.$$

Thus, the beamformer design optimization problem in this setup can be formulated as

$$(\mathrm{P}_5) \quad \max_{\substack{\{\boldsymbol{u}_j, \boldsymbol{v}_i, \\ i=1,\cdots,N_1, \\ j=1,\cdots,N_2,\}}} \frac{\sum_{i=1}^{N_1} \mathcal{R}_{2i}}{\sum_{i=1}^{N_1} \|\boldsymbol{v}_i\|_2^2 + \sum_{j=1}^{N_2} \|\boldsymbol{u}_j\|_2^2}, \quad \text{s.t. Eq. (1)} \geq \Gamma_i.$$

Problem (P_5) is hard to solve due to the nonconvexity of both the objective function and the constraint [26]. However, by some mathematical manipulations, we can transform Problem (P_5) into a convex problem which is easy to tackle. In what follows, we will design the beamformer in centralized scheme, followed by that in distributed scheme.

A. CENTRALIZED DESIGN

Similar to the setup 1, introducing $\boldsymbol{V}_i = \boldsymbol{v}_i\boldsymbol{v}_i^H$ and $\boldsymbol{U}_j = \boldsymbol{u}_j\boldsymbol{u}_j^H$, the information rate in the second WIET architecture can be expressed by

$$\mathcal{R}_{2i} = \frac{B}{2}\log_2\left(1 + \frac{\boldsymbol{h}_{ii}^H \boldsymbol{V}_i \boldsymbol{h}_{ii}}{\sum_{\substack{r=1,\\ r\neq i}}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{V}_r \boldsymbol{h}_{ir} + N_0\, B/2}\right),$$

which can be further lower bounded as follows:

$$\mathcal{R}_{2i} \geq \frac{B}{2}\left[\log_2 \frac{\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{V}_r \boldsymbol{h}_{ir} + N_0\, B/2}{s_i^{[n-1]}} - \frac{\sum_{\substack{r=1,\\ r\neq i}}^{N_1} \boldsymbol{h}_{ir}^H (\boldsymbol{V}_r - \boldsymbol{V}_r^{[n-1]}) \boldsymbol{h}_{ir}}{s_i^{[n-1]} \ln 2}\right],$$

where

$$s_i^{[n-1]} = \sum_{\substack{r=1,\\ r\neq i}}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{V}_r^{[n-1]} \boldsymbol{h}_{ir} + N_0\, B/2.$$

The second constraint in Problem (P_5) can be expressed by

$$\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{V}_r \boldsymbol{h}_{ir} + \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \boldsymbol{U}_j \boldsymbol{f}_{ij} \geq \frac{B\Gamma_i}{2\gamma}.$$

Introducing a slack variable t, we can approximately reformulate Problem (P_5) as

$$\begin{aligned} \max_{\substack{\{t, \boldsymbol{V}_i, \boldsymbol{U}_j, \\ i=1,\cdots,N_1, \\ j=1,\cdots,N_2,\}}} \; & t \sum_{i=1}^{N_1} \frac{B}{2}\left[\log_2 \frac{\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{V}_r \boldsymbol{h}_{ir} + N_0\, B/2}{s_i^{[n-1]}}\right] \\ & - t\left[\sum_{i=1}^{N_1} \frac{B}{2} \frac{\sum_{\substack{r=1,\\ r\neq i}}^{N_1} \boldsymbol{h}_{ir}^H (\boldsymbol{V}_r - \boldsymbol{V}_r^{[n-1]}) \boldsymbol{h}_{ir}}{s_i^{[n-1]} \ln 2}\right], \\ \text{s.t. } & \sum_{i=1}^{N_1} \mathrm{tr}(\boldsymbol{V}_i) + \sum_{j=1}^{N_2} \mathrm{tr}(\boldsymbol{U}_j) = \frac{1}{t}, \\ & \sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{V}_r \boldsymbol{h}_{ir} + \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \boldsymbol{U}_j \boldsymbol{f}_{ij} \geq \frac{B\Gamma_i}{2\gamma}, \\ & \boldsymbol{V}_i \succeq \boldsymbol{0}, \quad \boldsymbol{U}_j \succeq \boldsymbol{0}, \\ & \mathrm{rank}(\boldsymbol{V}_i) = 1, \quad \mathrm{rank}(\boldsymbol{U}_j) = 1. \end{aligned} \tag{11}$$

Discarding $\mathrm{rank}(\boldsymbol{V}_i) = 1$ and $\mathrm{rank}(\boldsymbol{U}_j) = 1$, we can approximately reformulate problem (11) as

$$\begin{aligned} \max_{\substack{\{t, \boldsymbol{V}_i, \boldsymbol{U}_j, \\ i=1,\cdots,N_1, \\ j=1,\cdots,N_2,\}}} \; & t \sum_{i=1}^{N_1} \frac{B}{2}\left[\log_2 \frac{\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{V}_r \boldsymbol{h}_{ir} + N_0\, B/2}{s_i^{[n-1]}}\right] \\ & - t \sum_{i=1}^{N_1} \frac{B}{2}\left[\frac{\sum_{\substack{r=1,\\ r\neq i}}^{N_1} \boldsymbol{h}_{ir}^H (\boldsymbol{V}_r - \boldsymbol{V}_r^{[n-1]}) \boldsymbol{h}_{ir}}{s_i^{[n-1]} \ln 2}\right], \\ \text{s.t. } & \sum_{i=1}^{N_1} \mathrm{tr}(\boldsymbol{V}_i) + \sum_{j=1}^{N_2} \mathrm{tr}(\boldsymbol{U}_j) = \frac{1}{t}, \\ & \sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \boldsymbol{V}_r \boldsymbol{h}_{ir} + \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \boldsymbol{U}_j \boldsymbol{f}_{ij} \geq \frac{B\Gamma_i}{2\gamma}, \\ & \boldsymbol{V}_i \succeq \boldsymbol{0}, \quad \boldsymbol{U}_j \succeq \boldsymbol{0}. \end{aligned} \tag{12}$$

Letting

$$\bar{\boldsymbol{V}}_i = t\boldsymbol{V}_i, \quad i = 1, \cdots, N_1,$$
$$\bar{\boldsymbol{U}}_j = t\boldsymbol{U}_j, \quad j = 1, \cdots, N_2.$$

Each term in the sum of the objective function in (12) can be rewritten as

$$\frac{B}{2}\left[t \log_2 \frac{\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} + tN_0\, B/2}{s_i^{[n-1]} t} - \frac{\sum_{\substack{r=1,\\ r\neq i}}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} + tN_0\, B/2}{s_i^{[n-1]} \ln 2} + \frac{t}{\ln 2}\right].$$

The corresponding harvested energy constraint can be rewritten as

$$\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} + \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \bar{\boldsymbol{U}}_j \boldsymbol{f}_{ij} \geq \frac{B\Gamma_i t}{2\gamma}, \quad i = 1, \cdots, N_1.$$

Therefore, the problem (12) can be reformulated as

$$\begin{aligned}
(\mathrm{P}_6) \quad & \max_{\substack{\{t, \bar{\boldsymbol{U}}_i, \bar{\boldsymbol{V}}_j, \\ i=1,\cdots,N_1, \\ j=1,\cdots,N_2,\}}} \frac{B}{2} \sum_{i=1}^{N_1} \left[t \log_2 \frac{\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} + tN_0 B/2}{s_i^{[n-1]} t} \right] \\
& \quad - \frac{B}{2} \sum_{\substack{r=1, \\ r \neq i}}^{N_1} \left[\frac{\boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} + tN_0 B/2}{s_i^{[n-1]} \ln 2} - \frac{t}{\ln 2} \right], \\
& \text{s.t.} \sum_{i=1}^{N_1} tr(\bar{\boldsymbol{V}}_i) + \sum_{j=1}^{N_2} tr(\bar{\boldsymbol{U}}_j) = 1, \\
& \quad \sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} + \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \bar{\boldsymbol{U}}_j \boldsymbol{f}_{ij} \geq \frac{B\Gamma_i t}{2\gamma}, \\
& \quad \bar{\boldsymbol{V}}_i \succeq \boldsymbol{0}, \quad \bar{\boldsymbol{U}}_j \succeq \boldsymbol{0}.
\end{aligned}$$

Since the first item in each term in the objective function in Problem (P_6) is the perspective function of the concave function $\log\left(\frac{\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir}}{s_i^{[n-1]}} + \frac{tN_0 B/2}{s_i^{[n-1]}}\right)$, it is also a concave function [24]. The second term and the third term in the objective function in Problem (P_6) are respectively linear in variables $\bar{\boldsymbol{V}}_r$ and t. Therefore, the objective function in Problem (P_6) is convcave. In addition, the constraints are a convex set. Thus, Problem (P_6) is convex, which can attain its global optimal solution by directly solving it using off-the-shelf software CVX.

