Energy Efficiency Optimization for D2D Underlay Communication in Distributed Antenna System over Composite Fading Channels

Guangying WANG [1], *Arvind DHAKA* [2], *Tao TENG* [1], *Kai YU* [1]

[1] College of Electronic and Information Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing, China
[2] Dept. of Computer and Communication Engineering, Manipal University Jaipur, Rajasthan, India

guangying@nuaa.edu.cn

Submitted March 19, 2022 / Accepted August 2, 2022 / Online first August 16, 2022

Abstract. *Device-to-Device (D2D) communication is a potential technology to improve the spectral and energy efficiency (EE) of communication networks. In this paper, we study energy-efficient power allocation (PA) schemes in uplink distributed antenna system (DAS) with device-to-device underlay communication. Our goal is to maximize the total EE of all D2D pairs while guaranteeing the data rate and transmit power requirements of the cellular user and D2D links. To solve this non-convex constrained optimization problem, we propose an energy-efficient near-optimal PA algorithm based on the concave-convex procedure and fractional programming theory. This near-optimal algorithm can achieve the EE performance close to the optimal exhaustive search. To reduce the complexity, we furthermore present an efficient sub-optimal algorithm with the antenna selection method which can obtain the closed-form power allocation expressions. Simulation results demonstrate the significant EE performance of our proposed PA schemes.*

Keywords

Device-to-Device (D2D) communication, energy efficiency, power allocation, distributed antenna system, rate constraint

1. Introduction

Recently, with the increasing demand for energy resources and the requirements for higher data rates, green communication has attracted considerable attention in communication networks [1], [2]. The major goal of green communication is to pursue higher spectrum efficiency (SE) and energy efficiency (EE). Therefore, how to improve EE performance has become a critical issue in mobile communication systems.

As a potential green technology in next-generation networks, Device-to-Device (D2D) communication allows direct communication between two adjacent devices. This short-range communication can improve the system EE and enhance the reliability of communication links with reduced energy consumption [3], [4]. Distributed antenna system (DAS) is proved as an effective green communication technology for increasing the EE and improving the coverage which has attracted worldwide research interest [5], [6]. By proper coordination, D2D communication and DAS can greatly increase network capabilities, EE, and reduce energy consumption.

Some related references have discussed the effective power allocation (PA) schemes in D2D communications [7–13]. The authors in [7] considered optimal resource allocation for energy-efficient D2D communications in an overlay cellular network. The authors in [8] jointly considered the cellular user (CU)-D2D matching and rate maximization problems. The proposed power control scheme can efficiently find feasible solutions. In [9], a resource allocation method for maximizing the system throughput in D2D communication system was studied. The authors in [10] investigated power consumption minimization and beamforming design in a cellular system underlying D2D communications, which assumed that the base station is not aware of the channel state information. In [11], the authors presented a robust power allocation problem in downlink D2D communication underlaying unmanned aerial vehicle (UAV)-assisted networks. In [12], a D2D underlaying non-orthogonal multiple access (NOMA)-based cellular network with resource allocation was studied. The authors in [13] developed the productive resource control algorithm with the goal of EE maximization in D2D communication-assisted cellular networks. In addition, the authors also addressed a distributed method to realize optimal EE performance. In [14], the authors jointly studied power and channel allocation schemes for EE maximization. The authors also analyzed the important characteristics of D2D underlay communication which provided a theoretical basis for future research. In [15], the authors studied an alternating optimization scheme to solve the sum-rate maximization problem under the requirements of data rates. The optimization problem of weighted sum EE maximization was solved by fractional programming

DOI: 10.13164/re.2022.0440

theory in [16]. The authors jointly optimized the bandwidth, power allocation, and relay selection. The studies in [17] proposed a beneficial iterative scheme based on D2D-CU matching strategy for maximizing EE in downlink D2D communication networks. Meanwhile, the quality-of-service (QoS) and power constraints of CUs were guaranteed.

