Energy-Efficient Resource Allocation in Multi-User AF Two-Way Relay Channels

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Abstract: **In this paper, we investigate an energy-efficient resource allocation problem in a two-way relay (TWR) network consisting of multiple user pairs and an amplify-and-forward (AF) relay. As the users and relay have individual energy efficiencies (EE), we formulate a multi-objective optimization problem (MOOP). A single-objective optimization problem (SOOP) of the MOOP is introduced using a weighted-sum method, which achieves a single Pareto optimal point of the MOOP. To derive the algorithm for the SOOP, we propose a more tractable equivalent problem using the Karush-Kuhn-Tucker conditions of the SOOP, which guarantees convergence at the local optimal points. The proposed equivalent problem can be efficiently solved by the proposed iterative algorithm. Numerical results demonstrate the effectiveness of the proposed algorithm in achieving the optimal EE in multi-user AF TWR networks.**

Index Terms: **Energy efficiency (EE), Karush-Kuhn-Tucker (KKT) conditions, optimization, spectral efficiency, two-way relay (TWR).**

I. INTRODUCTION

RECENTLY, energy efficiency (EE) has attracted considerable attention as a new performance metric for designing wireless communications systems. Energy efficiency is defined as the number of transmitted bits per energy consumed (in bits-per-Joule). A comprehensive review of EE is given in [1]. While EE optimization has been considered a range of communications scenarios, the deployment of relays is regarded as being a promising approach to improving EE by shortening the transmission distance and reducing the number of retransmissions. Owing to its bidirectional nature, a two-way relay (TWR) can achieve not only a higher spectral efficiency (SE) but also a higher EE than a half-duplex one-way relay [2], [3].

Before considering EE, the spectral efficiency maximization was studied for the TWR channels [4], [5]. An investigation of the power minimization problem for TWR with amplify-and-forward (AF) relaying includes the power allocation scheme described in [6], the transmit beamformer and receive combiner design for TWR with multiple antennas [7], and a hybrid of the one-way and two-way relaying for power-efficient transmission [8]. In [9], on the other hand, full duplex AF relays for spectrum sharing in cooperative single carrier systems was investigated.

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The problem of EE maximization (EEM) in TWR networks has been studied under various scenarios. In [10], the quasi-concavity of EE in terms of the relay's transmission power was proven and the optimization of EE was considered under a decode-and-forward (DF) TWR scenario. For AF TWR networks, spectral- and energy-efficiency trade-off and a rate-control algorithm were proposed in [11], and an energy-efficient power allocation algorithm with individual power constraints was studied in [12]. Under frequency selective fading channels, energy-efficient bit allocation [13] and power allocation [14] in an orthogonal frequency division multiplex (OFDM) AF TWR system were investigated. The previous works mentioned above considered network-wise EE, which is defined as the sum rate over the total power consumption in the overall network.

In this paper, the energy-efficient resource allocation problem is considered in an orthogonal frequency division multiple access (OFDMA) TWR network in which multiple user pairs exchange information via a single AF relay. A multi-objective optimization problem (MOOP) including the individual EE of each user pair, as well as the relay, was investigated. To handle multiple objectives, we exploited the weighted sum of the objectives to convert the MOOP to a single-objective optimization problem (SOOP). Because the converted SOOP remains non-convex, the equivalent problem is formulated with auxiliary variables and the solution to the equivalent problem is found based on the Karush-Kuhn-Tucker (KKT) conditions. We propose an iterative algorithm to efficiently solve the optimization problem. Through numerical simulations, we verified that the proposed algorithm efficiently manages resource allocation between the users and relay, and achieves better energy efficiency.

The remainder of this paper is organized as follows. Section II describes the considered system model and the proposed multi-objective problem. Sections III and IV describe the conversion to a single-objective problem and the design of the proposed algorithm. The simulation results are presented in Section V and the conclusion is given in Section VI.

II. SYSTEM DESCRIPTION

We consider an AF TWR channel including a single relay and K user pairs in an OFDMA system model, as shown in Fig. 1. All users and relay are equipped with a single antenna. Each user pair exchanges information through the relay with two phases and the direct link between two users in each pair is ignored. In the first phase, each user transmits a signal to the relay, while in the second phase, the relay amplifies and forwards the received signal in the first phase. We assume that a central unit exists to assign N subcarriers to the user pairs based on channel gain measurements. s_n^k represents the scheduling index of

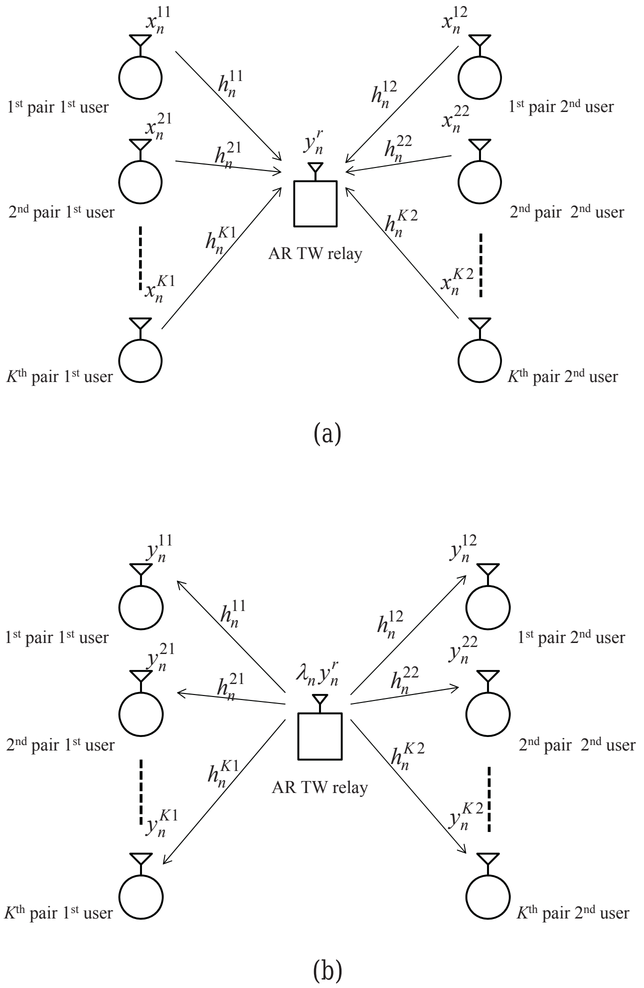


Fig. 1. System model and two-phase operation of AF TWR: (a) Phase 1 and (b) phase 2.

the kth user pair on the nth subcarrier. Its value is 1 if the nth subcarrier is allocated to the kth user pair, while 0 is assigned otherwise. The orthogonal resource allocation is assumed, i.e., the central unit assigns only a single user pair to each subcarrier. Additionally, the block-fading channel for which channel coefficients do not change during a two-phase relay protocol, is assumed. It is also assumed that all of the nodes can accurately estimate the channel gain and share the channel state information with the central unit.

