Wireless Information and Energy Transfer in MIMO Communication with Interference Channels

XIAOMEI LUO1, HANG LI2, AND XIANGFENG WANG3

1Department of Electronic Information Engineering, Nanchang University, Nanchang, 330031, China. (e-mail: xxmluo@gmail.com)
2Shenzhen Research Institute of Big Data, Shenzhen, 518172, China. (e-mail: hangdavidli@163.com)
3Shanghai Key Lab. of Trustworthy Computing, Software Engineering Institute, East China Normal University, 200062, Shanghai, China. (e-mail: xfwang@sci.ecnu.edu.cn)

Corresponding author: Xiaomei Luo (e-mail: xxmluo@gmail.com).

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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 et al. 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 informa-
tion 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 appli-
cations of RF-enabled wireless energy transfer (WET) tech-
nologies in wireless power communication networks (WPC-
N). Lu et. al. [18] provided a survey about RF energy harvest-
ning 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 effi-
ciciency for transferring energy is not satisfying [20, simula-
tion 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 trans-
mission in this paper. To be more specific, the new structure
includes several transmitters, of which more than one tra-
mitter are dedicated to transmitting the energy. Moreover,
the joint transmission of information and energy can be
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 effi-
ciently 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 formul-
ation 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 frequen-
cy bands). We consider the so called alternating direction
method of multipliers (ADMM) [25], [26] to tackle this prob-
lem. ADMM was first introduced in [27], [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 con-
ventional 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 investigat-
ed 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 $h_{ij} \in \mathbb{C}^{M_1 \times 1}$ 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

$$y_i = h_{i1}^H v_i s_i + \sum_{r=1, r \neq i}^{N_1} h_{ir}^H v_r s_r + z_i,$$

where $(\cdot)^H$ denotes Hermitian transform, $s_i \in \mathbb{C}$ is a random
transmitted signal with the normalized power $\mathbb{E}[|s_i|^2] = 1$,
$v_i \in \mathbb{C}^{M_1 \times 1}$ 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
The communication system is shown in Fig. 1. To the receivers and the channel there are additional ETs transferring energy to the receivers in order to satisfy the energy harvesting requirement. Therefore, we consider to add additional ETs to exclusively harvest the energy. Then, a band passing (BP) filter with half the total bandwidth serves the ID-EH pair, which is shown in Fig. 2. The corresponding information signal $y_{i1} \in \mathbb{C}$, $i = 1, \cdots, N_1$, using the power splitting scheme is denoted by

$$y_{i1} = \sqrt{\rho_i} \left( \sum_{r=1}^{N_1} h_{ir}^H v_r s_r + z_i \right) + z_{i1},$$

where $\rho_i$ denotes the portion of the power split to the information decoder at the receiver $i$, while $z_{i1} \in \mathbb{C}$ is the complex Gaussian noise with distribution $\mathcal{CN}(0, \sigma^2_{i1})$.

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

$$Q_i = \gamma \Delta \mathbb{E} [y_{Ei} y_{Ei}^H] = \gamma \frac{(1 - \rho_i) \sum_{r=1}^{N_1} \| v_r^H h_{ir} \|^2}{B},$$

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 $f_{ij} \in \mathbb{C}^{M_2 \times 1}$ denoting the channel from the ET $j$ to the receiver $i$. The whole communication system is shown in Fig. 1.

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.

The received signal $y_{i1} \in \mathbb{C}$ at the ID $i$, $i = 1, \cdots, N_1$, is

$$y_{i1} = \sqrt{\rho_i} \left( \sum_{r=1}^{N_1} h_{ir}^H v_r s_r + \sum_{j=1}^{N_2} f_{ij}^H u_j s_{Ej} + z_i \right) + z_{i1}.$$ 

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 $z_i$),

$$R_{i1} = B \log_2 \left( 1 + \sum_{r=1}^{N_1} \| v_r^H h_{ir} \|^2 + \sum_{j=1}^{N_2} \| u_j^H f_{ij} \|^2 + N_0 B \right),$$

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

$$y_{Ei} = \sqrt{1 - \rho_i} \left( \sum_{r=1}^{N_1} h_{ir}^H v_r s_r + \sum_{j=1}^{N_2} f_{ij}^H u_j s_{Ej} + z_i \right).$$

Thus, the harvested energy $Q_i$, at the EH $i$, $i = 1, \cdots, N_1$, can be represented by (ignoring the noise $z_i$)

$$Q_i = \gamma \frac{(1 - \rho_i) \sum_{r=1}^{N_1} \| v_r^H h_{ir} \|^2 + \sum_{j=1}^{N_2} \| u_j^H f_{ij} \|^2}{B}.$$
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

$$\text{(P}_1\text{)} \quad \max \frac{\sum_{i=1}^{N_1} R_{1i}}{\sum_{i=1}^{N_1} \|v_i\|^2 + \sum_{j=1}^{N_2} \|u_j\|^2},$$

subject to

$$\text{Eq. (22)} \geq \Gamma_i,$$

$$0 \leq \rho_i \leq 1.$$ 

where $\Gamma_i$ is the harvested energy limit, the maximum value of the harvested energy.

Problem (P1) 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 (P1) 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 $V_i = v_i v_i^H$ and $U_i = u_i u_i^H$, we can write the objective function in Problem (P1) as

$$\frac{\sum_{i=1}^{N_1} R_{1i}}{\sum_{i=1}^{N_1} \text{tr}(V_i) + \sum_{j=1}^{N_2} \text{tr}(U_j)},$$

where

$$R_{1i} = \log_2 \left( 1 + \sum_{j=1}^{N_2} f_{ij}^2 \right) \left( 1 + \frac{\rho_i h_{ir}^H V_i h_{ir} + \rho_i \sum_{j=1}^{N_2} f_{ij}^H U_j f_{ij} + N_0 B}{\rho_i \sum_{j=1}^{N_1} f_{ij}^H V_i h_{ir}} \right).$$

The harvested energy $Q_i$ at the EH $i$, $i = 1, \cdots, N_1$, can be rewritten as

$$Q_i = \gamma \frac{2 \left( \sum_{j=1}^{N_2} \|f_{ij}\|^2 \right) + \sum_{r=1}^{N_1} \|h_{ir}\|^2}{B}.$$

Therefore, Problem (P1) can be reformulated as

$$\max \frac{\sum_{i=1}^{N_1} R_{1i}}{\sum_{i=1}^{N_1} \text{tr}(V_i) + \sum_{j=1}^{N_2} \text{tr}(U_j)},$$

subject to

$$\text{Eq. (22)} \geq \Gamma_i,$$

$$0 \leq \rho_i \leq 1.$$ 

$$V_i \succeq 0, \quad U_j \succeq 0,$$

$$\text{rank}(V_i) = 1, \quad \text{rank}(U_j) = 1.$$

III. BEAMFORMING DESIGN IN SAME FREQUENCY BANDS

In this section, we design the beamformers $\{v_i, u_j, i = 1, \cdots, N_1, j = 1, \cdots, N_2\}$ 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

$$\frac{\sum_{i=1}^{N_1} R_{1i}}{\sum_{i=1}^{N_1} \|v_i\|^2 + \sum_{j=1}^{N_2} \|u_j\|^2},$$
Assume that
\[ \tilde{V}_i = tV_i, \quad i = 1, \ldots, N_1, \]
\[ \tilde{U}_j = tU_j, \quad j = 1, \ldots, N_2, \]
\[ \tilde{\theta}_i = \frac{t}{\rho_i} = \theta_i. \]