The above works are all based on the D2D communications in co-located antenna system (CAS). There are some research works about resource allocation and EE optimization in DAS and D2D communication [18–21]. In [18], the authors developed an energy-efficient PA scheme in the uplink DAS with D2D communication, which only considered individual D2D pair. In [19], the authors presented a multiple criteria scheme to optimize EE in downlink DAS. In addition, the requirements of transmit power and data rates were guaranteed and an optimal scheme was developed to allocate the available power. The authors in [20] proposed an effective PA method to maximize EE in downlink DAS. The optimal solution as a closed-form can be derived with reduced computational complexity. The studies in [21] presented PA criteria to obtain the optimal SE and EE performance in a downlink system. The results confirmed the advantages of D2D communication in DAS. It is observed that the above articles are focused on EE performance in downlink D2D communication underlaying DAS. To the best of our knowledge, there is less research on the problem of considering together with multiple D2D pairs in the uplink DAS scenario.

Inspired by aforesaid observations, we present the EE maximization problem for the uplink D2D communication underlaying DAS over composite Rayleigh fading channels. Specifically, the scenarios of multiple D2D pairs are considered and two effective PA algorithms are proposed to improve the EE. The contributions of this paper are summarized as follows:

- The multiple D2D pairs and uplink communication scene are considered in the system model. Subject to the constraints of minimum rate and maximum transmit power of CU and D2D pairs, we formulate a constrained non-convex EE maximization problem.
- To solve the non-convex optimization problems, an alternating iterative algorithm is proposed. Then the concave-convex procedure (CCCP) algorithm is presented and the objective function is transformed into a sub-tractive form with fractional programming (FP) theory. The results show that the proposed PA algorithm can achieve the EE performance close to the exhaustive search.
- To further reduce the complexity, a sub-optimal algorithm based on the antenna selection is designed. Moreover, the closed-form PA of CU is derived and the complexity is reduced. The sub-optimal algorithm can achieve excellent performance in terms of EE. In addition, the computational complexities are analyzed.

The rest of the paper is organized as follows. The system model of D2D-DAS is introduced and the EE maximization problem is formulated in Sec. 2. Section 3 presents two effective PA algorithms and gives the complexities of algorithms. The results and analysis are shown in Sec. 4 and the conclusion is summarized in Sec. 5.

2. System Model and Problem Formulation

2.1 System Model

In this section, we model the uplink single-cell multiple D2D pairs underlay communication in DAS. Let K ($k = 1,\dots, K$) denote the total number of D2D pairs. One CU intends to communicate with N ($i = 1,\dots, N$) remote antenna units (RAUs) while several other D2D pairs are communicating with the same spectrum. The RAUs are uniformly distributed in the cell. We consider that the CU and K D2D pairs share the same spectrum. For convenience, each user is equipped with a single antenna and has a maximum power constraint, i.e., $p_c \le P_{\max,c}$ and $p_k \le P_{\max,d}$. The system model with D2D-enabled DAS is shown in Fig. 1.

The signal to interference plus noise ratio (SINR) of the uplink DAS is expressed as

$$\gamma_c = \sum\nolimits_{i=1}^{N} \gamma_{c,i} = \sum\nolimits_{i=1}^{N} \frac{p_c g_{c,i}^c}{\sum\nolimits_{k=1}^{K} p_k g_{k,i}^c + \sigma^2}. \tag{1}$$

The SINR of k-th D2D link is given by

$$\gamma_{d,k} = \frac{p_k g_{k,k}^d}{p_c g_{c,k}^d + \sum\nolimits_{m=1,\neq k}^{K} p_m g_{m,k}^d + \sigma^2}. \tag{2}$$

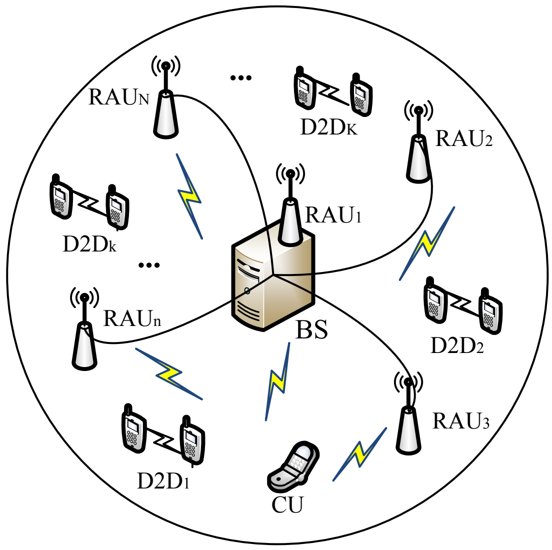

Fig. 1. D2D underlay communication in DAS.