A. Signal Model

Assuming perfect synchronization between the user pairs, the received signal at the relay on the nth subcarrier in the first phase is expressed as

$$y_n^r = \sqrt{p_n^{k1}} h_n^{k1} x_n^{k1} + \sqrt{p_n^{k2}} h_n^{k2} x_n^{k2} + n_n^r \tag{1}$$

where h_n^{ki} for $i \in \{1, 2\}$ denotes the complex channel gain between the ith user in the kth pair and relay, and $x_n^{ki}(|x_n^{ki}| = 1)$ for $i \in \{1, 2\}$ is the transmit symbol for the ith user of the kth user pair in the nth subcarrier. The transmit power for each user of the kth pair in the nth subcarrier is p_n^{ki} and n_n^r is the additive white Gaussian noise at the relay with unit variance.

The relay amplifies and forwards the received y_n^r where the scaling factor is given by

$$\lambda_n = \sqrt{\frac{p_n^r}{p_n^{k1}|h_n^{k1}|^2 + p_n^{k2}|h_n^{k2}|^2 + 1}} \tag{2}$$

where p_n^r can be regarded as the transmission power at the relay in the nth subcarrier.

The received signal of the ith user of the kth user pair in the second phase is given by

$$\begin{aligned} y_n^{ki} &= h_n^{ki} \lambda_n y_n^r + n_n^{ki} \\ &= h_n^{ki} \lambda_n \sqrt{p_n^{k1}} h_n^{k1} x_n^{k1} + h_n^{ki} \lambda_n \sqrt{p_n^{k2}} h_n^{k2} x_n^{k2} \\ &+ h_n^{ki} \lambda_n n_n^r + n_n^{ki} \end{aligned} \tag{3}$$

where n_n^{ki} is the additive white Gaussian noise with unit variance at the ith user. Here, we assume that the channels are reciprocal.

After subtracting its own signal, i.e., self-interference, from the received signal, the signal-to-interference-plus-noise ratio γ_n^{ki} for the nth subcarrier of the kth user pair is

$$\gamma_n^{ki} = \frac{|h_n^{k1}|^2 |h_n^{k2}|^2 p_n^{kj} p_n^r}{|h_n^{k1}|^2 p_n^{k1} + |h_n^{k2}|^2 p_n^{k2} + |h_n^{ki}|^2 p_n^r + 1} \tag{4}$$

where $j = \mathrm{mod}(i, 2) + 1$ for $i \in \{1, 2\}$.

The corresponding achievable rate of the nth subcarrier is given by

$$r_n^k = \frac{1}{2} \left(\log(1 + \gamma_n^{k1}) + \log(1 + \gamma_n^{k2}) \right). \tag{5}$$

B. Power Consumption Model

The power consumption model consists of two terms; one is the power consumed in the power amplifier (PA), while the other is the power consumed in the other circuits. The power consumption of the PA is expressed by the multiplication of $\alpha^{ki} (> 1)$, which represents the inverse of the efficiency of the PA and the transmit power. Power consumption in the other circuits is modeled by a constant, P_c^{ki}, which is dissipated in the signal processing performed by the mixer, digital-to-analog converter (DAC), filters and so on. Then, the total power consumption of the ith user in the kth user pair is given as

$$P_{cspt}^{ki} = \alpha^{ki} \sum_{n=1}^{N} p_n^{ki} + P_c^{ki}. \tag{6}$$

Additionally, $P_{cspt}^k = P_{cspt}^{k1} + P_{cspt}^{k2}$ and $P_{cspt}^r = \alpha^r \sum_{n=1}^N p_n^r + P_c^r$. In this paper, a simple power consumption model with PA transmit power and another constant power is considered. The consideration of a more realistic power consumption model, including a channel-estimation and a rate-dependent power consumption in channel coding [15], can be a further research topic. The rate-dependent power consumption model makes the problem complicated but interesting.

C. Energy Efficiency Model

In this paper, we focus on the multi-objective function of the EE for the user pairs and relay. The energy efficiency [bit/J] of the kth user pair and relay are defined as

$$\eta_{EE}^{k} = \frac{\sum_{n=1}^{N} s_n^k r_n^k}{\sum_{i=1}^{2}\left(\alpha^{ki}\sum_{n=1}^{N} p_n^{ki} + P_c^{ki}\right)} = \frac{\sum_{n=1}^{N} s_n^k r_n^k}{P_{cspt}^{k}} \quad (7)$$

and

$$\eta_{EE}^{r} = \frac{\sum_{n=1}^{N}\sum_{k=1}^{K} s_n^k r_n^k}{\alpha^{r}\sum_{n=1}^{N} p_n^{r} + P_c^{r}} = \frac{\sum_{n=1}^{N}\sum_{k=1}^{K} s_n^k r_n^k}{P_{cspt}^{r}}, \quad (8)$$

respectively. As shown in the above equations, η_{EE}^{k} corresponds to the rate and the power consumption of the kth user pair, except for the relay power consumption; and η_{EE}^{r} corresponds to the network-wise rate and relay power consumption. For η_{EE}^{r}, the sum of the achievable rates for all K user pairs is considered because the relay expends its power on improving the achievable rates of all users.

The MOOP can be defined as

$$\max_{\{s_n^k, p_n^{ki}, p_n^r\}} \{\eta_{EE}^{1}, \cdots, \eta_{EE}^{k}, \eta_{EE}^{r}\}. \quad (9)$$

This can be solved with Pareto optimality. The Pareto optimal point is defined as that point at which there is no other point that can achieve an element-wise better objective function for all objectives. Even though the Pareto optimality is a basic tool for solving (9), it is difficult to find such optimal points because (9) is a non-convex, integer programming problem. Hence, we introduce an alternative approach to finding a single local optimal point in the a priori articulated preferences. The pre-defined weighted factors of EE for the user pairs and relay are assumed to be provided as the a priori articulated preferences. In this paper, the weighted sum method [16] with the weighted factor is adopted to convert the MOOP to a SOOP. With SOOP conversion, the proposed optimization problem provides a unique solution to (9).

In [14], the network EE has been studied with the following definition.

$$\eta_{EE}^{net} = \frac{\sum_{n=1}^{N}\sum_{k=1}^{K} s_n^k r_n^k}{\sum_{k=1}^{K} P_{cspt}^{k} + P_{cspt}^{r}}. \quad (10)$$

However, η_{EE}^{net} cannot handle the individual EE of the user pairs and relay. The proposed MOOP formulation can achieve a more flexible resource and power allocation by taking the priority between the user pairs and relay into account.

The detailed optimization problem will be described in the following sections.

III. PROPOSED OPTIMIZATION PROBLEM

To make a single objective function, the weighed sum of the multiple objectives in (9) is introduced as

$$\max_{\{s_n^k, p_n^{ki}, p_n^r\}} \sum_{k=1}^{K} w^k \eta_{EE}^{k} + w^r \eta_{EE}^{r} \quad (11a)$$

$$s.t.\ \alpha_{ki}\sum_{n=1}^{N} p_n^{ki} \le P_{\max}^{ki}, \forall\, k, i, \quad (11b)$$

$$\alpha_r \sum_{n=1}^{N} p_n^{r} \le P_{\max}^{r}, \quad (11c)$$

$$\sum_{k=1}^{K} s_n^k = 1, \forall\, n, \quad (11d)$$

$$p_n^{ki}, p_n^{r} \ge 0, \forall\, k,\ i,\ n, \quad (11e)$$

$$s_n^k \in \{0,\ 1\}, \forall\, k,\ n \quad (11f)$$

where w^k and w^r are the weight factors for the a priori articulated preferences, and it is generally assumed that $\sum_{k=1}^{K} w^k + w^r = 1$.