Each term in the sum of (6) can be rewritten as
\[ B \left[ \sum_{r=1}^{N_1} h_{ir}^H \tilde{V}_i h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \tilde{U}_j f_{ij} + \tilde{\theta}_i N_0 B \right] - \sum_{r \neq i} r_{[n-1]}^{[n]} \ln 2 = \sum_{r \neq i} r_{[n-1]}^{[n]} \ln 2 + t \ln 2 \]  
(7)
The first term of (7) is concave with respect to $t, \tilde{V}_i, \tilde{U}_j$, and $\tilde{\theta}_i$ because it is the perspective function of the concave function $B \log_2 \frac{\sum_{r=1}^{N_1} h_{ir}^H \tilde{V}_i h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \tilde{U}_j f_{ij} + \tilde{\theta}_i N_0 B}{r_{[n-1]}^{[n]} \ln 2}$, while the second term of (7) is linear with respect to $\tilde{V}_i, \tilde{U}_j$ and $\tilde{\theta}_i$. Thus, the objective function of (7) is a concave function. The first constraint of (5) can be rewritten as
\[ \sum_{i=1}^{N_1} \text{tr}(V_i) + \sum_{j=1}^{N_2} \text{tr}(U_j) = 1. \]

Obviously, it is convex.

The second constraint of (5) can be rewritten as
\[ (1 - \rho_i) \left[ \sum_{r=1}^{N_1} h_{ir}^H \tilde{V}_i h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \tilde{U}_j f_{ij} \right] \geq \frac{B \Gamma_i t}{\gamma}. \]

Therefore, problem (5) can be reformulated as
\[ (P_2) \max \sum_{i=1}^{N_1} \text{tr}(V_i) + \sum_{j=1}^{N_2} \text{tr}(U_j) = 1, \]
\[ (1 - \rho_i) \left[ \sum_{r=1}^{N_1} h_{ir}^H \tilde{V}_i h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \tilde{U}_j f_{ij} \right] \geq \frac{B \Gamma_i t}{\gamma}, \]
where
\[ r_{[n-1]}^{[n]} = \sum_{r=1}^{N_1} h_{ir}^H V_{[n]}^{[n]} h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H U_{[n]}^{[n]} f_{ij} + \theta_i^{[n-1]} N_0 B. \]

It is obvious that the approximation information rate (6) is a concave function in variables $U_j, V_r, \theta_i$.

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:

\[
\log(1 - \rho_i) + \log \left[ \sum_{r=1}^{N_1} h_{ir}^H \tilde{V}_r, h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \tilde{U}_j f_{ij} \right] \\
\geq \log t + \log \frac{B \Gamma_i}{\gamma}.
\]

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

\[
\log t \leq \log t - \frac{1}{t} - 1 \left( t - t^{k-1} \right),
\]

which makes (8) further approximated as

\[
\log(1 - \rho_i) + \log \left[ \sum_{r=1}^{N_1} h_{ir}^H \tilde{V}_r, h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \tilde{U}_j f_{ij} \right] \\
\geq \log B \Gamma_i + \log t - \frac{1}{t} - 1 \left( t - t^{k-1} \right).
\]

Obviously, this constraint is convex.

Using similar mathematical manipulations to the third constraint of (P2), we can approximate it by

\[
\log \tilde{\theta}_i + \log \rho_i \geq \log t - \frac{1}{t} - 1 \left( t - t^{k-1} \right).
\]

Therefore, problem (5) can be reformulated as

\[
(P_3) \max_{\{t, \rho_i, \tilde{\theta}_i\} } t \log^2 \sum_{r=1}^{N_1} h_{ir}^H \tilde{V}_r, h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \tilde{U}_j f_{ij} + \tilde{\theta}_i, N_0 B \]

\[
\sum_{r \neq i}^{N_1} h_{ir}^H \tilde{V}_r, h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \tilde{U}_j f_{ij} + \tilde{\theta}_i, N_0 B \]

\[
= \frac{t}{2} \ln 2,
\]

\[
\text{s.t.} \quad \sum_{i=1}^{N_1} t r(\tilde{V}_i) + \sum_{j=1}^{N_2} t r(\tilde{U}_j) = 1,
\]

\[
\sum_{i=1}^{N_1} \log(1 - \rho_i) + \sum_{j=1}^{N_2} \log f_{ij}^H \tilde{U}_j f_{ij} \geq \log t + \log \frac{B \Gamma_i}{\gamma}.
\]

Problem (P2) can be reformulated as

\[
\min_{\mathbf{x}} -B \sum_{i=1}^{N_1} \left[ \sum_{j=1}^{N_2} h_{ir}^H \tilde{V}_r, h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \tilde{U}_j f_{ij} + \tilde{\theta}_i, N_0 B \right] \\
- \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} t r(\tilde{V}_i) + t r(\tilde{U}_j) = 1,
\]

\[
\text{s.t.} \quad (x_i + y_i) - (\tilde{x}_i + \tilde{y}_i) - p_i = \frac{B \Gamma_i t_i}{\gamma},
\]

\[
\tilde{\theta}_i p_i = t_i, \quad t_i, \quad \tilde{z}_i = h_{ir}^H \tilde{V}_r, h_{ir},
\]

\[
\tilde{V}_i \geq 0, \tilde{U}_j \geq 0,
\]

\[
0 \leq \tilde{x}_i \leq x_i, \quad 0 \leq \tilde{y}_i \leq y_i,
\]

\[
0 \leq \rho_i \leq 1, \quad p_i \geq 0.
\]
which can be further simplified as

$$
\min x \quad -B \sum_{i=1}^{N_1} \left[ t_i \log_2 \left( \frac{x_i + y_i + \bar{\theta}_i N_0 B}{r_i^{(n-1)}} + \frac{t_i}{\ln 2} \right) \right] \\
- \sum_{i=1}^{N_1} \left[ \frac{x_i + y_i + \bar{\theta}_i N_0 B}{r_i^{(n-1)}} + \frac{z_i}{r_i^{(n-1)}} \right],
$$

s.t.

$$
\sum_{i=1}^{N_1} tr(V_i) + \sum_{j=1}^{N_2} tr(U_j) = 1,
$$

(P_4)

$$
A_1 \begin{bmatrix} x_i \\ y_i \end{bmatrix} - A_2 \begin{bmatrix} \bar{x}_i \\ \bar{y}_i \end{bmatrix} - \alpha_3 p_i = c_i,
$$

$$
z_i = h_i^H V_i h_{ii}, \bar{\theta}_i p_i = t_i, \quad t = t_i,
$$

$$
V_i \succeq 0, \quad U_j \succeq 0,
$$

$$
0 \leq \bar{x}_i \leq x_i, \quad 0 \leq \bar{y}_i \leq y_i,
$$

$$
0 \leq p_i \leq 1, \quad p_i \geq 0,
$$

where

$$
A_1 = \begin{bmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}^T, \quad A_2 = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}^T,
$$

$$
\alpha_3 = \begin{bmatrix} 1 & 0 \end{bmatrix}^T, \quad c_i = \begin{bmatrix} B \gamma_1 \gamma_2 \\ \sum_{i=1}^{N_1} h_i^H V_i h_{ii} \\ \sum_{j=1}^{N_2} f_i U_j f_{ij} \end{bmatrix}.
$$