The achievable rate of CU is given by

$$R_c = \log_2\left(1+\gamma_c\right) = \log_2\left(1+\sum_{i=1}^{N}\frac{p_c g_{c,i}^c}{\sum_{k=1}^{K} p_k g_{k,i}^c + \sigma^2}\right). \quad (3)$$

The achievable rate of the k -th D2D users is

$$R_d = \log_2\left(1+\gamma_{d,k}\right) = \log_2\left(1+\frac{p_k g_{k,k}^d}{p_c g_{c,k}^d + \sum_{m=1,\neq k}^{K} p_m g_{m,k}^d + \sigma^2}\right) \quad (4)$$

where $g_{c,i}^c$ and $g_{k,i}^c$ represent the channel gains from the CU and the k-th transmitter of D2D to the i-th RAU's receiver, respectively. $g_{c,k}^d$ and $g_{m,k}^d$ are the channel gains from the CU and the m-th transmitter of D2D to the D2D receiver k, respectively.

In this paper, the composite fading channel included path loss and Rayleigh fading is considered. Accordingly, the channel power gains are listed as follows

$$g_{c,i}^c = d_{c,i}^{-\beta}\left|h_{c,i}\right|^2,\ g_{k,i}^c = d_{k,i}^{-\beta}\left|h_{k,i}\right|^2,$$
$$g_{k,k}^d = d_{k,k}^{-\beta}\left|h_{k,k}\right|^2,\ g_{c,k}^d = d_{c,k}^{-\beta}\left|h_{c,k}\right|^2,$$
$$g_{m,k}^d = d_{m,k}^{-\beta}\left|h_{m,k}\right|^2$$

where β is the path loss exponent. $d_{c,i}$ and $d_{k,i}$ indicate the distances from CU and the k-th D2D user to the i-th RAU's receiver, respectively. $d_{k,k}$ and $d_{m,k}$ are the distances of the k-th and m-th D2D pair from D2D transmitter to D2D receiver. $d_{c,k}$ represent the distance from CU to the D2D receiver k. $h_{c,i}$ and $h_{k,i}$ denote the small-scale fading coefficients between CU and RAU and between the k-th D2D and RAU. $h_{k,k}$ and $h_{m,k}$ are the small-scale fading coefficients of the k-th and m-th D2D pair from D2D transmitter to D2D receiver. $h_{c,k}$ denote the small-scale fading coefficient between CU and D2D pair k.

2.2 Problem Formulation

Based on the definition, the EE of all D2D users can be expressed as the ratio of the total rate and the total power consumption [5], [6], i.e.,

$$\eta_{\mathrm{EE}} = \frac{\sum_{k=1}^{K} R_d}{\sum_{k=1}^{K} p_k + P_{\mathrm{s}}} \quad (5)$$

where P_{s} means the static circuit power consumption with a constant value.

For the uplink multi-D2D pairs underlay communications in DAS, we formulate the objective problem for EE maximization under minimum rate requirements and maximum transmit power constraints, which can be written as

$$\max_{\{\mathbf{p},p_c\}} \eta_{\mathrm{EE}} = \frac{\sum_{k=1}^{K} R_d}{\sum_{k=1}^{K} p_k + P_{\mathrm{s}}} \quad (6)$$

$$\text{s.t.} \quad R_c \ge R_{\min,c}, \quad (6a)$$

$$R_d \ge R_{\min,d}, \quad (6b)$$

$$0 \le p_c \le P_{\max,c}, \quad (6c)$$

$$0 \le p_k \le P_{\max,d}, \quad k = 1,\dots,K \quad (6d)$$

where $\mathbf{p} = \left[p_1,\cdots,p_k,\cdots p_K\right]$ represents the power allocation vector of the D2D pairs. The observations reveal that the function in objective problem (6) is non-concave, (6a) and (6b) are non-convex constraints. It is very challenging and intractable to directly derive the global optimal value for the problem (6). Consequently, this EE maximization objective problem cannot be directly solved by the existing optimization methods, which will be further discussed below.