The formulation of problem in [5] is similar to that in (11). However, the objective function is clearly different. The objective function of [5] is the overall sum rate of the user pairs while the objective function of (11) is the weighted sum of the EEs for a relay as well as the user pairs. Each EE in the objective function is a fractional function, i.e., it includes the optimization variables in both the numerator and denominator. Therefore, we need an additional conversion of the original problem and the problem becomes more complicated due to this conversion.

To illustrate the motivation for considering each individual EE instead of the network-wise EE, we can consider two different network scenarios. In the first scenario (a fixed relay network), a relay is plugged in, i.e., has a nearly infinite energy source, and the mobile user equipments are battery-powered, i.e., have a finite energy source. Then, the EE of the user equipment is more important than that of the relay. In this case, we can set a higher value for w^k than that for w^r in the objective function of the proposed problem, which is a weighted sum of individual EEs. In the second scenario of an ad-hoc network, on the other hand, both the relay and user pairs are battery-powered and the relay expends its energy forwarding the other users' signals. The relay in the second scenario sacrifices its energy for the other users. Hence, any improvement of the relay's EE can be more significant than that of the users' EE and we can set a higher value for w^r than that for w^k. Additionally, the EE for each user can have a different priority depending on the remaining battery power of the mobile terminal. To take these scenarios into account, the weighted sum of individual EEs provides a more suitable measure than the network EE.

Each η_{EE}^{k} and η_{EE}^{r} have a quasi-concave trade-off between EE and SE. That is, when the power approaches infinity, EE is bounded but SE increases without any bound. Because the sum of the quasi-concave functions, however, is not quasi-concave, the proposed optimization problem does not have an explicit trade-off between EE and SE.

The SOOP given by (11) is still difficult to solve directly because the objective function is non-convex and includes binary constraints on $\{s_n^k\}$. It can be solved by an iterative optimization algorithm after relaxing the binary constraints of (11f) as real-valued $s_n^k \ge 0, \forall\, k,\ n$.

The MOOP of (9) does not include the rate constraints of the user pairs for simple formulation. Because the rate constraints are convex after relaxing the binary (integer) constraints on $\{s_n^k\}$

to real numbers, they can be included in the optimization problem with a minor modification to the proposed algorithm. With the relaxation, the KKT conditions, which are explained later, remain applicable with the rate constraints. It can be seen that the optimization algorithm based on these KKT conditions is still valid. Therefore, we have omitted the rate constraints form this paper.

Additionally, by introducing auxiliary variables, the objective function of (11a) can be converted into a new objective function and additional constraints, as follows:

$$\max_{\{s_n^k, p_n^{ki}, p_n^r, \beta_k, \beta_r\}} \sum_{k=1}^{K} w^k \beta_k + w^r \beta_r \tag{12a}$$

$$s.t.\ \eta_{EE}^k \geq \beta_k\ \forall k, \quad \eta_{EE}^r \geq \beta_r \tag{12b}$$

$$(11b) - (11e) \tag{12c}$$

where $\{\beta_k, k = 1, \cdots, K\}$ and β_r are auxiliary variables. For notational simplicity, we define $\boldsymbol{\beta} \triangleq [\beta_1, \cdots, \beta_K, \beta_r]$. The other constraints of (11b-11e) are maintained as is. To obtain greater insight from the problem structure, the KKT conditions of the optimization problem of (12) are exploited. As discussed in Theorem 1 of [17], we first evaluate the KKT conditions of (12) and find the necessary conditions for optimality.

The Lagrangian function corresponding to (12) is given by

$$\begin{aligned}
&\mathcal{L}\left(\{s_n^k, p_n^{ki}, p_n^r, \boldsymbol{\beta}\}, \{\lambda_k\}, \lambda_r, \{\nu_{ki}\}, \nu_r, \{\rho_n\}\right) \\
&= \sum_{k=1}^{K} w^k \beta_k + w^r \beta_r \\
&+ \sum_{k=1}^{K} \lambda_k \left(\sum_{n=1}^{N} s_n^k r_n^k - \beta_k P_{cspt}^k \right) \\
&+ \lambda_r \left(\sum_{n=1}^{N} \sum_{k=1}^{K} s_n^k r_n^k - \beta_r P_{cspt}^r) \right) \\
&- \sum_{k=1}^{K} \sum_{i=1}^{2} \nu_{ki} \left(\alpha_{ki} \sum_{n=1}^{N} p_n^{ki} - P_{\max}^r \right) \\
&- \nu_r \left(\alpha_r \sum_{n=1}^{N} p_n^r - P_{\max}^r \right) \\
&+ \sum_{n=1}^{N} \rho_n \left(\sum_{k=1}^{K} s_n^k - 1 \right)
\end{aligned} \tag{13}$$

for $s_n^k \geq 0$, $p_n^{ki} \geq 0$, and $p_n^r \geq 0$. Here, $\{\lambda_k\}$, λ_r, $\{\nu_{ki}\}, \nu_r$, and $\{\rho_n\}$ are the Lagrangian multipliers. In the same way as in the definition of $\boldsymbol{\beta}$, we define $\boldsymbol{\lambda} \triangleq [\lambda_1, \cdots, \lambda_K, \lambda_r]$, $\boldsymbol{\nu} \triangleq [\nu_{11}, \cdots, \lambda_{K2}, \nu_r]$ and $\boldsymbol{\rho} \triangleq [\rho_1, \cdots, \rho_N]$. If the solution to (12) is given by $\{s_n^{k*}, p_n^{ki*}, p_n^{r*}\}$, there exists a value of $\boldsymbol{\lambda}^*$ satisfying the KKT conditions of (12). For all the KKT conditions, the conditions of interest for $\boldsymbol{\lambda}^*$ and $\boldsymbol{\beta}^*$ are expressed by

$$\begin{aligned}
\lambda_k^* \frac{\partial \mathcal{L}}{\partial \lambda_k} = \quad & \lambda_k^* \left(\textstyle\sum_{n=1}^{N} s_n^{k*} r_n^{k*} - \beta_k^* P_{cspt}^{k*} \right) = 0, \\
\forall k \in \quad & \{1, \cdots, K\}
\end{aligned} \tag{14a}$$

$$\lambda_r^* \frac{\partial \mathcal{L}}{\partial \lambda_r} = \lambda_r^* \left(\sum_{n=1}^{N} \sum_{k=1}^{K} s_n^{k*} r_n^{k*} - \beta_r^* P_{cspt}^{r*} \right) = 0 \tag{14b}$$

$$\frac{\partial \mathcal{L}}{\partial \beta_k} = w^k - \lambda_k^* P_{cspt}^{k*} = 0, \ \ \forall k \in \{1, \cdots, K\} \tag{14c}$$

$$\frac{\partial \mathcal{L}}{\partial \beta_r} = w^r - \lambda_r^* P_{cspt}^{r*} = 0. \tag{14d}$$

$$\lambda_k^* \ \ \geq \ \ 0, \ \ \forall k \in \{1, \cdots, K\}, \ \lambda_r^* \geq 0 \tag{14e}$$

where $\{r_n^{k*}\}$ denotes the achievable rate for users of the nth subcarrier in the kth pair with $\{p_n^{ki*}\}$ and p_n^{r*}. Similarly, P_{cspt}^{k*} and P_{cspt}^{r*} are defined with $\{p_n^{ki*}\}$ and p_n^{r*}. Because $P_{cspt}^{k*} > 0$ and $P_{cspt}^{r*} > 0$, we can rewrite (14c) and (14d) as

$$\begin{aligned}
\lambda_k^* &= \frac{w^k}{P_{cspt}^{k*}}, \\
\lambda_r^* &= \frac{w^r}{P_{cspt}^{r*}}.
\end{aligned} \tag{15}$$