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

$$
\mathcal{L}(\mathbf{x}) = -B \sum_{i=1}^{N_1} \left[ t_i \log_2 \left( \frac{x_i + y_i + \bar{\theta}_i N_0 B}{r_i^{(n-1)}} + \frac{t_i}{\ln 2} \right) \right] + \sum_{i=1}^{N_1} \left[ \frac{x_i + y_i + \bar{\theta}_i N_0 B}{r_i^{(n-1)}} + \frac{z_i}{r_i^{(n-1)}} \right] + \sum_{i=1}^{N_1} \eta_i^H \left( A_1 \begin{bmatrix} x_i \\ y_i \end{bmatrix} - A_2 \begin{bmatrix} \bar{x}_i \\ \bar{y}_i \end{bmatrix} - \alpha_3 p_i - c_i \right) + \frac{\xi_i}{2} \left( \bar{\theta}_i p_i - t_i \right)^2 + \frac{\lambda_i}{2} \left( \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} tr(V_i) + \sum_{j=1}^{N_2} tr(U_j) - 1 \right)^2
$$

$$
+ \sum_{i=1}^{N_1} \frac{\beta}{2} \left( z_i - h_i^H V_i h_{ii} \right)^2 + \sum_{i=1}^{N_1} \frac{\beta}{2} \left( t - t_i \right)^2
$$

s.t.

$$
V_i \succeq 0, \quad U_j \succeq 0,
$$

$$
0 \leq \bar{x}_i \leq x_i, \quad 0 \leq \bar{y}_i \leq y_i,
$$

$$
0 \leq p_i \leq 1, \quad p_i \geq 0.
$$

Dividing the set $\mathbf{x}$ into four subsets $\mathbf{x}_1 = \{U_j, \bar{V}_i, i = 1, \ldots, N_1, j = 1, \ldots, N_2\}$, $\mathbf{x}_2 = \{t_i, x_i, y_i, \bar{x}_i, \bar{y}_i, \bar{\theta}_i, \bar{p}_i, t_i, i = 1, \ldots, N_1\}$, $\mathbf{x}_3 = \{t\}$ and $\mathbf{x}_4 = \{\rho_i, i = 1, \ldots, N_1\}$, we can solve the original problem (P_1) by solving the following four subproblems.

Firstly, the subproblem for $\mathbf{x}_1 = \{U_j, \bar{V}_i, i = 1, \ldots, N_1, j = 1, \ldots, N_2\}$ is

$$
\min_{x_1} \frac{\beta}{2} \left( \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} t_i \log_2 \left( \frac{x_i + y_i + \bar{\theta}_i N_0 B}{r_i^{(n-1)}} + \frac{t_i}{\ln 2} \right) \right) + \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} \left[ \frac{x_i + y_i + \bar{\theta}_i N_0 B}{r_i^{(n-1)}} + \frac{z_i}{r_i^{(n-1)}} \right] + \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} \eta_i^H \left( A_1 \begin{bmatrix} x_i \\ y_i \end{bmatrix} - A_2 \begin{bmatrix} \bar{x}_i \\ \bar{y}_i \end{bmatrix} - \alpha_3 p_i - c_i \right) + \sum_{i=1}^{N_1} \frac{\beta}{2} \left( z_i - h_i^H V_i h_{ii} \right)^2 + \sum_{i=1}^{N_1} \frac{\beta}{2} \left( t - t_i \right)^2
$$

s.t.

$$
V_i \succeq 0, \quad U_j \succeq 0,
$$

$$
0 \leq x_i, \quad 0 \leq y_i, \quad 0 \leq \bar{x}_i \leq x_i, \quad 0 \leq \bar{y}_i \leq y_i,
$$

$$
0 \leq \bar{\theta}_i \leq 1, \quad \bar{p}_i \geq 0,
$$

$$
0 \leq t_i \leq 1, \quad t_i \geq 0, \quad i = 1, \ldots, N_1, j = 1, \ldots, N_2.
$$

We can update each $\bar{V}_i$ in order assuming other $V_i \neq m$ and $U_n$ are fixed and then update each $U_n$ in order assuming other $V_i$ and $U_j \neq n$ are fixed.

Secondly, the subproblem for $\mathbf{x}_2 = \{t_i, x_i, y_i, \bar{x}_i, \bar{y}_i, \bar{\theta}_i, \bar{p}_i, t_i, i = 1, \ldots, N_1\}$ is

$$
\min_{x_2} \frac{\beta}{2} \left( \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} t_i \log_2 \left( \frac{x_i + y_i + \bar{\theta}_i N_0 B}{r_i^{(n-1)}} + \frac{t_i}{\ln 2} \right) \right) + \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} \left[ \frac{x_i + y_i + \bar{\theta}_i N_0 B}{r_i^{(n-1)}} + \frac{z_i}{r_i^{(n-1)}} \right] + \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} \eta_i^H \left( A_1 \begin{bmatrix} x_i \\ y_i \end{bmatrix} - A_2 \begin{bmatrix} \bar{x}_i \\ \bar{y}_i \end{bmatrix} - \alpha_3 p_i - c_i \right) + \sum_{i=1}^{N_1} \frac{\beta}{2} \left( z_i - h_i^H V_i h_{ii} \right)^2 + \sum_{i=1}^{N_1} \frac{\beta}{2} \left( t - t_i \right)^2
$$

s.t.

$$
0 \leq x_i, \quad 0 \leq y_i, \quad 0 \leq \bar{x}_i \leq x_i, \quad 0 \leq \bar{y}_i \leq y_i,
$$

$$
0 \leq t_i \leq 1, \quad t_i \geq 0, \quad i = 1, \ldots, N_1.
$$

by solving the following four subproblems.
where
\[
c_i^{k+1} = \left[ \sum_{r=1}^{N_t} \mathbf{h}_r^H \mathbf{V}_r^{k+1} \mathbf{h}_r \right] \cdot \frac{N_t}{N_i} \sum_{j=1}^{N_i} \mathbf{f}_j^H \mathbf{C}_{ij}^{k+1} \mathbf{f}_j.
\]

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

\[
\min_{\Xi_2i} -B \left[ t_i \log_2 \left( x_i + y_i + \bar{\theta}_i N_0 B + \frac{z_i}{r_i^{n-1} \ln 2} \right) + \frac{t_i}{\ln 2} \right]
- \frac{B}{r_i^{n-1} \ln 2} \left( x_i + y_i + \bar{\theta}_i N_0 B + \frac{z_i}{r_i^{n-1} \ln 2} \right)
+ \frac{\beta}{2} \left[ \bar{\theta}_i p_i^k - t_i + \frac{\lambda_i}{\beta} \right]^2
+ \frac{\beta}{2} \left[ \bar{\theta}_i p_i^k - t_i + \frac{\lambda_i}{\beta} \right] \Bigg[ \left( x_i + y_i + \bar{\theta}_i N_0 B + \frac{z_i}{r_i^{n-1} \ln 2} \right) - a_3 p_i - c_i^{k+1} + \eta_i^{k+1} \Bigg] \Bigg] \] 

\[
+ \frac{\beta}{2} \left[ \bar{\theta}_i p_i^k - t_i + \frac{\lambda_i}{\beta} \right] \Bigg[ \left( x_i + y_i + \bar{\theta}_i N_0 B + \frac{z_i}{r_i^{n-1} \ln 2} \right) - a_3 p_i - c_i^{k+1} + \eta_i^{k+1} \Bigg] \Bigg],
\]
s.t. \(0 \leq x_i \leq x_i^0, 0 \leq y_i \leq y_i^0, p_i \geq 0, i = 1, \ldots, N_1.\)

We can update each \(\{t_i, x_i, y_i, \bar{\theta}_i, z_i, \bar{\theta}_i\}\), followed by updating \(p_i\).