3. Power Allocation Scheme for EE Maximization

3.1 Near-Optimal PA Scheme

In this section, we present an efficient PA scheme for solving this non-convex problem. We will firstly adopt the alternating iterative algorithm [22] to optimize the transmit power $\mathbf{p}$ of D2D pairs and the power p_c of CU. For given p_c and without considering the inequality in (6a), the objective problem (6) is transformed into

$$\max_{\mathbf{p}} \frac{\sum_{k=1}^{K} R_d}{\sum_{k=1}^{K} p_k + P_{\mathrm{s}}}$$
$$\text{s.t.} \quad R_d \ge R_{\min,d}, \quad (7)$$
$$0 \le p_k \le P_{\max,d}, \quad k = 1,\dots,K.$$

The inequality constraint of the minimum rate R_d has a special difference of concave function (D.C.). The sequential convex programming (SCP) method can be utilized to convert the non-convex constraint into a series of convex constraints. Accordingly, we note that R_d in (4) can be rewritten as the subtraction of two concave functions

$$\begin{aligned} R_d &= \log_2\left(\frac{p_c g_{c,k}^d + \sum_{m=1}^{K} p_m g_{m,k}^d + \sigma^2}{p_c g_{c,k}^d + \sum_{m=1,\neq k}^{K} p_m g_{m,k}^d + \sigma^2}\right) \\ &= \log_2\left(p_c g_{c,k}^d + \sum_{m=1}^{K} p_m g_{m,k}^d + \sigma^2\right) \\ &\quad - \log_2\left(p_c g_{c,k}^d + \sum_{m=1,\neq k}^{K} p_m g_{m,k}^d + \sigma^2\right) \\ &= R_{d,1} - R_{d,2}. \end{aligned} \quad (8)$$

We linearize $R_{d,2}$ by using the first-order Taylor expansion. $R^*_{d,2}$ can be expressed as

$$R^*_{d,2} = \log_2\left(p_c g^d_{c,k} + \sum\nolimits_{m=1,\neq k}^{K} g^d_{m,k}\tilde{p}_m + \sigma^2\right) + \frac{1}{\ln 2}\frac{\sum\nolimits_{m=1,\neq k}^{K} g^d_{m,k}\left(p_m - \tilde{p}_m\right)}{p_c g^d_{c,j} + \sum\nolimits_{m=1,\neq k}^{K} g^d_{m,k}\tilde{p}_m + \sigma^2}. \tag{9}$$

We can get $R^*_d = R_{d,1} - R^*_{d,2}$. Therefore, the optimization problem in (7) can be transformed into

$$\begin{aligned} \max_{\mathbf{p}} \ & \frac{\sum\nolimits_{k=1}^{K} R_d}{\sum\nolimits_{k=1}^{K} p_k + P_{\mathrm{s}}} \\ \text{s.t.} \quad & R^*_d \geq R_{\min,d}, \\ & 0 \leq p_k \leq P_{\max,d}, \quad k = 1,...,K. \end{aligned} \tag{10}$$

The observations reveal that the function in objective problem (10) is still a non-concave one. According to the analysis, this special optimization problem can be solved by the CCCP method. The objective function can be rewritten as

$$\begin{aligned} \sum\nolimits_{k=1}^{K} R_d &= f_1(\mathbf{p}) - f_2(\mathbf{p}) \\ &= \sum\nolimits_{k=1}^{K} \log_2\left(p_c g^d_{c,k} + \sum\nolimits_{m=1}^{K} p_m g^d_{m,k} + \sigma^2\right) \\ &\quad - \sum\nolimits_{k=1}^{K} \log_2\left(p_c g^d_{c,k} + \sum\nolimits_{m=1,\neq k}^{K} p_m g^d_{m,k} + \sigma^2\right). \end{aligned} \tag{11}$$