In what follows, we analyze the rank property of the solution of Problem (P_6), which is written in the theorem.

Proposition 2: Denote the optimal solution of Problem (P_6) is $\bar{\boldsymbol{V}}_m^\star$, $\bar{\boldsymbol{U}}_n^\star$, $m = 1, \cdots, N_1$, $n = 1, \cdots, N_2$. Both $\bar{\boldsymbol{V}}_m^\star$ and $\bar{\boldsymbol{U}}_n^\star$ have rank greater than or equal to 1.

The proof is relegated in Appendix II.

According to *Proposition 2*, if $\text{rank}(\bar{\boldsymbol{V}}_m^\star) = 1$, we can obtain the optimal information beamformer by using the eigenvalue decomposition method. Otherwise, if $\text{rank}(\bar{\boldsymbol{V}}_m^\star) > 1$, we can run *rank reduction procedure* [36] to $\bar{\boldsymbol{V}}_m^\star$ to get a rank-one solution to Problem (P_6) and then perform eigen-decomposition on it to obtain the optimal solution to problem (P_5). Similar process can be applied to $\bar{\boldsymbol{U}}_n^\star$.

B. DISTRIBUTED DESIGN

Similar to Problem (P_3), we design an algorithm based on ADMM to solve Problem (P_6) in the following in order to attain the solution more numerically stable and faster in convergence.

Assume that

$$\begin{aligned}
x_i &= \sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir}, \quad y_i = \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \bar{\boldsymbol{U}}_j \boldsymbol{f}_{ij}, \\
z_i &= \boldsymbol{h}_{ii}^H \bar{\boldsymbol{V}}_i \boldsymbol{h}_{ii}, \\
\boldsymbol{\mathcal{X}} &= \{t, t_i, x_i, y_i, \bar{\boldsymbol{V}}_i, \bar{\boldsymbol{U}}_j, p_i, i = 1, \cdots, N_1, j = 1, \cdots, N_2\}.
\end{aligned}$$

Problem (P_6) can be reformulated as

$$\begin{aligned}
(\mathrm{P}_7) \quad & \min_{\boldsymbol{\mathcal{X}}} -\frac{B}{2} \sum_{i=1}^{N_1} \left[t_i \log_2 \frac{x_i + t_i N_0 B/2}{s_i^{[n-1]} t_i} + \frac{t_i}{\ln 2} \right] \\
& \quad -\frac{B}{2} \sum_{i=1}^{N_1} \left[-\frac{x_i + N_0 B t_i/2}{s_i^{[n-1]} \ln 2} + \frac{z_i}{s_i^{[n-1]} \ln 2} \right], \\
& \text{s.t.} \sum_{i=1}^{N_1} tr(\bar{\boldsymbol{V}}_i) + \sum_{j=1}^{N_2} tr(\bar{\boldsymbol{U}}_j) = 1, \\
& \quad x_i + y_i - p_i = \frac{\Gamma_i B t_i}{2\gamma}, \\
& \quad x_i = \sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir}, \\
& \quad y_i = \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \bar{\boldsymbol{U}}_j \boldsymbol{f}_{ij}, \\
& \quad z_i = \boldsymbol{h}_{ii}^H \bar{\boldsymbol{V}}_i \boldsymbol{h}_{ii}, \\
& \quad \bar{\boldsymbol{V}}_i \succeq \boldsymbol{0}, \quad \bar{\boldsymbol{U}}_j \succeq \boldsymbol{0}, \\
& \quad t = t_i, \quad p_i \geq 0.
\end{aligned}$$

The partial augmented Lagrangian function of Problem (P_7) can be written as follows:

$$\begin{aligned}
\mathcal{L}(\boldsymbol{\mathcal{Y}}) = & -\frac{B}{2} \sum_{i=1}^{N_1} \left[t_i \log_2 \frac{x_i + t_i N_0 B/2}{s_i^{[n-1]} t_i} + \frac{t_i}{\ln 2} \right] \\
& - \frac{B}{2} \sum_{i=1}^{N_1} \left[-\frac{x_i + t_i N_0 B/2}{s_i^{[n-1]} \ln 2} + \frac{z_i}{s_i^{[n-1]} \ln 2} \right] \\
& + \sum_{i=1}^{N_1} \eta_{1i} \left(x_i - \sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} \right) \\
& + \sum_{i=1}^{N_1} \eta_{2i} \left(y_i - \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \bar{\boldsymbol{U}}_j \boldsymbol{f}_{ij} \right) \\
& + \sum_{i=1}^{N_1} \eta_{3i} \left(z_i - \boldsymbol{h}_{ii}^H \bar{\boldsymbol{V}}_i \boldsymbol{h}_{ii} \right) + \sum_{i=1}^{N_1} \lambda_i (t - t_i) \\
& + \sum_{i=1}^{N_1} \zeta_i \left(x_i + y_i - p_i - \frac{\Gamma_i B t_i}{2\gamma} \right) \\
& + \mu \left(\sum_{i=1}^{N_1} tr(\bar{\boldsymbol{V}}_i) + \sum_{j=1}^{N_2} tr(\bar{\boldsymbol{U}}_j) - 1 \right) \\
& + \sum_{i=1}^{N_1} \frac{\beta_1}{2} \left(x_i - \sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} \right)^2
\end{aligned}$$

$$+\sum_{i=1}^{N_1}\frac{\beta_2}{2}\left(y_i-\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}\right)^2$$
$$+\sum_{i=1}^{N_1}\frac{\beta_3}{2}\left(z_i-\boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i\boldsymbol{h}_{ii}\right)^2$$
$$+\sum_{i=1}^{N_1}\frac{\beta_4}{2}\left(x_i+y_i-p_i-\frac{\Gamma_iBt_i}{2\gamma}\right)^2$$
$$+\frac{\beta_5}{2}\left(\sum_{i=1}^{N_1}tr(\bar{\boldsymbol{V}}_i)+\sum_{j=1}^{N_2}tr(\bar{\boldsymbol{U}}_j)-1\right)^2$$
$$+\sum_{i=1}^{N_1}\frac{\beta_6}{2}(t-t_i)^2,$$
$$\text{s.t. } \bar{\boldsymbol{V}}_i\succeq\boldsymbol{0},\quad \bar{\boldsymbol{U}}_j\succeq\boldsymbol{0},\ p_i\geq 0.$$

Divide the set $\boldsymbol{\mathcal{Y}}$ into three sets $\boldsymbol{\mathcal{Y}}_1=\{\bar{\boldsymbol{V}}_i,\bar{\boldsymbol{U}}_j, i=1,\cdots,N_1, j=1,\cdots,N_2\}$, $\boldsymbol{\mathcal{Y}}_2=\{t_i,x_i,y_i,z_i,p_i, i=1,\cdots,N_1\}$ and $\boldsymbol{\mathcal{Y}}_3=\{t\}$. Since (P$_7$) is convex, it is convex for each set block variables. In the sequel, we will design an algorithm based on ADMM technique to solve each subproblem alternatively.

Firstly, the subproblem for computing $\boldsymbol{\mathcal{Y}}_1=\{\bar{\boldsymbol{V}}_i,\bar{\boldsymbol{U}}_j, i=1,\cdots,N_1, j=1,\cdots,N_2\}$ is as follows:

$$(\mathrm{P}_7-1)\quad \min_{\boldsymbol{\mathcal{Y}}_1}\sum_{i=1}^{N_1}\frac{\beta_1}{2}\left(x_i^k-\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\frac{\eta_{1i}^k}{\beta_1}\right)^2$$
$$+\sum_{i=1}^{N_1}\frac{\beta_2}{2}\left(y_i^k-\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}+\frac{\eta_{2i}^k}{\beta_2}\right)^2$$
$$+\sum_{i=1}^{N_1}\frac{\beta_3}{2}\left(z_i^k-\boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i\boldsymbol{h}_{ii}+\frac{\eta_{3i}^k}{\beta_3}\right)^2$$
$$+\frac{\beta_5}{2}\left(\sum_{i=1}^{N_1}tr(\bar{\boldsymbol{V}}_i)+\sum_{j=1}^{N_2}tr(\bar{\boldsymbol{U}}_j)-1+\frac{\mu^k}{\beta_5}\right)^2,$$
$$\text{s.t. } \bar{\boldsymbol{V}}_i\succeq\boldsymbol{0},\quad \bar{\boldsymbol{U}}_j\succeq\boldsymbol{0}.$$

We update each $\bar{\boldsymbol{V}}_m,\ m=1,\cdots,N_1$, followed by each $\bar{\boldsymbol{U}}_n,\ n=1,\cdots,N_2$.