Thirdly, the subproblem \(\Xi_3 = \{t\}\) is

\[
(P_4 - 3) \min_{\Xi_3} \sum_{i=1}^{N_1} \frac{\beta}{2} \left( t_i - t_i^{k+1} + \frac{\lambda_i}{\beta} \right)^2.
\]

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

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

Fourthly, the subproblem for \(\Xi_4 = \{p_i, i = 1, \ldots, N_1\}\) is

\[
(P_4 - 4) \min_{\Xi_4} \sum_{i=1}^{N_1} \frac{\beta}{2} \left( \bar{\theta}_i - t_i^{k+1} + \frac{\xi_i}{\beta} \right)^2,
\]
s.t. \(0 \leq \rho_i \leq 1, \) for \(i = 1, \ldots, N_1\)

which can be further decoupled into \(N_1\) subproblems for \(i = 1, \ldots, N_1\)

\[
\min_{\Xi_{4i}} \frac{\beta}{2} \left( \bar{\theta}_i - t_i^{k+1} + \frac{\xi_i}{\beta} \right)^2,
\]
s.t. \(0 \leq \rho_i \leq 1, \)

Finally, the dual variables \(\eta_1, \eta_2, \lambda_i, \xi_i, \mu\) are updated as follows:

\[
\eta_1^{k+1} = \eta_1^{k} + \beta \left( A_1 \left[ x_i^{k+1} - y_i^{k+1} - a_3 p_i^{k+1} - c_i^{k+1} \right] \right),
\]

\[
\eta_2^{k+1} = \eta_2^{k} + \beta \left( h_i^H \tilde{\mathbf{V}}_i^{k+1} \mathbf{h}_i \right),
\]

\[
\lambda_i^{k+1} = \lambda_i^{k} + \beta \left( t_i^{k+1} - t_i^{k} \right),
\]

\[
\xi_i^{k+1} = \xi_i^{k} + \beta \left( \bar{\theta}_i^{k+1} - \bar{\theta}_i^{k} \right),
\]

\[
\mu^{k+1} = \mu^{k} + \beta \left( \sum_{i=1}^{N_1} tr(\tilde{\mathbf{V}}_i^{k+1}) + \sum_{i=1}^{N_2} tr(\tilde{\mathbf{U}}_i^{k+1}) - 1 \right).
\]

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 \(x_i^0, y_i^0, x_i^0, y_i^0, x_i^0, y_i^0, \eta_1^0, \eta_2^0\), and \(\mu^0\).
2. **Repeat:**
3. \(k = k + 1,\)
4. obtain the solution \(\mathbf{X}_3 = \{t_i^k, \tilde{\mathbf{V}}_i^k, \tilde{\mathbf{V}}_i^k, \} i = 1, \ldots, N_1, j = 1, \ldots, N_2\} by solving \((P_4 - 1)\).
5. obtain the solution \(\mathbf{X}_2 = \{x_i^k, y_i^k, \tilde{\mathbf{V}}_i^k, y_i^k, \tilde{\mathbf{V}}_i^k, x_i^k, y_i^k, \tilde{\mathbf{V}}_i^k, \} i = 1, \ldots, N_1\} by solving \((P_4 - 2)\).
6. obtain the solution \(\mathbf{X}_3 = \{t_i^k\} \) using Eq. (9).
7. obtain the solution \(\mathbf{X}_4 = \{p_i^k, i = 1, \ldots, N_1\} \) by solving \((P_4 - 4)\).
8. updating \(\eta_1^k, \eta_2^k, \lambda_i^k, \xi_i^k, i = 1, \ldots, N_1\) and \(\mu^k\) using (10) respectively.
9. **until** the stopping criterion is met.
10. **Output** \(\mathbf{X}_1 = \{t_i^k, \tilde{\mathbf{V}}_i^k, \tilde{\mathbf{V}}_i^k, \} i = 1, \ldots, N_1, j = 1, \ldots, 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 \(\{\mathbf{v}_i, \mathbf{u}_j, i = 1, \ldots, N_1, j = 1, \ldots, N_2\}\) of the system for the proposed WIET architecture II, as described in Section II.B. Then, the
EE expression can be expressed by

\[ \mathcal{E} = \frac{1}{N_i} \sum_{i=1}^{N_i} \left( \sum_{j=1}^{N_j} \left\| \mathbf{v}_j \right\|^2_2 + \sum_{j=1}^{N_j} \left\| \mathbf{u}_j \right\|^2_2 \right). \]

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

\[ \text{(P}_5\text{)} \max_{\{\mathbf{u}_j, \mathbf{v}_j\}, \ j=1, \ldots, N_i} \sum_{i=1}^{N_i} \mathcal{R}_{2i}, \quad \text{s.t.} \quad \sum_{j=1}^{N_j} \left\| \mathbf{v}_j \right\|^2_2 + \sum_{j=1}^{N_j} \left\| \mathbf{u}_j \right\|^2_2 \geq \Gamma_i. \]

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 \( \mathbf{V}_i = \mathbf{v}_i \mathbf{v}_i^H \) and \( \mathbf{U}_j = \mathbf{u}_j \mathbf{u}_j^H \), the information rate in the second WIET architecture can be expressed by

\[ \mathcal{R}_{2i} = \frac{B}{2} \log_2 \left( 1 + \frac{\sum_{r=1}^{N_i} \mathbf{h}_{ir}^H \mathbf{V}_r \mathbf{h}_{ir} + N_0 B/2}{\sum_{j=1}^{N_j} \left\| \mathbf{v}_j \right\|^2_2 + \sum_{j=1}^{N_j} \left\| \mathbf{u}_j \right\|^2_2} \right), \]

which can be further lower bounded as follows:

\[ \mathcal{R}_{2i} \geq \frac{B}{2} \log_2 \left( 1 + \frac{\sum_{r=1}^{N_i} \mathbf{h}_{ir}^H \mathbf{V}_r \mathbf{h}_{ir} + N_0 B/2}{\sum_{j=1}^{N_j} \left\| \mathbf{v}_j \right\|^2_2 + \sum_{j=1}^{N_j} \left\| \mathbf{u}_j \right\|^2_2} \right), \]

where

\[ s_i^{[n-1]} = \sum_{r=1}^{N_i} \mathbf{h}_{ir}^H \mathbf{V}_r \mathbf{h}_{ir} + N_0 B/2. \]

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

\[ \sum_{r=1}^{N_i} \mathbf{h}_{ir}^H \mathbf{V}_r \mathbf{h}_{ir} + \sum_{j=1}^{N_j} f_{ij}^H U_j f_{ij} \geq \frac{B \Gamma_i}{2\gamma}, \]

Introducing a slack variable \( t \), we can approximately re-formulate Problem (P_5) as

\[ \text{(P}_5\text{'}) \max_{\{\mathbf{v}_j, \mathbf{u}_j\}, \ j=1, \ldots, N_i} \sum_{i=1}^{N_i} \mathcal{R}_{2i}, \quad \text{s.t.} \quad \sum_{j=1}^{N_j} \left\| \mathbf{v}_j \right\|^2_2 + \sum_{j=1}^{N_j} \left\| \mathbf{u}_j \right\|^2_2 \geq \Gamma_i, \]

\[ \sum_{j=1}^{N_j} f_{ij}^H U_j f_{ij} \geq \frac{B \Gamma_i}{2\gamma}, \quad \forall i \in \{1, \ldots, N_i\}, \]

\[ \mathbf{v}_i \succeq 0, \mathbf{U}_j \succeq 0, \quad \text{rank}(\mathbf{V}_i) = 1, \text{rank}(\mathbf{U}_j) = 1. \]