As shown in (11), we can find that the term $(p_c g^d_{c,k} + \sum\nolimits_{m=1}^{K} p_m g^d_{m,k} + \sigma^2)$ is the linear function in p_k. According to the concave-preserving property of the logarithmic function, $f_1(\mathbf{p})$ is the concave one in $\mathbf{p}$ strictly. Similarly, $f_2(\mathbf{p})$ is the concave one in $\mathbf{p}$.

We adopt the first-order Taylor expansion to linearize the $f_2(\mathbf{p})$ at the initial value $\mathbf{p}_0$

$$f_2(\mathbf{p} \mid \mathbf{p}_0) \simeq f_2(\mathbf{p}_0) + \nabla f_2(\mathbf{p}_0)(\mathbf{p} - \mathbf{p}_0)^{\mathrm{T}} \tag{12}$$

where $\nabla f_2(\mathbf{p_0})$ is the gradient of $f_2(\mathbf{p})$ at $\mathbf{p}_0$

$$\nabla f_2(\mathbf{p}_0)(\mathbf{p} - \mathbf{p}_0)^{\mathrm{T}} = \frac{1}{\ln 2}\sum_{k=1}^{K}\sum_{j=1,j\neq k}^{K}\frac{g^d_{k,j}\left(p_k - p_0\right)}{p_c g^d_{c,j} + \sum\nolimits_{m=1,m\neq j}^{K} p_m g^d_{m,j} + \sigma^2}. \tag{13}$$

As discussed above, given the initial value, the problem (10) can be transformed

$$\begin{aligned} \max_{\mathbf{p}} \ & \eta_1 = \frac{f_1(\mathbf{p}) - f_2(\mathbf{p}_0) - \nabla f_2(\mathbf{p}_0)(\mathbf{p} - \mathbf{p}_0)^{\mathrm{T}}}{F(\mathbf{p})} \\ \text{s.t.} \quad & R^*_d \geq R_{\min,d}, \\ & 0 \leq p_k \leq P_{\max,d}, \quad k = 1,...,K \end{aligned} \tag{14}$$

where $F(\mathbf{p}) = \sum\nolimits_{k=1}^{K} p_k + P_{\mathrm{s}}$.

Through analyzing the structure of the objective function in (14), the denominator $F(\mathbf{p})$ is affine function and the numerator $f_1(\mathbf{p}) - f_2(\mathbf{p}_0) - \nabla f_2(\mathbf{p}_0)(\mathbf{p} - \mathbf{p}_0)^{\mathrm{T}}$ is concave one. Hence, the function in (14) is a pseudo-concave one. The optimal value of optimization problem (14) can be derived correspondingly. Moreover, the fractional form can be easily found in this objective function. In terms of the fractional programming theory [23], the optimal solution in (14) can be obtained by solving the objective problem in the transformed subtractive form

$$\begin{aligned} \max_{\mathbf{p}} \ & \eta_2 = f_1(\mathbf{p}) - f_2(\mathbf{p}_0) - \nabla f_2(\mathbf{p}_0)(\mathbf{p} - \mathbf{p}_0)^{\mathrm{T}} - \omega_1 F(\mathbf{p}) \\ \text{s.t.} \quad & R^*_d \geq R_{\min,d}, \\ & 0 \leq p_k \leq P_{\max,d}, \quad k = 1,...,K \end{aligned} \tag{15}$$

where ω_1 is non-negative FP factor and it can be written as

$$\omega_1 = \frac{f_1(\mathbf{p}) - f_2(\mathbf{p}_0) - \nabla f_2(\mathbf{p}_0)(\mathbf{p} - \mathbf{p}_0)^{\mathrm{T}}}{F(\mathbf{p})}. \tag{16}$$