Moreover, (14a) and (14b) are equivalent to

$$\begin{aligned}
\beta_k^* &= \frac{\sum_{n=1}^{N} s_n^{k*} r_n^{k*}}{P_{cspt}^{k*}}, \\
\beta_r^* &= \frac{\sum_{k=1}^{K} \sum_{n=1}^{N} s_n^{k*} r_n^{k*}}{P_{cspt}^{r*}}.
\end{aligned} \tag{16}$$

The other KKT conditions of (12) except (14), are identical to those of the following problem with $\boldsymbol{\lambda} = \boldsymbol{\lambda}^*$ and $\boldsymbol{\beta} = \boldsymbol{\beta}^*$:[1]

$$\begin{aligned}
\max_{\{s_n^k, p_n^{ki}, p_n^r\}} & \left\{ \sum_{k=1}^{K} \lambda_k (\sum_{n=1}^{N} s_n^k r_n^k - \beta_k P_{cspt}^k) \right. \\
& \left. + \lambda_r (\sum_{k=1}^{K} \sum_{n=1}^{N} s_n^k r_n^k - \beta_r P_{cspt}^r) \right\}
\end{aligned} \tag{17a}$$

$$s.t\ (11b) - (11e). \tag{17b}$$

Based on the above discussions, we can make the following observation.

Observation 1 If $\{s_n^{k*}, p_n^{ki*}, p_n^{r*}, \boldsymbol{\beta}^*\}$ is a solution to (12), where the value of $\boldsymbol{\lambda}^*$ is such that $\{s_n^{k*}, p_n^{ki*}, p_n^{r*}\}$ satisfies the KKT conditions of (17) with $\boldsymbol{\lambda} = \boldsymbol{\lambda}^*$ and $\boldsymbol{\beta} = \boldsymbol{\beta}^*$. Moreover, if $\{s_n^{k*}, p_n^{ki*}, p_n^{r*}\}$ is a solution to (17) and satisfies both (15) and (16) with $\boldsymbol{\lambda} = \boldsymbol{\lambda}^*$ and $\boldsymbol{\beta} = \boldsymbol{\beta}^*$, then $\{s_n^{k*}, p_n^{ki*}, p_n^{r*}, \boldsymbol{\beta}^*\}$ satisfies the KKT conditions of (12) with the Lagrangian multipliers of $\boldsymbol{\lambda} = \boldsymbol{\lambda}^*$.

Proof: The first part of the remark is proven by the KKT condition of (12a) and (17). The KKT conditions of s_n^k, p_n^{ki}, p_n^r of (12a) and (17) are given as follows:

$$\frac{\partial \mathcal{L}}{\partial s_n^k} = (\lambda_k^* + \lambda_r^*) r_n^k + \rho^k \tag{18a}$$

$$\frac{\partial \mathcal{L}}{\partial p_n^{ki}} = (\lambda_k^* + \lambda_r^*) \frac{\partial r_n^k}{\partial p_n^{ki}} + (\lambda_k^* \beta_k^* + \nu_{ki}) \alpha^{ki} \tag{18b}$$

[1]With the definition of network EE given by (10), the network EE maximization problem can be written as $max_{\{s_n^k, p_n^{ki}, p_n^r\}} \sum_{n=1}^{N} \sum_{k=1}^{K} s_n^k r_n^k - \beta_{net} \left(\sum_{k=1}^{K} P_{cspt}^k + P_{cspt}^r \right)$ by the Dinkelbach algorithm [18] converting the fractional form of η_{EE}^{net} into a subtract form with an auxiliary variable of β_{net}. This can be solved with the proposed algorithm with some modification.

$$\frac{\partial \mathcal{L}}{\partial p_n^r} = (\lambda_k^* + \lambda_r^*)\frac{\partial r_n^k}{\partial p_n^r} + (\lambda_r^* \beta_r^* + \nu_r)\alpha^r \quad (18c)$$

where $\boldsymbol{\nu}$ and $\boldsymbol{\rho}$ are Lagrangian dual variables of the constraints (11b) to (11f). So, (12a) and (17) have same solution $\{s_n^{k*}, p_n^{ki*}, p_n^{r*}\}$ with $\boldsymbol{\lambda} = \boldsymbol{\lambda}^*$ and $\boldsymbol{\beta} = \boldsymbol{\beta}^*$. The second part of the observation can be obtained by a procedure similar to that used in the first part. ■

We derived the proposed optimization problem, consisting of finding $\boldsymbol{\lambda}^*$, $\boldsymbol{\beta}^*$ and solving (17), by exploiting the KKT conditions of (11). The proposed algorithm updates $\boldsymbol{\lambda}$ and $\boldsymbol{\beta}$, and solves (17) iteratively until it converges. This means that the local optimal solution of (11) can be obtained by the proposed algorithm, because the conditions of (14) for $\boldsymbol{\lambda}$ and $\boldsymbol{\beta}$ are required. The details the algorithm are discussed in the following sections.

IV. PROPOSED ALGORITHM

The overall structure of the algorithm is shown in Algorithm 1. The details of each step are investigated in the following subsections.

A. Finding $\boldsymbol{\lambda}^*$ and $\boldsymbol{\beta}^*$

First, the optimal values of $\boldsymbol{\lambda}^*$ and $\boldsymbol{\beta}^*$ can be found by application of the modified Newton method as follows

$$\begin{aligned}
\lambda_k(i+1) &= (1-\xi(i))\lambda_k(i) + \xi(i)\frac{w^k}{P_{cspt}^{k*}(i)}, \\
&\qquad \forall k \in \{1,\cdots,K\}, \\
\lambda_r(i+1) &= (1-\xi(i))\lambda_r(i) + \xi(i)\frac{w^r}{P_{cspt}^{r*}(i)} \\
\beta_k(i+1) &= (1-\xi(i))\beta_k(i) + \xi(i)\frac{\sum_{n=1}^{N} s_n^{k*}(i) r_n^{k*}(i)}{P_{cspt}^{k*}(i)}, \\
&\qquad \forall k \in \{1,\cdots,K\}, \\
\beta_r(i+1) &= (1-\xi(i))\beta_r(i) + \xi(i)\frac{\sum_{k=1}^{K}\sum_{n=1}^{N} s_n^{k*}(i) r_n^{k*}(i)}{P_{cspt}^{r*}(i)}
\end{aligned} \quad (19)$$

where $r_n^{k*}(i)$, $s_n^{k*}(i)$, $P_{cspt}^{k*}(i)$, and $P_{cspt}^{r*}(i)$ are the optimal value rate, scheduling index, and power consumption, respectively, obtained from (17) at the ith iteration with the given $\boldsymbol{\lambda}(i)$ and $\boldsymbol{\beta}(i)$. To determine the step size $\xi(i)$, we choose $\zeta \in (0,1)$, $\epsilon \in (0,1)$ and define the following:

$$\begin{aligned}
\varphi_k^1(\lambda_k) &= 1 - \lambda_k \frac{P_{cspt}^k}{w_k}, \quad \forall k \in \{1,\cdots,K\}, \\
\varphi_r^1(\lambda_r) &= 1 - \lambda_r \frac{P_{cspt}^r}{w_r}, \\
\varphi_k^2(\beta_k) &= \sum_{n=1}^{N} s_n^k r_n^k - \beta_k P_{cspt}^k, \quad \forall k \in \{1,\cdots,K\}, \\
\varphi_r^2(\beta_r) &= \sum_{k=1}^{K}\sum_{n=1}^{N} s_n^k r_n^k - \beta_r P_{cspt}^r.
\end{aligned} \quad (20)$$