Discarding rank(\mathbf{V}_i) = 1 and rank(\mathbf{U}_j) = 1, we can approximately re-formulate problem (11) as

\[ \text{(P}_5\text{'}) \max_{\{\mathbf{v}_j, \mathbf{u}_j\}, \ j=1, \ldots, N_i} \sum_{i=1}^{N_i} \mathcal{R}_{2i}, \quad \text{s.t.} \quad \sum_{j=1}^{N_j} \left\| \mathbf{v}_j \right\|^2_2 + \sum_{j=1}^{N_j} \left\| \mathbf{u}_j \right\|^2_2 \geq \Gamma_i, \]

\[ \sum_{j=1}^{N_j} f_{ij}^H U_j f_{ij} \geq \frac{B \Gamma_i}{2\gamma}, \quad \forall i \in \{1, \ldots, N_i\}, \]

\[ \mathbf{v}_i \succeq 0, \mathbf{U}_j \succeq 0, \quad \text{rank}(\mathbf{V}_i) = 1, \text{rank}(\mathbf{U}_j) = 1. \]

Letting

\[ \mathbf{V}_i = t \mathbf{V}_i, \ i = 1, \ldots, N_i, \]
\[ \mathbf{U}_j = t \mathbf{U}_j, \ j = 1, \ldots, N_j. \]

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

\[ \frac{B}{2} \log_2 \left( 1 + \frac{\sum_{r=1}^{N_i} \mathbf{h}_{ir}^H \mathbf{V}_r \mathbf{h}_{ir} + t N_0 B/2}{\sum_{j=1}^{N_j} \left\| \mathbf{v}_j \right\|^2_2 + \sum_{j=1}^{N_j} \left\| \mathbf{u}_j \right\|^2_2} \right), \]

\[ \sum_{r=1}^{N_i} \mathbf{h}_{ir}^H \mathbf{V}_r \mathbf{h}_{ir} + t N_0 B/2 \]

\[ \sum_{j=1}^{N_j} f_{ij}^H U_j f_{ij} \geq \frac{B \Gamma_i}{2\gamma}, \quad \forall i \in \{1, \ldots, N_i\}, \]

The corresponding harvested energy constraint can be rewritten as

\[ \sum_{r=1}^{N_i} \mathbf{h}_{ir}^H \mathbf{V}_r \mathbf{h}_{ir} + \sum_{j=1}^{N_j} f_{ij}^H U_j f_{ij} \geq \frac{B \Gamma_i}{2\gamma}, \quad \forall i \in \{1, \ldots, N_i\}. \]
Therefore, the problem (12) can be reformulated as

\[
(P_6) \quad \max_{\{t, U_r, V_r, y_r, x_i, z_i\}} \sum_{i=1}^{N_1} \left[ t \log_2 \left( \frac{\sum_{r=1}^{N_2} h_{ir}^H V_r h_{ir} + t N_0 B/2}{s_i^{[n-1]} t} \right) \right]
\]

\[
- \frac{B}{2} \sum_{r=1}^{N_2} \left[ \frac{h_{ir}^H V_r h_{ir} + t N_0 B/2}{s_i^{[n-1]} t} - \frac{t}{\ln 2} \right],
\]

s.t. \( \sum_{i=1}^{N_1} tr(V_i) + \sum_{j=1}^{N_2} tr(U_j) = 1, \)

\[
\sum_{i=1}^{N_1} h_{ir}^H V_r h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H U_j f_{ij} \geq \beta \Gamma t \gamma, \]

\( V_i \geq 0, U_j \geq 0. \)

Since the first item in each term in the objective function in Problem (P_6) is the perspective function of the concave function \( \log \left( \frac{\sum_{i=1}^{N_1} h_{ir}^H V_r h_{ir} + t N_0 B/2}{s_i^{[n-1]} t} \right) \), 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 \( V_r \) and \( t \). Therefore, the objective function in Problem (P_6) is concave. 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 \( \bar{V}_m^* \), \( \bar{U}_m^* \), \( m = 1, \ldots, N_1 \), \( n = 1, \ldots, N_2 \). Both \( \bar{V}_m^* \) and \( \bar{U}_m^* \) rank higher than or equal to 1.

The proof is relegated in Appendix II.

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

**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

\[
x_i = \sum_{r=1}^{N_1} h_{ir}^H V_r h_{ir}, \quad y_i = \sum_{j=1}^{N_2} f_{ij}^H U_j f_{ij},
\]

\[
z_i = h_{ii}^H V_i h_{ii},
\]

\[
\mathcal{X} = \{t, t_i, x_i, y_i, V_i, U_j, p_i, i = 1, \ldots, N_1, j = 1, \ldots, N_2\}.
\]

**Problem (P_7) can be reformulated as**

\[
(P_7) \quad \min_{\mathcal{X}} \quad - \frac{B}{2} \sum_{i=1}^{N_1} \left[ \frac{t_i \log_2 \left( \frac{x_i + t_i N_0 B/2}{s_i^{[n-1]} t_i} \right) + t_i}{\ln 2} \right]
\]

\[
- \frac{B}{2} \sum_{i=1}^{N_1} \left[ \frac{-x_i + N_0 B t_i/2}{s_i^{[n-1]} t_i} + \frac{z_i}{\ln 2} \right],
\]

s.t. \( \sum_{i=1}^{N_1} tr(V_i) + \sum_{j=1}^{N_2} tr(U_j) = 1, \)

\( x_i + y_i - p_i = \frac{\Gamma_i B t_i}{2\gamma}, \)

\( x_i = \sum_{r=1}^{N_1} h_{ir}^H V_r h_{ir}, \)

\( y_i = \sum_{j=1}^{N_2} f_{ij}^H U_j f_{ij}, \)

\( z_i = h_{ii}^H V_i h_{ii}, \)

\( V_i \geq 0, U_j \geq 0, \)

\( t = t_i, p_i \geq 0. \)

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

\[
\mathcal{L}(y) = \frac{B}{2} \sum_{i=1}^{N_1} \left[ \frac{t_i \log_2 \left( \frac{x_i + t_i N_0 B/2}{s_i^{[n-1]} t_i} \right) + t_i}{\ln 2} \right]
\]

\[
- \frac{B}{2} \sum_{i=1}^{N_1} \left[ \frac{-x_i + N_0 B t_i/2}{s_i^{[n-1]} t_i} + \frac{z_i}{\ln 2} \right],
\]

\[
\sum_{i=1}^{N_1} \eta_{1i} \left( x_i - \sum_{r=1}^{N_1} h_{ir}^H V_r h_{ir} \right)
\]

\[
\sum_{i=1}^{N_1} \eta_{2i} \left( y_i - \sum_{j=1}^{N_2} f_{ij}^H U_j f_{ij} \right)
\]

\[
\sum_{i=1}^{N_1} \eta_{3i} \left( z_i - h_{ii}^H V_i h_{ii} \right) + \sum_{i=1}^{N_1} \lambda_i (t_i - t_i)
\]

\[
\sum_{i=1}^{N_1} \sum_{j=1}^{N_2} \zeta_i \left( x_i + y_i - p_i - \frac{\Gamma_i B t_i}{2\gamma} \right)
\]

\[
+ \mu \left( \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} \left( x_i - \sum_{r=1}^{N_1} h_{ir}^H V_r h_{ir} \right)^2 \right)
\]

\[
+ \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} \left( y_i - \sum_{j=1}^{N_2} f_{ij}^H U_j f_{ij} \right)^2
\]

\[
+ \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} \left( z_i - h_{ii}^H V_i h_{ii} \right)^2
\]

\[
+ \sum_{i=1}^{N_1} \left( x_i + y_i - p_i - \frac{\Gamma_i B t_i}{2\gamma} \right)^2.
\]


\[
\frac{\beta_0}{2} \left( \sum_{i=1}^{N_1} tr(\mathbf{V}_i) + \sum_{j=1}^{N_2} tr(\mathbf{U}_j) - 1 \right) ^2 \\
+ \sum_{i=1}^{N_1} \frac{\beta_1}{2} (t - t_i)^2,
\]

s.t. \( \mathbf{V}_i \succeq 0, \mathbf{U}_j \succeq 0, p_i \geq 0. \)