Since the converted optimization problem in (15) is convex, the optimal solution can be obtained by standard convex optimization toolbox, i.e. CVX. Considering the high complexity, we adopt an efficient gradient descent (GD) algorithm with Armijo rule for obtaining the optimal value $\mathbf{p}^*$. What's more, the derivative of η_2 w.r.t p_k is

$$\begin{aligned} \nabla \eta_2(\mathbf{p}) &= \frac{\partial \eta_2}{\partial p_k} \\ &= \frac{1}{\ln 2}\sum\nolimits_{j=1}^{K}\frac{g^d_{k,j}}{p_c g^d_{c,k} + \sum\nolimits_{m=1}^{K} p_m g^d_{m,j} + \sigma^2} \\ &\quad - \frac{1}{\ln 2}\sum\nolimits_{j=1,j\neq k}^{K}\frac{g^d_{k,j}}{p_c g^d_{c,j} + \sum\nolimits_{m=1,m\neq j}^{K} p_m g^d_{m,j} + \sigma^2} - \omega_1. \end{aligned} \tag{17}$$

Furthermore, the optimal value $\mathbf{p}^*$ can be calculated

$$\mathbf{p}^{(u+1)} = \mathbf{p}^{(u)} - \xi * \nabla \eta_2(\mathbf{p}) \tag{18}$$

where $\mathbf{p}^{(u)}$ is the u-th iteration of $\mathbf{p}$, ξ is the step size.

For the near-optimal PA solution we can transform the minimum rate constraint (6a) as

$$p_c \geq \gamma_{\mathrm{th}} / \sum\nolimits_{i=1}^{N}\frac{g^c_{c,i}}{\sum\nolimits_{k=1}^{K} p_k g^c_{k,i} + \sigma^2} \tag{19}$$

where $2^{R_{\min}} - 1 = \gamma_{\mathrm{th}}$. Herein, the optimization problem (6) can be transformed into

$$\begin{aligned} \max_{p_c} \ & \eta_3 = \frac{R_d}{\sum\nolimits_{k=1}^{K} p_k + P_{\mathrm{s}}} \\ \text{s.t.} \quad & p_c \geq \gamma_{\mathrm{th}} / \sum\nolimits_{i=1}^{N}\frac{g^c_{c,i}}{\sum\nolimits_{k=1}^{K} p_k g^c_{k,i} + \sigma^2}, \\ & p_c \leq P_{\max,c}. \end{aligned} \tag{20}$$

It can be found that η_3 is a monotonically decreasing function of p_c. We can derive two cases of the optimal solution for p_c^*.

Case 1: If $\gamma_{\text{th}} / \sum_{i=1}^{N} \frac{g_{c,i}^c}{\sum_{k=1}^{K} p_k g_{k,i}^c + \sigma^2} > P_{\max,c}$, then the problem has no solution.

Case 2: If $\gamma_{\text{th}} / \sum_{i=1}^{N} \frac{g_{c,i}^c}{\sum_{k=1}^{K} p_k g_{k,i}^c + \sigma^2} \le p_c \le P_{\max,c}$, then we can get

$$p_c^* = \gamma_{\text{th}} / \sum_{i=1}^{N} \frac{g_{c,i}^c}{\sum_{k=1}^{K} p_k g_{k,i}^c + \sigma^2}. \quad (21)$$

The specific procedure of near-optimal power allocation algorithm is shown as the Algorithm 1.

Algorithm 1 Near-Optimal Power Allocation Algorithm

1: **Initialize** iterative index $l = 0$, initial point $p_{c,0}^{(l)}, \mathbf{p}_0^{(l)}$
2: **Repeat**
3: **Initialize** iterative index $t = 0$, initial point $\mathbf{p}_0^{(t)}$
4: **Repeat**
5: **Initialize** tolerance $\varepsilon > 0$, $\omega_1 = 0$
6: **Repeat**
7: Compute $\mathbf{p}^{(u+1)}$, η_2 and update ω_1
8: **Until** $\eta_2 < \varepsilon$
9: $t = t + 1$
10: Update $\mathbf{p}_0^{(t)} = \mathbf{p}^{(u+1)}$
11: **Until** $\mathbf{p}_0^{(t)}$ converges
12: $l = l + 1$
13: Update $\mathbf{p}_0^{(l)} = \mathbf{p}_0^{(t)}$
14: Fix $\mathbf{p}_0^{(l)}$, compute $p_{c,0}^{(l)}$ by (21)
15: **Until** $\mathbf{p}_0^{(l)}, p_{c,0}^{(l)}$ converges.