Specifically, we first update each $\bar{\boldsymbol{V}}_m,\ m=1,\cdots,N_1$.

(P$_7-1$a)

$$\min_{\bar{\boldsymbol{V}}_m}\sum_{i=1}^{N_1}\frac{\beta_1}{2}\left(x_i^k-\sum_{\substack{r=1,\\r\neq m}}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r^k\boldsymbol{h}_{ir}-\boldsymbol{h}_{im}^H\bar{\boldsymbol{V}}_m\boldsymbol{h}_{im}+\frac{\eta_{1i}^k}{\beta_1}\right)^2$$
$$+\sum_{\substack{i=1,\\i\neq m}}^{N_1}\frac{\beta_3}{2}\left(z_i^k-\boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i^k\boldsymbol{h}_{ii}+\frac{\eta_{2i}^k}{\beta_3}\right)^2$$
$$+\frac{\beta_3}{2}\left(z_m^k-\boldsymbol{h}_{mm}^H\bar{\boldsymbol{V}}_m\boldsymbol{h}_{mm}+\frac{\eta_{3m}^k}{\beta_3}\right)^2$$
$$+\frac{\beta_5}{2}\left(\sum_{\substack{i=1,\\i\neq m}}^{N_1}tr(\bar{\boldsymbol{V}}_i^k)+tr(\bar{\boldsymbol{V}}_m)+\sum_{j=1}^{N_2}tr(\bar{\boldsymbol{U}}_j^k)-1+\frac{\mu^k}{\beta_5}\right)^2,$$
$$\text{s.t. } \bar{\boldsymbol{V}}_m\succeq\boldsymbol{0}.$$

Then we update each $\bar{\boldsymbol{U}}_n,\ n=1,\cdots,N_2$.

(P$_7-1$b)

$$\min_{\bar{\boldsymbol{U}}_n}\sum_{i=1}^{N_1}\frac{\beta_2}{2}\left(y_i^k-\sum_{\substack{r=1\\r\neq n}}^{N_2}\boldsymbol{f}_{ir}^H\bar{\boldsymbol{U}}_r^k\boldsymbol{f}_{ir}-\boldsymbol{f}_{in}^H\bar{\boldsymbol{U}}_n\boldsymbol{f}_{in}+\frac{\eta_{2i}^k}{\beta_2}\right)^2$$
$$+\frac{\beta_5}{2}\left(\sum_{i=1}^{N_1}tr(\bar{\boldsymbol{V}}_i^{k+1})+\sum_{\substack{j=1,\\j\neq n}}^{N_2}tr(\bar{\boldsymbol{U}}_j^k)+tr(\bar{\boldsymbol{U}}_n)-1+\frac{\mu^k}{\beta_5}\right)^2,$$
$$\text{s.t. } \bar{\boldsymbol{U}}_n\succeq\boldsymbol{0}.$$

Secondly, the subproblem with set $\boldsymbol{\mathcal{Y}}_2=\{t_i,x_i,y_i,z_i,p_i, i=1,\cdots,N_1\}$ is to solve the following problem

(P$_7-2$)

$$\min_{\left\{\substack{p_i\geq 0,\\t_i,x_i,y_i,z_i\\i=1,\cdots,N_1,}\right\}} -\frac{B}{2}\sum_{i=1}^{N_1}\left[t_i\log_2\frac{x_i+t_iN_0\,B/2}{s_i^{[k]}t_i}+\frac{t_i}{\ln 2}\right]$$
$$-\frac{B}{2}\sum_{i=1}^{N_1}\left[-\frac{x_i+t_iN_0\,B/2}{s_i^{[k]}\ln 2}+\frac{z_i}{s_i^{[k]}\ln 2}\right]$$
$$+\sum_{i=1}^{N_1}\frac{\beta_1}{2}\left(x_i-\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r^{k+1}\boldsymbol{h}_{ir}+\frac{\eta_{1i}^k}{\beta_1}\right)^2$$
$$+\sum_{i=1}^{N_1}\frac{\beta_2}{2}\left(y_i-\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j^{k+1}\boldsymbol{f}_{ij}+\frac{\eta_{2i}^k}{\beta_2}\right)^2$$
$$+\sum_{i=1}^{N_1}\frac{\beta_3}{2}\left(z_i-\boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i^{k+1}\boldsymbol{h}_{ii}+\frac{\eta_{3i}^k}{\beta_3}\right)^2$$
$$+\sum_{i=1}^{N_1}\frac{\beta_4}{2}\left(x_i+y_i-p_i-\frac{\Gamma_iBt_i}{2\gamma}+\frac{\zeta_i^k}{\beta_4}\right)^2$$
$$+\sum_{i=1}^{N_1}\frac{\beta_6}{2}\left(t^k-t_i+\frac{\lambda_i^k}{\beta_6}\right)^2,$$

In order to lower the computational complexity, Problem (P$_7-2$) can be further decoupled into the following N_1 subproblems with $i=1,\cdots,N_1$

$$\min_{\left\{\substack{p_i\geq 0,\\t_i,x_i,y_i,z_i,}\right\}} -\frac{B}{2}\left[t_i\log_2\frac{x_i+t_iN_0\,B/2}{s_i^{[k]}t_i}+\frac{t_i}{\ln 2}\right]$$
$$-\frac{B}{2}\left[-\frac{x_i+t_iN_0\,B/2}{s_i^{[k]}\ln 2}+\frac{z_i}{s_i^{[k]}\ln 2}\right]$$
$$+\frac{\beta_1}{2}\left(x_i-\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r^{k+1}\boldsymbol{h}_{ir}+\frac{\eta_{1i}^k}{\beta_1}\right)^2$$
$$+\frac{\beta_2}{2}\left(y_i-\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j^{k+1}\boldsymbol{f}_{ij}+\frac{\eta_{2i}^k}{\beta_2}\right)^2$$
$$+\frac{\beta_3}{2}\left(z_i-\boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i^{k+1}\boldsymbol{h}_{ii}+\frac{\eta_{3i}^k}{\beta_3}\right)^2$$
$$+\frac{\beta_4}{2}\left(x_i+y_i-p_i-\frac{\Gamma_iBt_i}{2\gamma}+\frac{\zeta_i^k}{\beta_4}\right)^2$$
$$+\frac{\beta_6}{2}\left(t^k-t_i+\frac{\lambda_i^k}{\beta_6}\right)^2.$$

We can update x_i, z_i, t_i, followed by updating p_i and y_i in order.

Thirdly, the subproblem $\mathcal{Y}_3 = \{t\}$ is

$$(\mathrm{P}_7-3)\ \min_{\mathcal{Y}_3} \frac{\beta_6}{2}\sum_{i=1}^{N_1}\left(t - t_i^{k+1} + \frac{\lambda_i^k}{\beta_6}\right)^2,$$

where the close-form solution t is

$$t = \frac{1}{N_1}\sum_{i=1}^{N_1}\left(t_i^{k+1} - \frac{\lambda_i^k}{\beta_6}\right). \tag{13}$$

Fourthly, the dual variables $\{\lambda_i,\ \xi_i,\ \eta_{1i},\ \eta_{2i},\ \eta_{3i},\ i = 1, \cdots, N_1\}$ are respectively updated as follows:

$$\begin{aligned}
\eta_{1i}^{k+1} &= \eta_{1i}^k + \beta_1\Big(x_i^{k+1} - \sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r^{k+1}\boldsymbol{h}_{ir}\Big),\\
\eta_{2i}^{k+1} &= \eta_{2i}^k + \beta_2\Big(y_i^{k+1} - \sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j^{k+1}\boldsymbol{f}_{ij}\Big),\\
\eta_{3i}^{k+1} &= \eta_{3i}^k + \beta_3\Big(z_i^{k+1} - \boldsymbol{h}_{ii}^H\bar{\boldsymbol{V}}_i^{k+1}\boldsymbol{h}_{ii}\Big),\\
\zeta_i^{k+1} &= \zeta_i^k + \beta_4\Big(x_i^{k+1} + y_i^{k+1} - p_i^{k+1} - \frac{\Gamma_i B t_i^{k+1}}{2\gamma}\Big),\\
\mu^{k+1} &= \mu^k + \beta_5\Big(\sum_{i=1}^{N_1} tr(\bar{\boldsymbol{V}}_i^{k+1}) + \sum_{j=1}^{N_2} tr(\bar{\boldsymbol{U}}_j^{k+1}) - 1\Big),\\
\lambda_i^{k+1} &= \lambda_i^k + \beta_6(t^{k+1} - t_i^{k+1}).
\end{aligned} \tag{14}$$

As such, the new algorithm for solving (P_7) based on ADMM is summarized in **Algorithm** 2.