Divide the set \( \mathbf{Y} \) into three sets \( \mathbf{Y}_1 = \{ \mathbf{V}_i, \mathbf{U}_j, i = 1, \ldots, N_1, j = 1, \ldots, N_2 \}, \mathbf{Y}_2 = \{ t_i, x_i, y_i, z_i, p_i, i = 1, \ldots, N_1 \} \) and \( \mathbf{Y}_3 = \{ t \}. \) Since (P_2) 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 \( \mathbf{Y}_1 = \{ \mathbf{V}_i, \mathbf{U}_j, i = 1, \ldots, N_1, j = 1, \ldots, N_2 \} \) is as follows:

\[
\min_{\mathbf{Y}_1} \sum_{i=1}^{N_1} \frac{\beta_1}{2} \left( x_i - \sum_{r=1}^{N_1} h_{ir}^H \mathbf{V}_r h_{ir} + \frac{\eta_1}{\beta_1} \right) ^2 \\
+ \sum_{i=1}^{N_1} \frac{\beta_2}{2} \left( y_i - \sum_{j=1}^{N_2} f_{ij}^H \mathbf{U}_j f_{ij} + \frac{\eta_2}{\beta_2} \right) ^2 \\
+ \sum_{i=1}^{N_1} \frac{\beta_3}{2} \left( z_i - h_{ii}^H \mathbf{V}_i h_{ii} + \frac{\eta_3}{\beta_3} \right) ^2 \\
+ \frac{\beta_4}{2} \left( \sum_{i=1}^{N_1} tr(\mathbf{V}_i) + \sum_{j=1}^{N_2} tr(\mathbf{U}_j) - 1 + \frac{\mu}{\beta_5} \right) ^2,
\]

s.t. \( \mathbf{V}_i \succeq 0, \mathbf{U}_j \succeq 0. \)

We update each \( \mathbf{V}_m, m = 1, \ldots, N_1, \) followed by each \( \mathbf{U}_n, n = 1, \ldots, N_2. \)

Specifically, we first update each \( \mathbf{V}_m, m = 1, \ldots, N_1. \)

\[
\min_{\mathbf{V}_m} \sum_{i=1}^{N_1} \frac{\beta_1}{2} \left( x_i - \sum_{r=1}^{N_1} h_{ir}^H \mathbf{V}_r h_{ir} - h_{im}^H \mathbf{V}_m h_{im} + \frac{\eta_1}{\beta_1} \right) ^2 \\
+ \sum_{i=1}^{N_1} \frac{\beta_3}{2} \left( z_i - h_{ii}^H \mathbf{V}_i h_{ii} + \frac{\eta_3}{\beta_3} \right) ^2 \\
+ \frac{\beta_4}{2} \left( \sum_{i=1}^{N_1} tr(\mathbf{V}_i) + tr(\mathbf{V}_m) + tr(\mathbf{U}_j) - 1 + \frac{\mu}{\beta_5} \right) ^2,
\]

s.t. \( \mathbf{V}_m \succeq 0. \)

Then we update each \( \mathbf{U}_n, n = 1, \ldots, N_2. \)

\[
\min_{\mathbf{U}_n} \sum_{i=1}^{N_1} \frac{\beta_2}{2} \left( y_i - \sum_{r=1}^{N_1} f_{ir}^H \mathbf{U}_r f_{ir} - f_{in}^H \mathbf{U}_n f_{in} + \frac{\eta_2}{\beta_2} \right) ^2 \\
+ \frac{\beta_4}{2} \left( \sum_{i=1}^{N_1} tr(\mathbf{V}_i) + tr(\mathbf{U}_j) + tr(\mathbf{U}_n) - 1 + \frac{\mu}{\beta_5} \right) ^2,
\]

s.t. \( \mathbf{U}_n \succeq 0. \)

Secondly, the subproblem with set \( \mathbf{Y}_2 = \{ t_i, x_i, y_i, z_i, p_i, i = 1, \ldots, N_1 \} \) is to solve the following problem

\[
\min_{t_i \geq 0, (i = 1, \ldots, N_1)} \left\{ \begin{array}{l}
\frac{\beta_0}{2} \left( \sum_{i=1}^{N_1} x_i + t_i N_0 B/2 \right) + \frac{t_i}{\ln 2} \\
- B \sum_{i=1}^{N_1} \frac{N_i}{N_0} x_i + t_i N_0 B/2 + \frac{z_i}{\ln 2} \\
+ \sum_{j=1}^{N_2} \frac{\beta_1}{2} (y_j - \sum_{i=1}^{N_1} h_{ir}^H \mathbf{V}_r h_{ir} + \frac{\eta_1}{\beta_1}) ^2 \\
+ \sum_{j=1}^{N_2} \frac{\beta_2}{2} (y_j - \sum_{i=1}^{N_1} f_{ij}^H \mathbf{U}_j f_{ij} + \frac{\eta_2}{\beta_2}) ^2 \\
+ \sum_{i=1}^{N_1} \frac{\beta_3}{2} (z_i - h_{ii}^H \mathbf{V}_i h_{ii} + \frac{\eta_3}{\beta_3}) ^2 \\
+ \sum_{i=1}^{N_1} \frac{\beta_4}{2} (x_i + y_i - p_i - \frac{\Gamma_i B t_i}{2 \gamma} + \frac{c_i}{\beta_4}) ^2 \\
+ \sum_{i=1}^{N_1} \frac{\beta_6}{2} (t_k - t_i + \frac{\lambda_i}{\beta_6}) ^2,
\end{array} \right. \]

In order to lower the computational complexity, Problem (P_7 - 2) can be further decoupled into the following \( N_1 \) subproblems with \( i = 1, \ldots, N_1 \)

\[
\min_{t_i \geq 0} \left\{ \begin{array}{l}
\frac{\beta_0}{2} \left( \sum_{i=1}^{N_1} x_i + t_i N_0 B/2 \right) + \frac{t_i}{\ln 2} \\
- B \sum_{i=1}^{N_1} \frac{N_i}{N_0} x_i + t_i N_0 B/2 + \frac{z_i}{\ln 2} \\
+ \frac{\beta_1}{2} (x_i - \sum_{r=1}^{N_1} h_{ir}^H \mathbf{V}_r h_{ir} + \frac{\eta_1}{\beta_1}) ^2 \\
+ \frac{\beta_3}{2} (z_i - h_{ii}^H \mathbf{V}_i h_{ii} + \frac{\eta_3}{\beta_3}) ^2 \\
+ \frac{\beta_4}{2} (x_i + y_i - p_i - \frac{\Gamma_i B t_i}{2 \gamma} + \frac{c_i}{\beta_4}) ^2 \\
+ \frac{\beta_6}{2} (t_k - t_i + \frac{\lambda_i}{\beta_6}) ^2,
\end{array} \right. \]

We can update \( x_i, z_i, t_i, \) followed by updating \( p_i, x_i \) in order.