If the current values of $\boldsymbol{\lambda}(i)$ and $\boldsymbol{\beta}(i)$ do not satisfy the stopping conditions for the iterations, we update $\boldsymbol{\lambda}$ and $\boldsymbol{\beta}$. Upon updating equation (19), $\xi(i) = \zeta^{\bar{m}}$ where $\bar{m}$ is the smallest integer among $m \in \{0,1,2,\cdots\}$ satisfying the condition of (21) described on the next page.

With the modified Newton method, the update of λ_k, λ_r, β_k, and β_r guarantees a linear rate of convergence. For brevity, we present a sketch of the proof. A detailed discussion of the convergence is given in Theorem 3.2 of [19].

It can be shown that $\boldsymbol{\varphi}(\boldsymbol{\lambda},\boldsymbol{\beta}) = 0$ is equivalent to (15) and (16), where $\boldsymbol{\varphi}$ is a collection of φ_k^1, φ_r^1, φ_k^2, and φ_r^2. Then, $\{\boldsymbol{\lambda},\boldsymbol{\beta}\}$ is a local optimal solution of (12) if $\boldsymbol{\varphi}(\boldsymbol{\lambda},\boldsymbol{\beta}) = 0$. Assuming $\boldsymbol{\varphi}(\boldsymbol{\lambda}(0),\boldsymbol{\beta}(0)) \neq 0$, we need to show that the iterative update (19) guarantees that $\boldsymbol{\varphi}(\boldsymbol{\lambda}(i),\boldsymbol{\beta}(i)) = 0$ as i approaches infinity.

From Theorem 3.2 of [19], ζ satisfying (21) always exists if $\boldsymbol{\varphi}$ can be differentiated (with respect to $\boldsymbol{\lambda}$ and $\boldsymbol{\beta}$), $\boldsymbol{\varphi}'$ is Lipschitz continuous, and $||(\boldsymbol{\varphi}')^{-1}||$ is bounded. Moreover, the above three conditions are guaranteed because the power consumption P_{cspt}^k and P_{cspt}^r are Lipschitz continuous by Theorem 3.3 of [19]. Then, the iterative update (19) with a step size satisfying (21) implies $|\boldsymbol{\varphi}(\boldsymbol{\lambda}(i+1),\boldsymbol{\beta}(i+1))| \leq |\boldsymbol{\varphi}(\boldsymbol{\lambda}(i),\boldsymbol{\beta}(i))|$, and guarantees $\boldsymbol{\varphi}(\boldsymbol{\lambda}(i),\boldsymbol{\beta}(i)) = 0$ as i approaches infinity.

B. Solving (17)

The steps required to solve (17) with the given $\boldsymbol{\lambda}$ and $\boldsymbol{\beta}$ are explained. To solve (17), we exploit the Lagrangian dual method with the relaxation of the binary constraints.

The Lagrangian dual problem of (17) is expressed by

$$\begin{aligned}
&\min_{\boldsymbol{\nu},\boldsymbol{\rho}\geq 0} \max_{\{s_n^k, p_n^{ki}, p_n^r\}} \sum_{k=1}^{K}\sum_{n=1}^{N} (\lambda_k + \lambda_r) s_n^k r_n^k \\
&- \sum_{k=1}^{K} \lambda_k \beta_k \sum_{i=1}^{2} \left(\alpha^{ki} \sum_{n=1}^{N} p_n^{ki} + P_c^{ki} \right) \\
&- \lambda_r \beta_r \left(\alpha^r \sum_{n=1}^{N} p_n^r + P_c^r \right) \\
&- \sum_{k=1}^{K}\sum_{i=1}^{2} \nu_{ki} \left(\alpha^{ki} \sum_{n=1}^{N} p_n^{ki} - P_{\max}^{ki} \right) \\
&- \nu_r \left(\alpha^r \sum_{n=1}^{N} p_n^r - P_{\max}^r \right) + \sum_{n=1}^{N} \rho^n \left(\sum_{k=1}^{K} s_n^k - 1 \right)
\end{aligned} \quad (22)$$

with the constraints of (11e) and $s_n^k \geq 0$. When $\boldsymbol{\nu}$ and $\boldsymbol{\rho}$ are given, the Lagrangian dual problem is decomposed into two parts, which are the power allocation required to determine $\{p_n^{ki}, p_n^r\}$ with the given $\{s_n^k\}$, and the subcarrier allocation problem needed to determine $\{s_n^k\}$ with the given $\{p_n^{ki}, p_n^r\}$.

B.1 Power Allocation Algorithm

When the subcarrier allocation, i.e., s_n^k, is fixed, (22) can be decomposed into N unconstrained optimization problems of all subcarriers as follows:

$$\begin{aligned}
&\max_{p_n^{k1}\geq 0, p_n^{k2}\geq 0, p_n^r \geq 0} (\lambda_{\bar{k}} + \lambda_r) r_n^{\bar{k}} \\
&\qquad - \sum_{i=1}^{2} (\lambda_{\bar{k}} \beta_{\bar{k}} + \nu_{\bar{k}i}) \alpha^{\bar{k}i} p_n^{\bar{k}i} - (\lambda_r \beta_r + \nu_r) \alpha^r p_n^r
\end{aligned} \quad (23)$$

$$\sum_{k=1}^{K}\left|\varphi_k^1\left((1-\zeta^m)\lambda_k(i)+\zeta^m\frac{w^k}{P_{cspt}^{k*}(i)}\right)\right|+\left|\varphi_r^1\left((1-\zeta^m)\lambda_r(i)+\zeta^m\frac{w^r}{P_{cspt}^{r*}(i)}\right)\right|$$
$$+\sum_{k=1}^{K}\left|\varphi_k^2\left((1-\zeta^m)\beta_k(i)+\zeta^m\frac{\sum_{n=1}^{N}s_n^{k*}(i)r_n^{k*}(i)}{P_{cspt}^{k*}(i)}\right)\right|+\left|\varphi_r^2\left((1-\zeta^m)\beta_r(i)+\zeta^m\frac{\sum_{n=1}^{N}s_n^{k*}(i)r_n^{k*}(i)}{P_{cspt}^{r*}(i)}\right)\right|$$
$$\leq(1-\epsilon\zeta^m)\left\{\sum_{k=1}^{K}\left|\varphi_k^1(\lambda_k(i))\right|+\left|\varphi_r^1(\lambda_r(i))\right|+\sum_{k=1}^{K}\left|\varphi_k^2(\beta_k(i))\right|+\left|\varphi_r^2(\beta_r(i))\right|\right\}. \quad (21)$$

where $\bar{k}$ is a user pair such that $s_n^{\bar{k}}=1$ for a given subcarrier index n. Even (23) is a non-convex, three-dimensional search over $[0,\ P_{\max}]^3$ can provide the optimal solution of p_n^{k1*}, p_n^{k2*}, and p_n^{r*}. Such a search method has generally been employed for power allocation in TWR systems [4], [5].