TABLE 2.

The Proposed **Algorithm** 2 for (P_7)
1: **Initialization**: set the initial values of $\bar{\boldsymbol{U}}_i^0$, $\bar{\boldsymbol{V}}_i^0$, λ_i^0, μ_i^0 and ξ_i^0, $i = 1, \cdots, N_1$.
2: **Repeat**:
3: $k = k + 1$.
4: obtain the solution $\mathcal{Y}_1 = \{\bar{\boldsymbol{U}}_i^k, \bar{\boldsymbol{V}}_j^k, i = 1, \cdots, N_1,\ j = 1, \cdots, N_2\}$ by solving (P_7-1a) and (P_7-1b) in turn.
5: obtain the solution $\mathcal{Y}_2 = \{t_i^k, x_i^k, y_i^k, z_i^k, p_i^k, i = 1, \cdots, N_1\}$ by solving (P_7-2).
6: obtain the closed-form solution $\mathcal{Y}_3 = \{t^k\}$ by using Eq. (13).
7: update λ_i^k, ζ_i^k, η_{1i}^k, η_{2i}^k, η_{3i}^k, $i = 1, \cdots, N_1$ and μ^k by using Eq. (14).
8: **until** the stopping criterion is met.
9: **Output** $\mathcal{Y}_1 = \{\bar{\boldsymbol{U}}_j^k, \bar{\boldsymbol{V}}_i^k, i = 1, \cdots, N_1,\ j = 1, \cdots, N_2\}$ as an approximate solution.

The general convergence and iteration complexity results of this setup are shown as follows:

1) Residual convergence: $\sum_{i=1}^{N_1} tr(\bar{\boldsymbol{V}}_i^k) + \sum_{j=1}^{N_2} tr(\bar{\boldsymbol{U}}_j^k) - 1 \to 0$, $x_i^k + y_i^k - p_i^k - \frac{\Gamma_i B t_i^k}{2\gamma} \to 0$ and $t^k - t_i^k \to 0$ as $k \to \infty$.
2) Objective convergence: $\lim_{k\to\infty} h(t^k, \bar{\boldsymbol{V}}_i^k, \bar{\boldsymbol{U}}_j^k) = p^\star$, where $p^\star$ is the optimal value of (P_7).
3) Iterate convergence: the iterates $\bar{\boldsymbol{U}}_i^k$, $\bar{\boldsymbol{V}}_i^k$, t^k, t_i^k, λ_i^k, ξ_i^k, η_{1i}^k, η_{2i}^k, η_{3i}^k and μ^k converge to their respective optimal solutions.

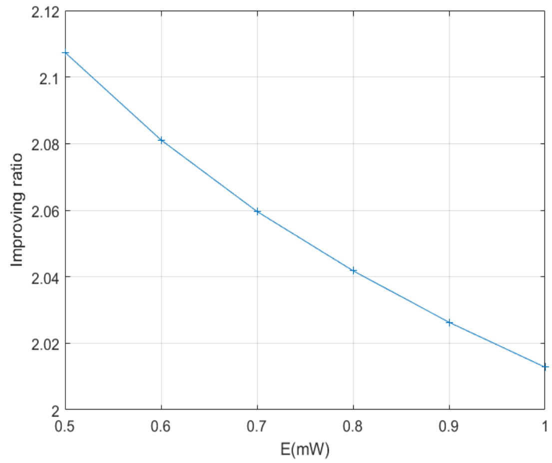

FIGURE 4. Improving ratio ∼ harvested energy.

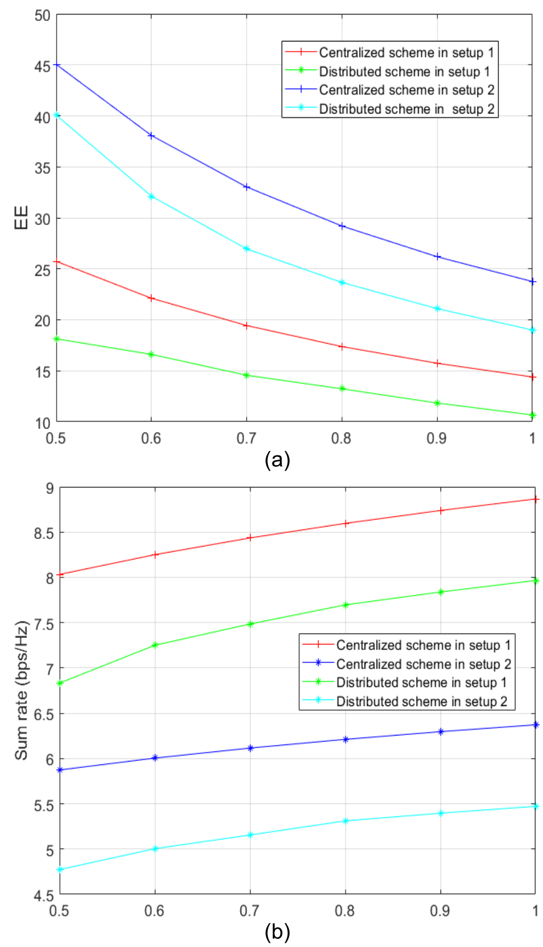

FIGURE 5. Energy efficiency ∼ harvested energy and Information transmission rate ∼ harvested energy.

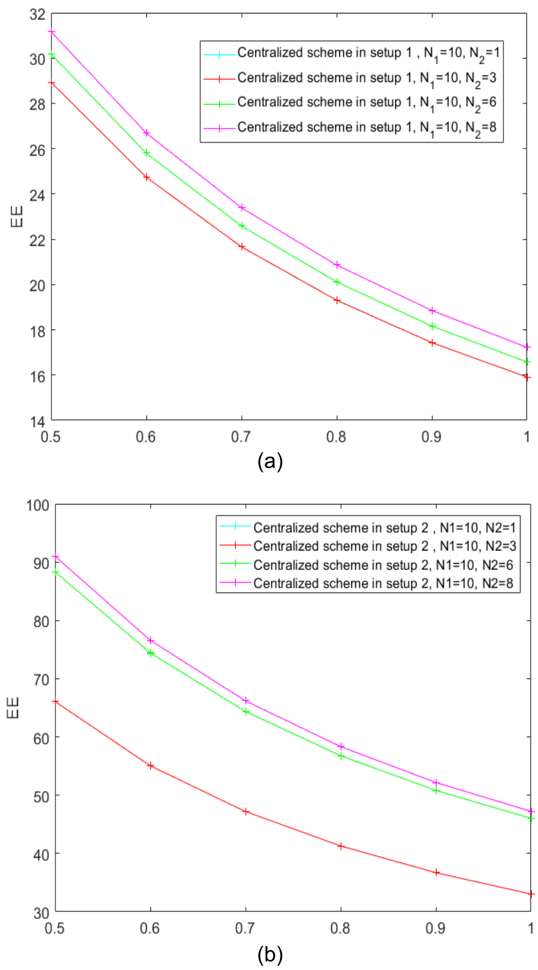

FIGURE 6. Energy efficiency ~ harvested energy.

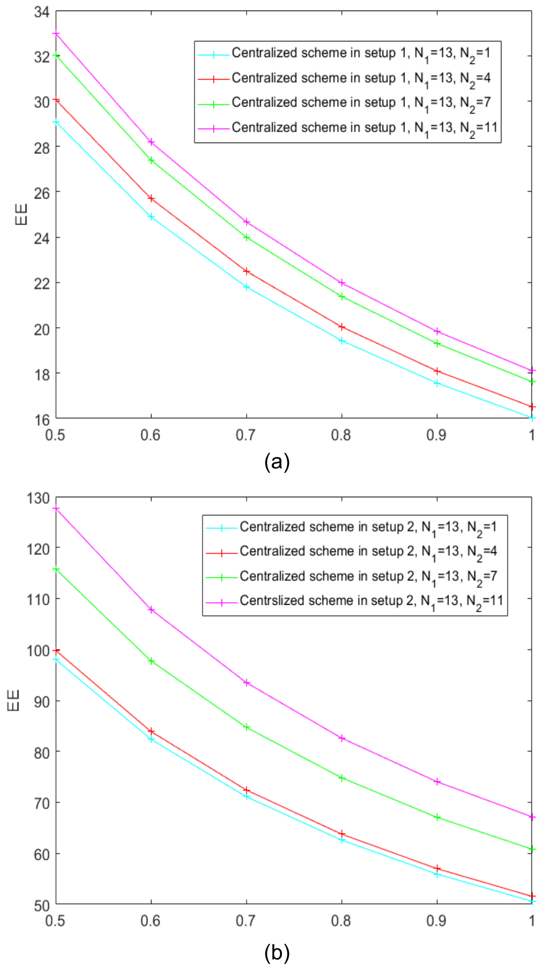

FIGURE 7. Energy efficiency ~ harvested energy.