Thirdly, the subproblem \( \mathbf{Y}_3 = \{ t \} \) is

\[
\min_{\mathbf{Y}_3} \frac{\beta_0}{2} \sum_{i=1}^{N_1} (t - t_i + \frac{\lambda_i}{\beta_6}) ^2,
\]

where the close-form solution is

\[
t = \frac{1}{N_1} \sum_{i=1}^{N_1} \left( t_i + \frac{\lambda_i}{\beta_6} \right).
\]
Fourthly, the dual variables \( \{ \lambda_i, \xi_i, \eta_{2i}, \eta_{3i}, i = 1, \ldots, N_1 \} \) are respectively updated as follows:

\[
\eta_{1i}^{k+1} = \eta_{1i}^k + \beta_1 \left( x_i^{k+1} - \sum_{r=1}^{N_1} h_{ir}^H V_r^{k+1} h_{ir} \right), \\
\eta_{2i}^{k+1} = \eta_{2i}^k + \beta_2 \left( y_i^{k+1} - \sum_{j=1}^{N_2} f_{ij}^H U_j^{k+1} f_{ij} \right), \\
\eta_{3i}^{k+1} = \eta_{3i}^k + \beta_3 \left( z_i^{k+1} - h_{i}^H T_{k+1}^1 h_{i} \right), \\
\end{align}
\]

\[
\begin{align}
\xi_i^{k+1} &= \xi_i^k + \beta_4 \left( x_i^{k+1} + y_i^{k+1} - p_i^k - \frac{\Gamma_i B_{i}^{k+1}}{2\gamma} \right), \\
\mu^{k+1} &= \mu^k + \beta_5 \left( \sum_{j=1}^{N_2} \text{tr}(V_i^{k+1}) + \sum_{j=1}^{N_2} \text{tr}(U_j^{k+1}) - 1 \right), \\
\lambda_i^{k+1} &= \lambda_i^k + \beta_6 (t^{k+1} - t_i^{k+1}) - t_i^{k+1}. \\
\end{align}
\]

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

**TABLE 2**

<table>
<thead>
<tr>
<th>The Proposed Algorithm 2 for ((P_7))</th>
</tr>
</thead>
</table>
| 1. Initialization: set the initial values of \( U_i^0, V_i^0, \ | \lambda_i^0, \mu_i^0 \text{ and } \xi_i^0, i = 1, \ldots, N_1 \).
| 2. Repeat:
| 3. \( k = k + 1 \).
| 4. obtain the solution \( Y_1 = \{ U_i^k, V_i^k, i = 1, \ldots, N_1, j = 1, \ldots, N_2 \} \) by solving \((P_7-1a)\) and \((P_7-1b)\) in turn.
| 5. obtain the solution \( Y_2 = \{ t_i^k, x_i^k, y_i^k, z_i^k, p_i^k, i = 1, \ldots, N_1 \} \) by solving \((P_7-2)\).
| 6. obtain the closed-form solution \( Y_3 = \{ t_i^k \} \) by using Eq. (13).
| 7. update \( \lambda_i^k, \xi_i^k, \eta_{2i}^k, \eta_{3i}^k, i = 1, \ldots, N_1 \) and \( \mu^k \) by using Eq. (14).
| 8. until the stopping criterion is met.
| 9. Output \( Y_1 = \{ U_i^k, V_i^k, i = 1, \ldots, N_1, j = 1, \ldots, N_2 \} \) as an approximate solution.

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

1. Residual convergence: \( \sum_{i=1}^{N_1} \text{tr}(V_i^k) + \sum_{j=1}^{N_2} \text{tr}(U_j^k) - 1 \to 0, x_i^{k+1} + y_i^{k+1} - p_i^k - \frac{\Gamma_i B_{i}^{k+1}}{2\gamma} \to 0 \) and \( t^{k+1} - t_i^{k+1} \to 0 \) as \( k \to \infty \).

2. Objective convergence: \( \lim_{k \to \infty} h(t^k, V_i^k, U_i^k) = p^* \), where \( p^* \) is the optimal value of \((P_7)\).

3. Iterate convergence: the itertes \( U_i^k, V_i^k, t_i^k, x_i^k, y_i^k, z_i^k, \lambda_i^k, \xi_i^k, \eta_{2i}^k, \eta_{3i}^k \) and \( \mu^k \) converge to their respective optimal solutions.

**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 \( h_{ij} \) and \( f_{ij} \) 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 WIT 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.

**FIGURE 4: Improving ratio ~ harvested energy**

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 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 A APPENDIX I

Proof: The lagrangian function of (P₃) can be written as follows:

\[
\mathcal{L}(\cdot) = \sum_{i=1}^{N_1} \left[ t \sum_{r=1}^{N_1} h_{ir}^H \dot{V}_r h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \dot{U}_j f_{ij} + \bar{\theta}_i \sigma_i^2 \right] + \sum_{i=1}^{N_1} \left[ \sum_{l=1}^{N_1} h_{il}^H \dot{V}_l h_{il} + \sum_{j=1}^{N_2} f_{ij}^H \dot{U}_j f_{ij} + \bar{\theta}_i N_0 B \right]
\]

where \( \lambda, \eta_i, \tau_{1i}, \tau_{2i}, \xi_i, \ Y_{1i}, \ Y_{2i} \) are the lagrangian dual multipliers respectively corresponding to each constraint.

The corresponding KKT conditions regarding to \( \dot{V}_{im}^* \) and \( \dot{U}_n^* \) can be written as follows:

\[
\begin{align*}
\sum_{i=1}^{N_1} \left[ \sum_{r=1}^{N_1} h_{ir}^H \dot{V}_r^* h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \dot{U}_j^* f_{ij} - \frac{t \tau_i}{1 - \rho_i} \right] + \eta_i + \sum_{i=1}^{N_1} \left[ \sum_{r=1}^{N_1} h_{ir}^H \dot{V}_r h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \dot{U}_j f_{ij} - \frac{t \tau_i}{1 - \rho_i} \right] - \frac{1}{r_i^{n-1}} & = 0, \\
\sum_{i=1}^{N_3} \left[ \sum_{r=1}^{N_3} h_{ir}^H \dot{V}_r^* h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \dot{U}_j^* f_{ij} - \frac{t \tau_i}{1 - \rho_i} \right] & = 0,
\end{align*}
\]