B.2 Subcarrier Allocation Algorithm

From (22), the subcarrier allocation problem with given $\{p_n^{ki},p_n^r\}$ is expressed by

$$\max_{s_n^k\geq 0}\sum_{k=1}^{K}\sum_{n=1}^{N}(\lambda_k+\lambda_r)s_n^k r_n^k \quad s.t.\ \sum_{k=1}^{K}s_n^k=1,\forall\, n. \quad (24)$$

The objective function can be re-arranged as $\sum_{n=1}^{N}\sum_{k=1}^{K}(\lambda_k+\lambda_r)s_n^k r_n^k$ by exchanging the order of the summation. Then, it can be seen that the optimal solution for each subcarrier maximizes $\sum_{k=1}^{K}(\lambda_k+\lambda_r)s_n^k r_n^k$ with a constraint of $\sum_{k=1}^{K}s_n^k=1$ in the corresponding subcarrier. Therefore, (24) is separated into N user pair selection problems of N subcarriers. In the original problem, s_n^k is a binary variable, i.e., 0 or 1. In $\{s_n^1,\cdots,s_n^K\}$, only one element is 1. All of the others are 0. For the nth subcarrier, the sub-problem is given by

$$\max_{s_n^k=\{0,1\}}(\lambda_k+\lambda_r)s_n^k r_n^k \quad s.t.\ \sum_{k=1}^{K}s_n^k=1 \quad (25)$$

without relaxation of the binary variables $\{s_n^k\}$. Hence, the optimal solution is to select the user pair with the highest value of $(\lambda_k+\lambda_r)r_n^k$ for $k=1,\cdots,K$, i.e.,

$$s_n^k=\begin{cases}1, & k=\arg\max_k(\lambda_k+\lambda_r)r_n^k.\\ 0, & \text{otherwise.}\end{cases}, \quad (26)$$

for $n\in\{1,\cdots,N\}$. Because (26) holds (11d), ρ^n is always 0.

B.3 Updating Dual Variables

After obtaining the solution of the power allocation and the resource allocation, we can rewrite (22) as follows by ignoring the constant terms.

$$\min_{\boldsymbol{\nu},\boldsymbol{\rho}\geq 0}-\sum_{k=1}^{K}\sum_{i=1}^{2}\nu_{ki}\left(\alpha^{ki}\sum_{n=1}^{N}p_n^{ki}-P_{\max}^{ki}\right)-\nu_r\left(\alpha^r\sum_{n=1}^{N}p_n^r-P_{\max}^r\right). \quad (27)$$

Because (22) is always a convex function with respect to the Lagrangian dual variables, a sub-gradient method [20] to solve (27) by gradually updating $\boldsymbol{\nu}$ in the direction of sub-gradient can be used. The sub-gradients of ν_{ki} and ν_r are given as $\alpha^{ki}\sum_{n=1}^{N}p_n^{ki}-P_{\max}^{ki}$ and $\alpha^r\sum_{n=1}^{N}p_n^r-P_{\max}^r$, respectively. After lth iteration of the power allocation and the resource allocation with ν_{ki}^l and ν_r^l, the $(l+1)$th updates of the dual variables are given by

$$\nu_{ki}^{l+1}=[\nu_{ki}^l+\delta^{ki}(\alpha^{ki}\sum_{n=1}^{N}p_n^{ki}-P_{\max}^{ki})]^+$$
$$\nu_r^{l+1}=[\nu_r^l+\delta^r(\alpha^r\sum_{n=1}^{N}p_n^r-P_{\max}^r)]^+ \quad (28)$$

where δ^{ki} and δ^r are control variables for the step size, $[x]^+=\max(x,0)$. As the step size falls, the sub-gradient method guarantees the convergence.

The overall optimization procedure is summarized by Algorithm 1. In the algorithm, the index i in $\boldsymbol{\lambda}(i)$, $\boldsymbol{\beta}(i)$ denotes the iteration index. The outer loop of the algorithm denotes the process to update $\boldsymbol{\lambda}$ and $\boldsymbol{\beta}$ with the tentative solution of $\{s_n^k,p_n^{ki},p_n^r\}$ and the inner one is the loop to find $\{s_n^k,p_n^{ki},p_n^r\}$ with iterations of power and subcarrier allocation given by (23) and (26).

The proposed algorithm consists of an outer-layer, power allocation, resource allocation and the updates of the Lagrangian variables. The complexity of the algorithm can be analyzed by taking the complexity of each loop into consideration. The outer-layer iteration, which updates λ_k, λ_r, β_k and β_r, has a complexity of $O(I_{\text{outer}})$ and $I_{\text{outer}}\leq I_{\max}$. Because the power allocation is different for each subcarrier, the complexity of the power allocation algorithm is $N\times L^3$ where L is a resolution of the search space of p_n^{k1}, p_n^{k2}, and p_n^r. The complexity of the resource allocation is $O(N\times K)$, which finds the maximum among K users for each subcarrier. The updating of the Lagrangian variables has a complexity of $O(I_L)$ by assuming convergence within I_L iterations. Then, the overall complexity of

Algorithm 1 Overall algorithm

Input: $I_{\max}$ (maximum number of iterations)
ϵ_t (convergence tolerance of outer loop)
$\boldsymbol{\lambda}(0), \boldsymbol{\beta}(0)$ (initial values)

$i = 0$
while do $\Big(\Big\{ \sum_{k=1}^{K} \left|\varphi_k^1(\lambda_k(i))\right| + \left|\varphi_r^1(\lambda_r(i))\right| + \sum_{k=1}^{K} \left|\varphi_k^2(\beta_k(i))\right| + \left|\varphi_r^2(\beta_r(i))\right| \Big\} > \epsilon_t$ and $i < I_{\max} \Big)$
With the given $\boldsymbol{\lambda}(i)$, $\boldsymbol{\beta}(i)$, find a solution to (17) with the following three steps iteratively.
Solve (23). (power allocation)
Solve (26). (resource allocation)
Solve (28). (update dual variables).
Update $\boldsymbol{\lambda}(i+1)$, $\boldsymbol{\beta}(i+1)$ with (19).
$i = i + 1$
end while

the proposed algorithm is given by $O(I_{\text{outer}} \times I_L \times N(K+L^3))$. The spectral efficiency maximization (SEM) algorithm has a similar complexity of $O(I_L \times N(K + L^3))$ which neglects the outer-layer iteration. Because I_{outer} is constant regardless of the value of K and N, i.e., the convergence of the outer loop is independent of the number of users and subcarriers, the proposed algorithm and SEM algorithm have the same order of complexity in terms of K and N.