V. NUMERICAL SIMULATIONS

In this section, we will give several experiments to evaluate the performance of our proposed two setups. Setup 1 is that the additional ETs use the same frequency bands as the transmitters, whereas setup 2 is that the additional ETs use different frequency bands. The channel vectors $\boldsymbol{h}_{ij}$ and $\boldsymbol{f}_{ij}$ are randomly generated according to Rayleigh fading with the average channel powers set as $(1 \times 10^{-3}) \times d^{-2}$ W, with d denoting the corresponding link distance in meters. The distances between the transmitters and the receivers are assumed to be 10 m, whereas those between the energy transmitters and the energy receivers are assumed to be 5 m. The symmetric energy to be harvested is set to change from 0.5 mW to 1 mW, where the stepsize is set as 0.1 mW. We assume that the total used bandwidths in two setups are set as 1 MHz and 0.5 MHz, respectively, the energy conversion efficiency at each receiver is $\eta = 0.8$ and the noise power at each information receiver is $\sigma^2 = -50$ dBm.

Scenario 1: In this scenario, we simulate the ratio of the maximum EE value of Problem (P_6) to that of Problem (P_1). In WIET system, assume that there are 6 information transmitter-receiver pairs with 3 antennas at each information transmitter side and 1 antennas at each information receiver side. Also, assume that there are 3 additional energy transmitters to transmit the energy. The number of antennas at each energy transmitter side and at each energy receiver side is the same as that at each information transmitter side and at each information receiver side. The simulation result is shown in Fig. 4.

Although the ratio of the maximum EE value of Problem (P_6) to that of Problem (P_1) is gradually decreasing with the increase of the harvested energy, the EE value of setup 2 is much larger than that of setup 1.

Scenario 2: In this scenario, we simulate the maximum EE and the corresponding information rate with different harvested energy value using the two setups in centralized and distributed schemes, respectively. In WIT, assume that there are 2 information transmitter-receiver pairs with 2 antennas at each information transmitter side and 1 antennas at each information receiver side, respectively. In WET, the number of energy transmitters, antennas at each energy transmitter side and at each energy receiver side is respectively the same as that in WIT. The simulation result is shown in Fig. 5.

It is obvious that the maximum EE value is decreasing with the increase of the harvested energy, while the corresponding

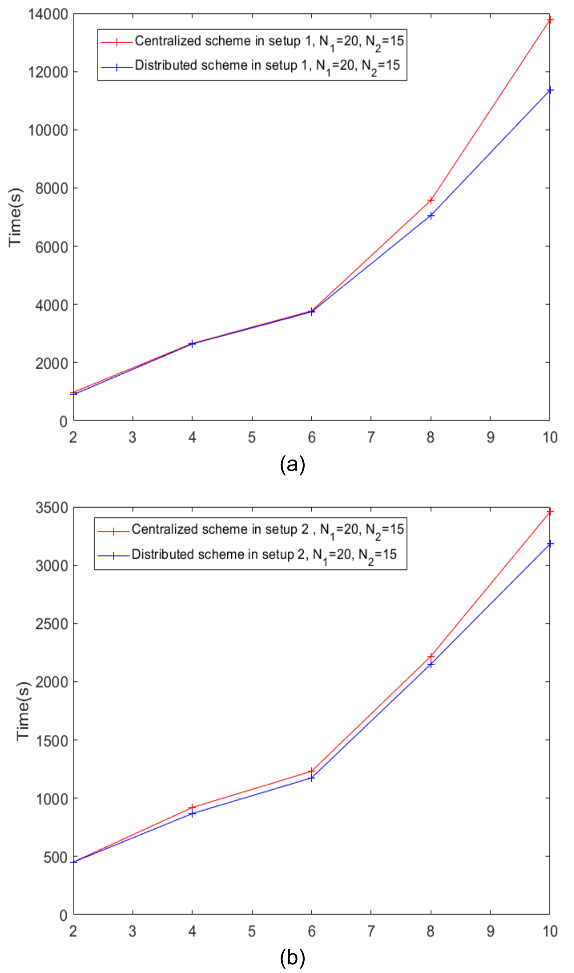

FIGURE 8. **Running time ∼ the number of antennas at each transmitter side.**

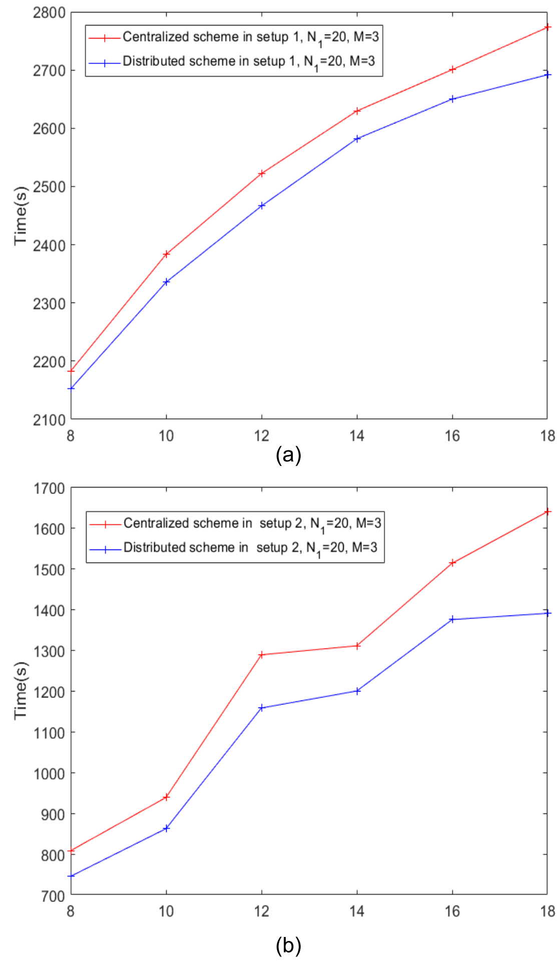

FIGURE 9. **Running time ∼ the number of additional energy transmitters.**

rate is increasing with the increase of the harvested energy for both the setups. Moreover, the maximum EE in setup 2 is better than that in setup 1, whereas the corresponding information rate in setup 2 is better than that in setup 1. Compared with the EE value and the rate value obtained from centralized scheme, the value of distributed scheme using the same setup is a little bit worse.

Scenario 3: In this scenario, we simulate the maximum EE value with the different number of additional energy transmitters using the centralized schemes in two setups, respectively. Consider the different two settings of the parameters in the two setups. The number of the information transmitters is set as 10 and that of the additional energy transmitters is set to change from 1 to 8 in the first setting, whereas the number of the information transmitters is set as 13 and that of the additional energy transmitters is set to change from 1 to 11 in the second setting. The number of the antennas at both each information transmitter side and each energy transmitter side is set as 3. The simulation results are shown respectively as follows.

From the simulation results shown in Fig. 6 and Fig. 7, it is obvious that the maximum EE value is increasing with the increasing number of addition energy transmitters. Although it seems that the two lines in the cases of $N_1 = 10$, $N_2 = 3$ and $N_1 = 10$, $N_2 = 1$ are the same both in Fig. 6(a) and Fig. 6(b), the values in the case of $N_1 = 10$, $N_2 = 3$ are a little bit larger than those in the case of $N_1 = 10$, $N_2 = 1$. Also, from each (a) and (b) of Fig. 6 and Fig. 7, the EE values of setup 2 are much larger than those of setup 1 in the same number of each information-energy transmitter pair and each additional energy transmitter. Moreover, the EE value increases with the increasing number of the information-energy transmitter pairs.

Scenario 4: In this scenario, we simulate the computational complexity of the two setups in centralized scheme and distributed scheme, respectively. The symmetric energy to be harvested is set as 0.7 mW. We consider the two settings of the parameters in the two setups. In the first setting, the number of the information-energy transmitter pairs is set as 20 and that of the additional energy transmitters is set as 15 The number of antennas at each energy transmitter side is set to change from 2 to 10. In the second setting, the number of the information-energy transmitter pairs is set as 20 and that of antennas at both each information transmitter side and each energy transmitter side is 3. The number of the additional energy transmitters is set to change from 8 to 18.