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

\[
\begin{align*}
\text{rank}(Y_{1m}^*) & = \text{rank} \left( \sum_{i=1}^{N_1} \left[ \sum_{r=1}^{N_1} h_{ir}^H \dot{V}_r h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \dot{U}_j f_{ij} - \frac{t \tau_i}{1 - \rho_i} \right] \right) = \text{rank} \left( \sum_{i=1}^{N_1} \left[ \sum_{r=1}^{N_1} h_{ir}^H \dot{V}_r h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \dot{U}_j f_{ij} - \frac{t \tau_i}{1 - \rho_i} \right] \right) - \frac{1}{r_i^{n-1}} \\
\end{align*}
\]

\[
\begin{align*}
\text{rank}(Y_{1m}^*) & = \text{rank} \left( \sum_{i=1}^{N_1} \left[ \sum_{r=1}^{N_1} h_{ir}^H \dot{V}_r h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \dot{U}_j f_{ij} - \frac{t \tau_i}{1 - \rho_i} \right] \right) - \frac{1}{r_i^{n-1}} , \\
\end{align*}
\]

\[
\begin{align*}
\text{rank}(Y_{1m}^*) & = \text{rank} \left( \sum_{i=1}^{N_1} \left[ \sum_{r=1}^{N_1} h_{ir}^H \dot{V}_r h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \dot{U}_j f_{ij} - \frac{t \tau_i}{1 - \rho_i} \right] \right) - \frac{1}{r_i^{n-1}} , \\
\end{align*}
\]

where \( \lambda, \eta_i, \tau_{1i}, \tau_{2i}, \xi_i, \ Y_{1i}, \ Y_{2i} \) are the lagrangian dual multipliers respectively corresponding to each constraint.
Assume that $A_i = a_i^* h_{im} h_{im}^H$, the second last inequality is due to $\sum_i \text{rank}(A_i) \geq \text{rank}(\sum_i A_i)$.

Assume that $A = \sum_{i=1}^{N_1} a_i^* h_{im} h_{im}^H$, $B = \lambda^* I$, the third last inequality is due to $\text{rank}(A - B) \geq \text{rank}(A) - \text{rank}(B)$.

Owing to nonzero values of $V_m$, rank($V_m$) is greater than or equal to 1. Similarly, rank($U_n^*$) is greater than or equal to 1.

**APPENDIX II**

Proof: The lagrangian function of (P0) can be written as follows:

$$
\mathcal{L}(\cdot) = \sum_{i=1}^{N_1} \left[ t \log_2 \left( \frac{\sum_{r=1}^{N_1} h_{ir}^H V_i h_{ir} + t N_0 B/2}{t} \right) \right] + \left[ \frac{1}{s_i[n-1]} \sum_{r=1}^{N_1} h_{ir}^H V_i h_{ir} + t N_0 B/2 \right] + \left[ \frac{t}{\ln 2} \sum_{r=1}^{N_1} \sum_{i=1}^{N_1} h_{ir}^H V_i h_{ir} + t N_0 B/2 \right]
$$

$$- \lambda \left( \sum_{i=1}^{N_1} t r(\tilde{V}_i) + \sum_{j=1}^{N_1} t r(\tilde{U}_j) - 1 \right)
$$

$$+ \sum_{i=1}^{N_1} \eta_i \left[ \sum_{r=1}^{N_1} h_{ir}^H V_i h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \tilde{U}_j f_{ij} - \frac{B \Gamma_i t}{2 \gamma} \right]
$$

$$+ \sum_{i=1}^{N_1} t r(Y_{1i}) + \sum_{j=1}^{N_2} t r(Y_{2j})
$$

where $\lambda$, $\eta_i$, $Y_{1i}$, $Y_{2j}$ are the lagrangian dual multipliers respectively corresponding to each constraint.

The corresponding KKT conditions regarding to $V_m^*$ and $U_n^*$ can be written as follows:

$$
\sum_{i=1}^{N_1} \left[ \frac{(t_i^*)^2}{s_i[n-1]} \sum_{r=1}^{N_1} h_{ir}^H V_i h_{ir} + t N_0 B/2 \right] + \sum_{i=1}^{N_1} \eta_i^* h_{im} h_{im}^H + \lambda^* I = \sum_{i=1}^{N_1} \eta_i^* f_{im} f_{im}^H + Y_{2n}^* = 0,
$$

$$- \lambda^* I + \sum_{i=1}^{N_1} \eta_i^* f_{im} f_{im}^H + Y_{2n}^* = 0,
$$

$$\lambda^* \left( \sum_{i=1}^{N_1} t r(\tilde{V}_i^*) + \sum_{j=1}^{N_2} t r(\tilde{U}_j^*) - 1 \right) = 0,
$$

$$\eta_i^* \left[ \sum_{r=1}^{N_1} h_{ir}^H V_i^* h_{ir} + \sum_{j=1}^{N_2} f_{ij}^H \tilde{U}_j^* f_{ij} - \frac{B \Gamma_i t}{2 \gamma} \right] = 0,
$$

$$\lambda^* \text{ is any scalar}, \eta_i^* \geq 0, Y_{1m}^* \geq 0, Y_{2n}^* \geq 0.
$$

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

$$
\text{rank}(V_{1m}^*)
$$

$$= \text{rank} \left( - \sum_{i=1}^{N_1} \sum_{r=1}^{N_1} h_{ir}^H V_i h_{ir} + t N_0 B/2 \right) - \frac{1}{s_i[n-1]}
$$

$$\text{rank}(U_n^*)
$$

$$= \text{rank} \left( - \sum_{i=1}^{N_1} a_i^* h_{im} h_{im}^H + \lambda^* I \right)
$$

where $a_i^* = \left\{ \begin{array}{ll}
- \sum_{r=1}^{N_1} h_{ir}^H V_i h_{ir} + t N_0 B/2 & \text{if } i \neq m,
- \sum_{r=1}^{N_1} h_{ir}^H V_i h_{ir} + t N_0 B/2 & \text{if } i = m.
\end{array} \right.$

The last inequality is due to $\text{rank}(h_{im} h_{im}^H) = 1$, $a_i^*$ may being 0 and $\lambda^* > 0$. Assume that $A_i = a_i^* h_{im} h_{im}^H$, the second last inequality is due to $\sum_i \text{rank}(A_i) \geq \text{rank}(\sum_i A_i)$.

Assume that $A = \sum_{i=1}^{N_1} a_i^* h_{im} h_{im}^H$, $B = \lambda^* I$, the third last inequality is due to $\text{rank}(A - B) \geq \text{rank}(A) - \text{rank}(B)$.

Owing to nonzero values of $Y_{1m}^*$, rank($Y_{1m}^*$) is greater than or equal to 1 of $\text{rank}(Y_{1m}^*) \geq 1$.

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XIAOMEI LUO received the B.S. degree in Industrial Enterprise Automation from Nanchang University, Jiangxi, China, in 1994, and the Ph.D. degree in Communications and Information System in School of Telecommunication Engineering from Xidian University, Xi’an, China, in 2015. She is currently a Vice Professor with the School of Information Engineering, Nanchang University. Her current research interests include wireless communications, localization, tracking and detection in wireless sensor network, microwave remote sensing processing, etc.

HANG LI received the B.E. and M.S. degrees from Beihang University, Beijing, China, in 2008 and 2011, respectively, and the Ph.D. degree from Texas A&M University, College Station, TX, USA, in 2016. He was a postdoctoral research associate with Texas A&M University (Sept. 2016- Aug. 2017) and University of California-Davis (Sept. 2017-Mar. 2018). Currently, he is a visiting research scholar at Shenzhen Research Institute of Big Data, Shenzhen, China. His current research interests include wireless networks, stochastic optimization, and applications of machine learning.

XIANGFENG WANG received the B.S. degree in mathematics and applied mathematics from Nanjing University, Nanjing, China, in 2009, and Ph.D. degree in computational mathematics also from Nanjing University, Nanjing, China, in 2014. He is currently an Assistant Professor at Software Engineering Institute, East China Normal University, Shanghai, China. His research interests lie in the areas of large-scale optimization and applications on machine learning, smart grid, etc.