V. SIMULATION RESULTS

The energy efficiency (in bits per Joule) with the proposed algorithm in the TWR network was examined through computer simulations. In the simulations, two user pairs ($K = 2$) exchange data through the relay. The total number of subcarriers is assumed to be 16, i.e., $N = 16$, and the subcarrier spacing is 15 kHz. Each channel realization follows a statistically independent Rayleigh distribution. The pathloss model with distance d in kilometers is given by $128.1 + 37.6 \log_{10}(d)$ (in decibels), and the noise power spectral density is assumed to be -174 dBm/Hz. The distance between each user pair is 500 m, and the relay is located in the middle of the users. We examine the energy efficiency using the following parameters: the power amplifier efficiency of the users and relay are given as $\alpha^{ki} = 3, \forall k, i$, and $\alpha^r = 2$, and the constant power consumptions of the user terminals and the relay are given by $P_c^{ki} = 0.5$ W, $\forall k, i$, and $P_c^r = 1$ W, respectively.

We examined the energy efficiency of the proposed algorithm with different weight factors ($\{w^k, w^r\}$) and a range of transmission power constraints. For comparison, the energy efficiency of the spectral efficient maximization (SEM) algorithm proposed in [5] is also evaluated.

To show the convergence of the outer layer algorithm, the behaviors of the sum of EE with iterations are shown in Fig. 2. These numerical results illustrate that the proposed algorithm converges under various conditions.

The performance of EE with different values of $\{w^1, w^2, w^r\}$ is shown in Fig. 3. Here, $P_{\max}^{ki}$ and $P_{\max}^r$ are equal and the values are increased from 0.01 to 5 W. For all cases, the sum EE of the proposed algorithm increases with the maximum allowable transmission power at each user pair and relay, and the sum of EE saturates when the maximum transmission power is high. In contrast, the SEM algorithm achieves the same level of performance as the proposed algorithm in the low-power region, but the EE of the SEM scenario decreases in the high-power region. The proposed algorithm suppresses the power consumption of the user and the relay to maximize the value of EE for each user pair and relay in the TWR network, while the SEM algorithm consumes the most power to achieve a higher SE, regardless of the value of EE. Because the optimal sum of EE with a higher w^r is larger than in the other cases, we can conclude that the EE of the relay dominantly affects the sum of the EE in the network

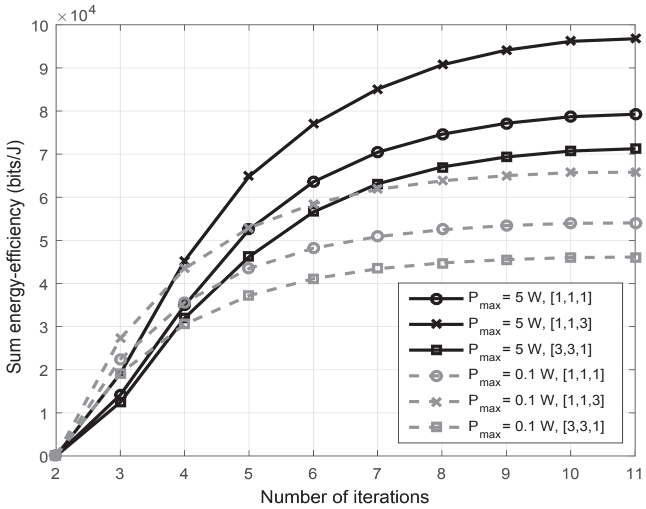


Fig. 2. Convergence of outer layer algorithm with $P_{\max}^{ki} = P_{\max}^r = P_{\max}$. The three values in square brackets denote the ratio of w^1, w^r, and w^r, respectively.

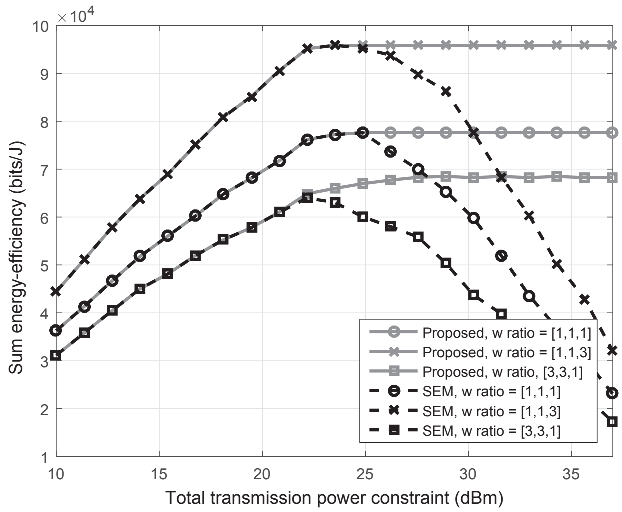
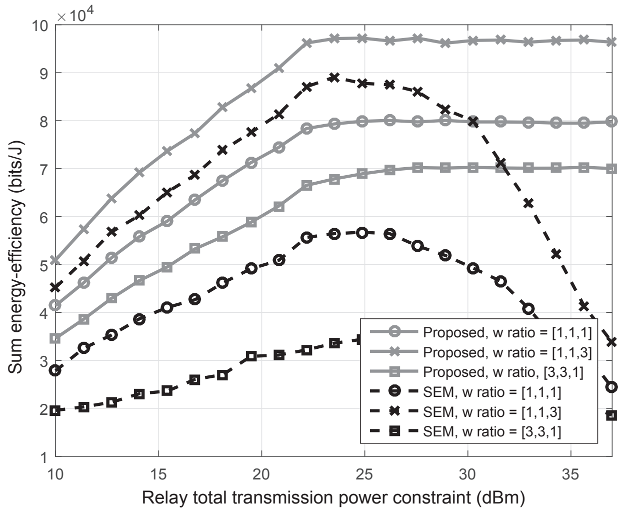
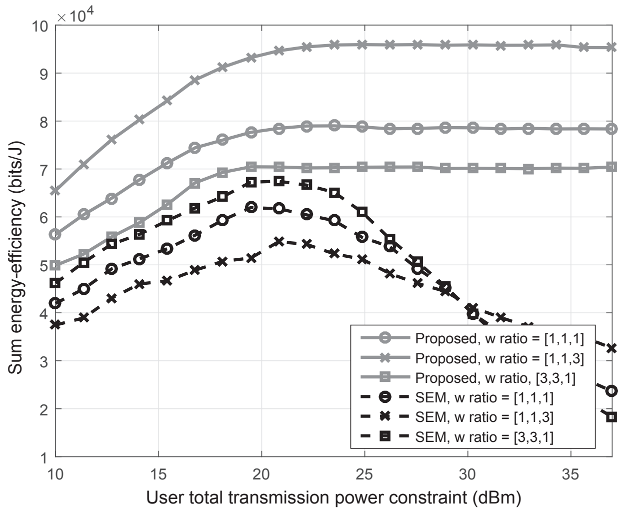


Fig. 3. Energy efficiency with varying transmission power constraints. The three values in square brackets denote the ratio of w^1, w^2, and w^r, respectively.