From the simulation result shown in Fig. 8, it is obvious that the computation complexity is increasing with the increasing number of antennas of both each information-energy pair and each additional energy transmitter. Although it seems that the two lines are almost the same from the begin in both Fig. 8(a) and Fig. 8(b), the computation complexity of distributed scheme increases more slowly compared with that of centralized one. From the simulation result shown in Fig. 9, it is obvious that the computation complexity is increasing with the increasing number of addition energy transmitters. Moreover, the computation complexity of distributed scheme is much smaller than that of centralized one, especially when the number of the additional energy transmitters is large.

VI. CONCLUDING REMARKS

In this paper, we introduce a novel structure for the WIET system based on two receiver structures: (a) PS with same frequency band and (b) BPF with different frequency bands, where additional energy transmitters (e.g., wireless power stations) are placed to enhance the efficiency of the wireless charging. Moreover, we investigate the EE maximization problem when additional energy transmitters use the same and different frequency bands, respectively. For each case, we propose both the centralized and distributed beamformer design. Our numerical results show that the WIET system with the different frequency bands can achieve a higher EE, while the WIET system with the same frequency bands can achieve a higher information transmission rate. Besides, for each case, the centralized beamformer can achieve slightly higher performance than the distributed one, while suffering from the higher computational complexity, especially when the number of the additional energy transmitters is large. Note that the time-splitting (TS) receiver structure is another widely studied setup, which is not discussed in this work. For this structure, we plan to consider its design as our future work.

APPENDIX I

Proof: The lagrangian function of (P_3) can be written as follows:

$$\begin{aligned}\mathcal{L}(\cdot) &= \sum_{i=1}^{N_1}\left[t\log_2\frac{\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}+\bar{\theta}_i\sigma_{Ii}^2}{t}\right]\\
&\quad\times\sum_{i=1}^{N_1}-\left[\frac{\sum_{r=1,r\neq i}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}+\bar{\theta}_iN_0B}{r_i^{[n-1]}}\right]\\
&\quad-\lambda\Big(\sum_{i=1}^{N_1}tr(\bar{\boldsymbol{V}}_i)+\sum_{j=1}^{N_2}tr(\bar{\boldsymbol{U}}_j)-1\Big)\\
&\quad+\sum_{i=1}^{N_1}\eta_i\left[\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j\boldsymbol{f}_{ij}-\frac{t\Gamma_i}{1-\rho_i}\right]\\
&\quad+\sum_{i=1}^{N_1}\xi_i\left(\bar{\theta}_i-\frac{t}{\rho_i}\right)+\sum_{i=1}^{N_1}\tau_{1i}\rho_i-\sum_{i=1}^{N_1}\tau_{2i}(\rho_i-1)\\
&\quad+\sum_{i=1}^{N_1}tr(\boldsymbol{Y}_{1i}\bar{\boldsymbol{V}}_i)+\sum_{i=1}^{N_2}tr(\boldsymbol{Y}_{2i}\bar{\boldsymbol{U}}_i),\end{aligned}$$

where $\lambda,\ \eta_i,\ \tau_{1i},\ \tau_{2i},\ \xi_i,\ \boldsymbol{Y}_{1i},\ \boldsymbol{Y}_{2i}$ are the lagrangian dual multipliers respectively corresponding to each constraint.

The corresponding KKT conditions regarding to $\bar{\boldsymbol{V}}_m^\star$ and $\bar{\boldsymbol{U}}_n^\star$ can be written as follows

$$\begin{aligned}&\sum_{i=1}^{N_1}\left[\frac{(t^\star)^2}{\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r^\star\boldsymbol{h}_{ir}+\sum_{j=1}^{N_1}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j^\star\boldsymbol{f}_{ij}+\bar{\theta}_i^\star N_0\,B}-\frac{1}{\boldsymbol{r}_i^{[n-1]}}\right]\\
&\quad\times\boldsymbol{h}_{im}\boldsymbol{h}_{im}^H+\frac{1}{\boldsymbol{r}_k^{[n-1]}}\boldsymbol{h}_{mm}\boldsymbol{h}_{mm}^H-\lambda^\star\boldsymbol{I}+\sum_{i=1}^{N_1}\eta_i^\star\boldsymbol{h}_{im}\boldsymbol{h}_{im}^H\\
&\quad+\boldsymbol{Y}_{1m}^\star=\boldsymbol{0},\end{aligned}\tag{15}$$

$$\begin{aligned}&\sum_{i=1}^{N_1}\left[\frac{(t^\star)^2}{\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r^\star\boldsymbol{h}_{ir}+\sum_{j=1}^{N_1}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j^\star\boldsymbol{f}_{ij}+\bar{\theta}_i^\star N_0B}-\frac{1}{\boldsymbol{r}_i^{[n-1]}}\right]\\
&\quad\times\boldsymbol{f}_{in}\boldsymbol{f}_{in}^H-\lambda^\star\boldsymbol{I}+\sum_{i=1}^{N_1}\eta_i^\star\boldsymbol{f}_{in}\boldsymbol{f}_{in}^H+\boldsymbol{Y}_{2n}^\star=\boldsymbol{0},\end{aligned}\tag{16}$$

$$\lambda^\star\Big(\sum_{i=1}^{N_1}tr(\bar{\boldsymbol{V}}_i^\star)+\sum_{j=1}^{N_2}tr(\bar{\boldsymbol{U}}_j^\star)-1\Big)=0,\tag{17}$$

$$\eta_i^\star\left[\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r^\star\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j^\star\boldsymbol{f}_{ij}-\frac{t^\star\Gamma_i}{1-\rho_i^\star}\right]=0,\tag{18}$$

$$tr(\boldsymbol{Y}_{1m}^\star\bar{\boldsymbol{V}}_m^\star)=0,\quad tr(\boldsymbol{Y}_{2n}^\star\bar{\boldsymbol{U}}_n^\star)=0,\tag{19}$$

$$\lambda^\star\text{ is any scalar},\quad \eta_i^\star\geq 0,\ \boldsymbol{Y}_{1m}^\star\succeq\boldsymbol{0},\ \boldsymbol{Y}_{2n}^\star\succeq\boldsymbol{0}.\tag{20}$$

From (15), it is not difficult to obtain that

$$\begin{aligned}&\mathrm{rank}(\boldsymbol{Y}_{1m}^\star)\\
&=\mathrm{rank}\Bigg(-\sum_{i=1}^{N_1}\Bigg[\frac{(t^\star)^2}{\sum_{r=1}^{N_1}\boldsymbol{h}_{ir}^H\bar{\boldsymbol{V}}_r^\star\boldsymbol{h}_{ir}+\sum_{j=1}^{N_2}\boldsymbol{f}_{ij}^H\bar{\boldsymbol{U}}_j^\star\boldsymbol{f}_{ij}+\bar{\theta}_i^\star N_0\,B}\\
&\quad-\frac{1}{r_i^{[n-1]}}\Bigg]\\
&\boldsymbol{h}_{im}\boldsymbol{h}_{im}^H+\frac{1}{r_m^{[n-1]}}\boldsymbol{h}_{mm}\boldsymbol{h}_{mm}^H+\lambda^\star\mathbf{I}-\sum_{i=1}^{N_1}\eta_i^\star\boldsymbol{h}_{im}\boldsymbol{h}_{im}^H\Bigg)\\
&=\mathrm{rank}\Big(-\sum_{i=1}^{N_1}a_i^\star\boldsymbol{h}_{im}\boldsymbol{h}_{im}^H+\lambda^\star\boldsymbol{I}\Big)\\
&\geq-\mathrm{rank}\Big(\sum_{i=1}^{N_1}a_i^\star\boldsymbol{h}_{im}\boldsymbol{h}_{im}^H\Big)+\mathrm{rank}\big(\lambda^\star\boldsymbol{I}\big)\\
&\geq-\sum_{i=1}^{N_1}a_i^\star\mathrm{rank}\big(\boldsymbol{h}_{im}\boldsymbol{h}_{im}^H\big)+\lambda^\star\mathrm{rank}\big(\boldsymbol{I}\big)\\
&\geq 0,\end{aligned}$$

where

$$a_i^\star = \begin{cases} -\dfrac{(t^\star)^2}{\sum\limits_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r^\star \boldsymbol{h}_{ir} + \sum\limits_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \bar{\boldsymbol{U}}_j^\star \boldsymbol{f}_{ij} + \bar{\theta}_i^\star N_0 B} \\ -\dfrac{1}{r_i^{[n-1]}} - \eta_i^\star, \quad i \neq m, \\ -\dfrac{(t^\star)^2}{\sum\limits_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r^\star \boldsymbol{h}_{ir} + \sum\limits_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \bar{\boldsymbol{U}}_j^\star \boldsymbol{f}_{ij} + \bar{\theta}_i^\star N_0 B} - \eta_i^\star, \\ i = m. \end{cases}$$

The last inequality is due to $\text{rank}(\boldsymbol{h}_{im}\boldsymbol{h}_{im}^H) = 1$, $a_i^\star$ may being 0 and $\lambda^\star > 0$. Assume that $\boldsymbol{A}_i = a_i^\star \boldsymbol{h}_{im}\boldsymbol{h}_{im}^H$, the second last inequality is due to $\sum_i \text{rank}(\boldsymbol{A}_i) \geq \text{rank}(\sum_i \boldsymbol{A}_i)$. Assume that $\boldsymbol{A} = \sum_{i=1}^{N_1} a_i^\star \boldsymbol{h}_{im}\boldsymbol{h}_{im}^H$, $\boldsymbol{B} = \lambda^\star \boldsymbol{I}$, the third last inequality is due to $\text{rank}(\boldsymbol{A}-\boldsymbol{B}) \geq \text{rank}(\boldsymbol{A}) - \text{rank}(\boldsymbol{B})$.