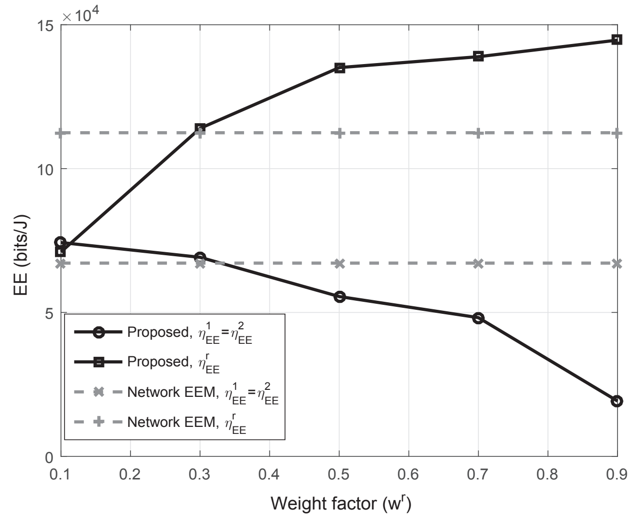


(a)

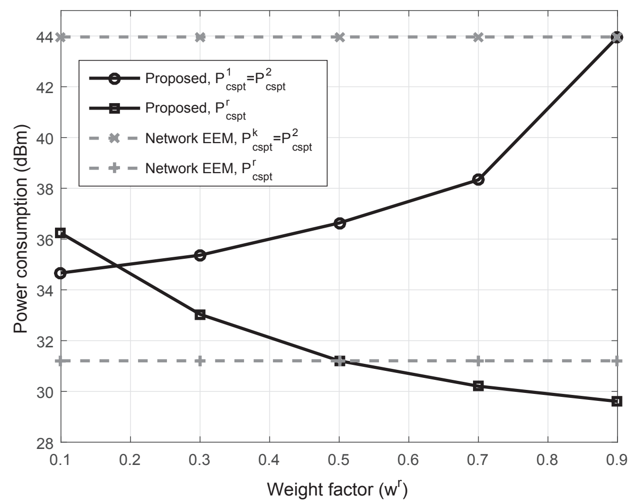


(b)

Fig. 4. Energy efficiency with different power constraints: (a) $P^{ki}_{\max} = 5W$ and (b) $P^r_{\max} = 5$ W. The three values in square brackets denote the ratio of w^1, w^2, and w^r, respectively.



(a)



(b)

Fig. 5. Effect of weight factor on: (a) Individual energy-efficiency and (b) power consumption, respectively.

over the EE of the user pairs.

In Fig. 4, the sum EE of the proposed algorithm is examined with different power constraints for the user terminals and relay. At first, the sum EE is evaluated as $P^r_{\max}$ increases from 0.01 to 5 W with the fixed $P^{ki}_{\max} = 5$ W in Fig. 4 (a). The proposed algorithm and the SEM algorithm have constant gaps for sum EE for all ranges of $P^r_{\max}$. This gap is shown because the SEM algorithm requires more transmission power for the user pairs than the transmission power achieving optimal EE. This gap in EE also increases with w^k, i.e., it decreases with w^r, because the optimal transmission power difference for the user pairs between the proposed algorithm and the SEM grows larger. Second, Fig. 4 (b) shows the sum EE depending on $\{P^{ki}_{\max}\}$ with the fixed $P^r_{\max} = 5$ W. The results are similar to those shown in Fig. 4 (a). The constant gap between the proposed and SEM algorithms increases with w^r. Based on the observation with Fig. 4, it is shown that the higher transmission power at the relay rather than at the user pairs is required to maximize the sum EE, because the transmission power of the relay affects all of the links of the TWR network.

In Fig. 5, the individual EE and power consumption depending on weight factor of the relay's EE, w^r, are shown for the proposed and the network EE maximization (network EEM) problems. Because the weight factors and channel distributions for the user pairs are same, η^1_{EE} and η^2_{EE}, which are averaged EE over channel realizations, have the same value. When the relay's weight factor w^r increases from 0.1 to 0.9, the weight factors of two user pairs are assumed to be $w^1 = w^2 = (1 - w^r)/2$. For example, if $w^r = 1/3$, the EEs of the user pairs and relay will have the same priority. As shown in Fig. 5 (a), η^r_{EE} increases with w^r and $\eta^1_{EE} = \eta^2_{EE}$ decreases with w^r for the proposed problem. In Fig. 5 (b), the power consumption of the user pairs and relay exhibit the opposite behavior to that of EE as expected. However, EE and the power consumption of the network EEM problem are constant regardless of the weight factors.

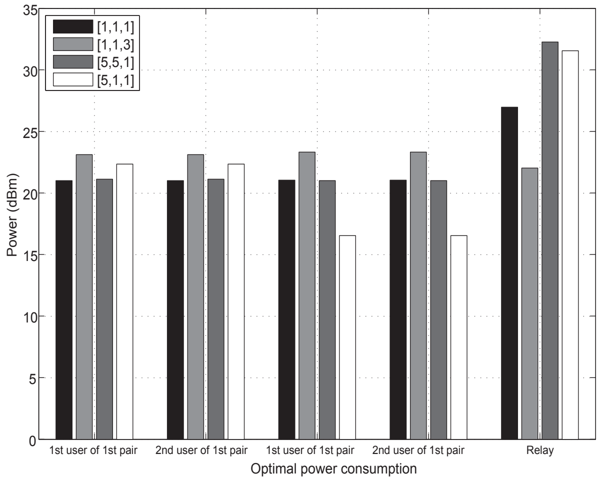


Fig. 6. Optimal power consumption with difference weight ratios when $P_{\max}^{ki} = P_{\max}^{r} = 5$ W. The three values in square brackets denote the ratio of w^1, w^2, and w^r, respectively.

Fig. 6 shows the average power consumption of the user terminals and relay at the optimal EE points with different ratios of $\{w^1, w^2, w^r\}$. Both $\{P_{\max}^{ki}\}$ and $P_{\max}^{r}$ are assumed to be 5 W. As w^r increases, the power consumption of the relay should be suppressed to maximize EE. On the other hand, when $\{w^1, w^2\}$ is high and w^r is low, the transmission power of the relay is increased because EE of the relay is a small portion of sum of EE. In summary, the proposed algorithm can control the power consumption of the user terminals and relay with $\{w^k, w^r\}$ because the ratio of $\{w^k, w^r\}$ defines the priority of EE between the user pairs and relay. When $[w^1, w^2, w^r] = [5, 1, 1]$, therefore, the power consumptions of the first user pair is higher than that of the second user pair. Because the overall resources are concentrated in the first user pair, the optimal power consumption of the first user pair also increases to accomplish the optimal EE point.

VI. CONCLUSION

In this paper, we study energy-efficient resource allocation in a multi-user AF TWR network. Instead of network-wise energy efficiency, a MOOP is considered with individual energy efficiencies of the user pairs and relay. The MOOP is converted into a SOOP to obtain a tractable problem. An efficient algorithm is proposed to solve the SOOP, which exploits the KKT conditions. The proposed iterative algorithm converges with the local optimal point of the SOOP. Numerical results demonstrate that the proposed algorithm efficiently manages the resource allocation between the users and relay, and achieves better energy efficiency than a conventional spectral efficiency maximization algorithm.

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