Owing to nonzero values of $\bar{\boldsymbol{V}}_m^\star$, $\text{rank}(\bar{\boldsymbol{V}}_m^\star)$ is greater than or equal to 1. Similarly, $\text{rank}(\bar{\boldsymbol{U}}_n^\star)$ is greater than or equal to 1. ■

APPENDIX II

Proof: The lagrangian function of (P_6) can be written as follows:

$$\begin{aligned} \mathcal{L}(\cdot) &= \sum_{i=1}^{N_1} \left[t \log_2 \frac{\sum\limits_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} + tN_0B/2}{t} \right] \\ &\quad - \sum_{i=1}^{N_1} \left[\frac{\sum\limits_{r=1, r\neq i}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} + tN_0B/2}{s_i^{[n-1]}} + \frac{t}{\ln 2} \right] \\ &\quad - \lambda\Big(\sum_{i=1}^{N_1} tr(\bar{\boldsymbol{V}}_i) + \sum_{j=1}^{N_2} tr(\bar{\boldsymbol{U}}_j) - 1 \Big) \\ &\quad + \sum_{i=1}^{N_1} \eta_i \left[\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r \boldsymbol{h}_{ir} + \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \bar{\boldsymbol{U}}_j \boldsymbol{f}_{ij} - \frac{B\Gamma_i t}{2\gamma} \right] \\ &\quad + \sum_{i=1}^{N_1} tr(\boldsymbol{Y}_{1i}\bar{\boldsymbol{V}}_i) + \sum_{j=1}^{N_2} tr(\boldsymbol{Y}_{2j}\bar{\boldsymbol{U}}_j), \end{aligned}$$

where λ, η_i, $\boldsymbol{Y}_{1i}$, $\boldsymbol{Y}_{2j}$ are the lagrangian dual multipliers respectively corresponding to each constraint.

The corresponding KKT conditions regarding to $\bar{\boldsymbol{V}}_m^\star$ and $\bar{\boldsymbol{U}}_n^\star$ can be written as follows:

$$\begin{aligned} &\sum_{i=1}^{N_1} \left[\frac{(t^\star)^2}{\sum\limits_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r^\star \boldsymbol{h}_{ir} + t^\star N_0B/2} - \frac{1}{s_i^{[n-1]}} \right] \boldsymbol{h}_{im}\boldsymbol{h}_{im}^H \\ &\quad + \frac{1}{s_m^{[n-1]}} \boldsymbol{h}_{mm}\boldsymbol{h}_{mm}^H - \lambda^\star \boldsymbol{I} \\ &\quad + \sum_{i=1}^{N_1} \eta_i^\star \boldsymbol{h}_{im}\boldsymbol{h}_{im}^H + \boldsymbol{Y}_{1m}^\star = \boldsymbol{0}, \end{aligned} \tag{21}$$

$$-\lambda^\star \boldsymbol{I} + \sum_{i=1}^{N_1} \eta_i^\star \boldsymbol{f}_{in}\boldsymbol{f}_{in}^H + \boldsymbol{Y}_{2n}^\star = \boldsymbol{0}, \tag{22}$$

$$\lambda^\star\Big(\sum_{i=1}^{N_1} tr(\bar{\boldsymbol{V}}_i^\star) + \sum_{j=1}^{N_2} tr(\bar{\boldsymbol{U}}_j^\star) - 1 \Big) = 0, \tag{23}$$

$$\eta_i^\star \left[\sum_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r^\star \boldsymbol{h}_{ir} + \sum_{j=1}^{N_2} \boldsymbol{f}_{ij}^H \bar{\boldsymbol{U}}_j^\star \boldsymbol{f}_{ij} - \frac{B\Gamma_i t}{2\gamma} \right] = 0, \tag{24}$$

$$tr(\boldsymbol{Y}_{1m}^\star \bar{\boldsymbol{V}}_m^\star) = 0, \quad tr(\boldsymbol{Y}_{2n}^\star \bar{\boldsymbol{U}}_n^\star) = 0, \tag{25}$$

$$\lambda^\star \text{ is any scalar}, \ \eta_j^\star \geq 0, \quad \boldsymbol{Y}_{1m}^\star \succeq \boldsymbol{0}, \ \boldsymbol{Y}_{2n}^\star \succeq \boldsymbol{0}. \tag{26}$$

From (22), it is not difficult to obtain that

$$\begin{aligned} &\text{rank}(\boldsymbol{Y}_{1m}^\star) \\ &= \text{rank}\Bigg(-\sum_{i=1}^{N1} \left[\frac{(t^\star)^2}{\sum\limits_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r^\star \boldsymbol{h}_{ir} + t^\star N_0B/2} - \frac{1}{s_i^{[n-1]}} \right] \\ &\quad \times \boldsymbol{h}_{im}\boldsymbol{h}_{im}^H + \frac{1}{s_m^{[n-1]}} \boldsymbol{h}_{mm}\boldsymbol{h}_{mm}^H + \lambda^\star \boldsymbol{I} - \sum_{i=1}^{N_1} \eta_i^\star \boldsymbol{h}_{im}\boldsymbol{h}_{im}^H \Bigg) \\ &= \text{rank}\Big(-\sum_{i=1}^{N_1} a_i^\star \boldsymbol{h}_{im}\boldsymbol{h}_{im}^H + \lambda^\star \boldsymbol{I} \Big) \\ &\geq -\text{rank}\Big(\sum_{i=1}^{N_1} a_i^\star \boldsymbol{h}_{im}\boldsymbol{h}_{im}^H \Big) + \text{rank}\big(\lambda^\star \boldsymbol{I}\big) \\ &\geq -\sum_{i=1}^{N_1} a_i^\star \text{rank}\big(\boldsymbol{h}_{im}\boldsymbol{h}_{im}^H\big) + \lambda^\star \text{rank}\big(\boldsymbol{I}\big) \\ &\geq 0, \end{aligned}$$

where

$$a_i^\star = \begin{cases} -\dfrac{(t^\star)^2}{\sum\limits_{r=1}^{N_1} \boldsymbol{h}_{ir}^H \bar{\boldsymbol{V}}_r^\star \boldsymbol{h}_{ir} + t^\star N_0B/2} - \dfrac{1}{s_i^{[n-1]}} - \eta_i^\star, & i \neq m, \\ -\dfrac{(t^\star)^2}{\sum\limits_{r=1}^{N_1} \boldsymbol{h}_{mr}^H \bar{\boldsymbol{V}}_r^\star \boldsymbol{h}_{mr} + t^\star N_0B/2} - \eta_m^\star, & i = m. \end{cases}$$

The last inequality is due to $\text{rank}(\boldsymbol{h}_{im}\boldsymbol{h}_{im}^H) = 1$, $a_i^\star$ may being 0 and $\lambda^\star > 0$. Assume that $\boldsymbol{A}_i = a_i^\star \boldsymbol{h}_{im}\boldsymbol{h}_{im}^H$, the second last inequality is due to $\sum_i \text{rank}(\boldsymbol{A}_i) \geq \text{rank}(\sum_i \boldsymbol{A}_i)$. Assume that $\boldsymbol{A} = \sum_{i=1}^{N_1} a_i^\star \boldsymbol{h}_{im}\boldsymbol{h}_{im}^H$, $\boldsymbol{B} = \lambda^\star \boldsymbol{I}$, the third last inequality is due to $\text{rank}(\boldsymbol{A}-\boldsymbol{B}) \geq \text{rank}(\boldsymbol{A}) - \text{rank}(\boldsymbol{B})$.

Owing to nonzero values of $\bar{\boldsymbol{Y}}_{1m}^\star$, $\text{rank}(\bar{\boldsymbol{Y}}_{1m}^\star) \geq 1$. Thus, $\text{rank}(\bar{\boldsymbol{V}}_m^\star)$ is greater than or equal to 1 because of $tr(\boldsymbol{Y}_{1m}^\star \bar{\boldsymbol{V}}_m^\star) = 0$. Similarly, $\text{rank}(\bar{\boldsymbol{U}}_n^\star)$ is greater than or equal to 1. ■

REFERENCES

[1] H. Sun, Y.-X. Guo, M. He, and Z. Zhong, "Design of a high-efficiency 2.45-GHz rectenna for low-input-power energy harvesting," *IEEE Antennas Wireless Propag. Lett.*, vol. 11, pp. 929–932, 2012.

[2] R. Zhang and C. K. Ho, "MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, pp. 1989–2001, May 2013.
[3] X. Zhou, R. Zhang, and C. K. Ho, "Wireless information and power transfer: Architecture design and rate-energy tradeoff," *IEEE Trans. Commun.*, vol. 61, no. 11, pp. 4754–4767, Nov. 2013.
[4] J. Park and B. Clerckx, "Joint wireless information and energy transfer in a two-user MIMO interference channel," *IEEE Trans. Wireless Commun.*, vol. 12, no. 8, pp. 4210–4221, Aug. 2013.
[5] J. Park and B. Clerckx, "Joint wireless information and energy transfer in a K-user MIMO interference channel," *IEEE Trans. Wireless Commun.*, vol. 13, no. 10, pp. 5781–5796, Oct. 2014.
[6] Q. Li and W.-K. Ma, "Spatially selective artificial-noise aided transmit optimization for MISO multi-eves secrecy rate maximization," *IEEE Trans. Signal Process.*, vol. 61, no. 10, pp. 2704–2717, May 2013.
[7] S. A. Vorobyov, A. B. Gershman, and Z.-Q. Luo, "Robust adaptive beamforming using worst-case performance optimization: A solution to the signal mismatch problem," *IEEE Trans. Signal Process.*, vol. 51, no. 2, pp. 313–324, Feb. 2003.
[8] Y. J. A. Zhang and A. M.-C. So, "Optimal spectrum sharing in MIMO cognitive radio networks via semidefinite programming," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 2, pp. 362–373, Feb. 2011.
[9] G. Yang, C. K. Ho, R. Zhang, and Y. L. Guan, "Throughput optimization for massive MIMO systems powered by wireless energy transfer," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 8, pp. 1640–1650, Aug. 2015.
[10] P. Grover and A. Sahai, "Shannon meets Tesla: Wireless information and power transfer," in *Proc. IEEE Int. Symp. Inf. Theory (ISIT)*, vol. 41, no. 3, Jun. 2010, pp. 2363–2367.
[11] C. Shen, W.-C. Li, and T.-H. Chang, "Wireless information and energy transfer in multi-antenna interference channel," *IEEE Trans. Signal Process.*, vol. 62, no. 23, pp. 6249–6264, Dec. 2014.
[12] L. R. Varshney, "Transporting information and energy simultaneously," in *Proc. IEEE Int. Symp. Inf. Theory (ISIT)*, Jul. 2008, pp. 1612–1616.
[13] L. Liu, R. Zhang, and K.-C. Chua, "Wireless information and power transfer: A dynamic power splitting approach," *IEEE Trans. Commun.*, vol. 61, no. 9, pp. 3990–4001, Sep. 2013.
[14] Q. Shi, L. Liu, W. Xu, and R. Zhang, "Joint transmit beamforming and receive power splitting for MISO SWIPT systems," *IEEE Trans. Wireless Commun.*, vol. 13, no. 6, pp. 3269–3280, Jun. 2014.
[15] J. Xu, L. Liu, and R. Zhang, "Multiuser MISO beamforming for simultaneous wireless information and power transfer," *IEEE Trans. Signal Process.*, vol. 62, no. 18, pp. 4798–4810, Sep. 2014.
[16] S. Timotheou, I. Krikidis, G. Zheng, and B. Ottersten, "Beamforming for MISO interference channels with QoS and RF energy transfer," *IEEE Trans. Wireless Commun.*, vol. 13, no. 5, pp. 2646–2658, May 2014.
[17] S. Bi, C. K. Ho, and R. Zhang, "Wireless powered communication: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 117–125, Apr. 2015.
[18] X. Lu, P. Wang, D. Niyato, D. I. Kim, and Z. Han, "Wireless networks with RF energy harvesting: A contemporary survey," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 2, pp. 757–789, 2nd Quart., 2015.
[19] J. Xu, S. Bi, and R. Zhang, "Multiuser MIMO wireless energy transfer with coexisting opportunistic communication," *IEEE Wireless Commun. Lett.*, vol. 4, no. 3, pp. 273–276, Jun. 2015.
[20] X. M. Luo, Y. Zeng, and R. Zhang, "Cognitive wireless power transfer with information helping," *IEEE Wireless Commun. Lett.*, vol. 6, no. 3, pp. 346–349, 2017.
[21] S. Lee and R. Zhang, "Cognitive wireless powered network: Spectrum sharing models and throughput maximization," *IEEE Trans. Cognit. Commun. Netw.*, vol. 1, no. 3, pp. 335–346, Mar. 2015.
[22] *Powercast*. [Online]. Available: https://www.powercastco.com/products/powercaster-transmitter/
[23] Z.-Q. Luo, W.-K. Ma, A. M.-C. So, Y. Y. Ye, and S. Z. Zhang, "Semidefinite relaxation of quadratic optimization problems," *IEEE Signal Process. Mag.*, vol. 27, no. 3, pp. 20–34, May 2010.
[24] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.
[25] D. P. Bertsekas and J. N. Tsitsiklis, *Parallel and Distributed Computation: Numerical Methods*. Upper Saddle River, NJ, USA: Prentice-Hall, 1989.
[26] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Found. Trends Mach. Learn.*, vol. 3, no. 1, pp. 1–122, Jan. 2011.
[27] D. Gabay and B. Mercier, "A dual algorithm for the solution of nonlinear variational problems via finite element approximation," *Comput. Optim. Appl.*, vol. 2, no. 1, pp. 17–40, 1976.
[28] R. Glowinski and A. Marrocco, "Sur l'approximation, par éléments finis d'ordre un, et la résolution, par pénalisation-dualité, d'une classe de problèmes de Dirichlet non linéaires," (in French), *Rev. FranÃğaise Automat. Informat. Recherche Opérationnelle Sér. Rouge Anal. Numér.*, vol. 9, no. R-2, pp. 41–76, 1975.
[29] J. Yang and Y. Zhang, "Alternating direction algorithms for ℓ_1-problems in compressive sensing," *SIAM J. Sci. Comput.*, vol. 33, no. 1, pp. 250–278, 2011.
[30] X. Yuan, "Alternating direction method for covariance selection models," *J. Sci. Comput.*, vol. 51, no. 2, pp. 261–273, 2012.
[31] D. P. Bertsekas and J. N. Tsitsiklis, *Nonlinear Programming*, 2nd ed. Belmont, MA, USA: Athena Scientific, 1999.
[32] X. Zhang, M. Burger, and S. Osher, "A unified primal-dual algorithm framework based on Bregman iteration," *J. Sci. Comput.*, vol. 46, no. 1, pp. 20–46, 2011.
[33] Z. K. M. Ho and D. Gesbert, "Balancing egoism and altruism on interference channel: The MIMO case," presented at the IEEE ICC, Cape Town, South Africa, 2010, pp. 1–5.
[34] M. Grant and S. Boyd. (Sep. 2013). *CVX: MATLAB Software for Disciplined Convex Programming, Version 2.0 Beta*. [Online]. Available: http://cvxr.com/cvx
[35] M. Razaviyayn, M. Hong, and Z.-Q. Luo, "A unified convergence analysis of block successive minimization methods for nonsmooth optimization," *SIAM J. Optim.*, vol. 23, no. 2, pp. 1126–1153, 2013.
[36] Y. Huang and D. P. Palomar, "Rank-constrained separable semidefinite programming with applications to optimal beamforming," *IEEE Trans. Signal Process.*, vol. 58, no. 2, pp. 664–678, Feb. 2010.
[37] M. Hong and Z.-Q. Luo, "On the linear convergence of the alternating direction method of multipliers," *Math. Program.*, vol. 162, nos. 1–2, pp. 165–199, 2017.

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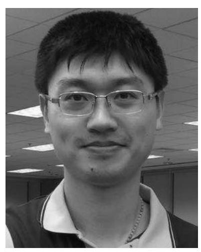

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