3.2 Sub-optimal PA Scheme

Based on the analysis of Algorithm 1, we can find that near-optimal algorithm requires more iterative operations and thus has relatively complexity. Hence, a sub-optimal PA algorithm based on antenna selection to achieve EE performance is further presented.

According to the inequality in (6a), we can get

$$\sum_{i=1}^{N} \frac{p_c g_{c,i}^c}{\sum_{k=1}^{K} p_k g_{k,i}^c + \sigma^2} \ge 2^{R_{\min}} - 1 = \gamma_{\text{th}}. \quad (22)$$

When selecting one of the RAUs with the maximum $\gamma_{c,i}$ for communication, p_c can be given as

$$p_c \ge \frac{\gamma_{\text{th}} \left(\sum_{k=1}^{K} p_k g_{k,i^*}^c + \sigma^2 \right)}{g_{c,i^*}^c} \quad (23)$$

where $i^* = \arg\max_{i=1,\dots,N} \{\gamma_{c,i}\}$. Therefore, we can obtain the optimal value of p_c

$$p_c^* = \frac{\gamma_{\text{th}} \left(\sum_{k=1}^{K} p_k g_{k,i^*}^c + \sigma^2 \right)}{g_{c,i^*}^c}. \quad (24)$$

Moreover, the minimum rate requirement can be automatically met $R_c \ge R_{i^*} > R_{\min}$

$$R_{i^*} = \log_2 \left(1 + \frac{p_c g_{c,i^*}^c}{\sum_{k=1}^{K} p_k g_{k,i^*}^c + \sigma^2} \right). \quad (25)$$

We transform the constraint (6b) into the convex one by using SCP, the original EE optimization problem in (6) can be rewritten as

$$\begin{aligned} &\max_{\mathbf{p}} J_1 \\ &\text{s.t.} \quad R_d^* \ge R_{\min,d}, \\ &\qquad 0 \le p_k \le P_{\max,d}, \quad k = 1,\dots,K \end{aligned} \quad (26)$$

where

$$J_1 = \frac{\sum_{k=1}^{K} \log_2 \left(1 + \frac{p_k g_{k,k}^d}{p_c^* g_{c,k}^d + \sum_{m=1,\ne k}^{K} p_m g_{m,k}^d + \sigma^2} \right)}{\sum_{k=1}^{K} p_k + P_s}.$$

It can be found that the function J_1 is still a non-concave one and cannot be solved directly. J_1 has a special difference of concave function form. Therefore, we utilize the CCCP method to transform the objective function. It can be transformed as

$$\begin{aligned} f(\mathbf{p}) &= f_3(\mathbf{p}) - f_4(\mathbf{p}) \\ &= \sum_{k=1}^{K} \log_2 \left(p_c^* g_{c,k}^d + \sum_{m=1}^{K} p_m g_{m,k}^d + \sigma^2 \right) \\ &- \sum_{k=1}^{K} \log_2 \left(p_c^* g_{c,k}^d + \sum_{m=1,\ne k}^{K} p_m g_{m,k}^d + \sigma^2 \right). \end{aligned} \quad (27)$$

Then we linearize $f_4(\mathbf{p})$ through first-order Taylor expansion at $\mathbf{p}_0$

$$f_4(\mathbf{p} \mid \mathbf{p}_0) \simeq f_4(\mathbf{p}_0) + \nabla f_4(\mathbf{p}_0)(\mathbf{p} - \mathbf{p}_0)^{\mathrm{T}} \quad (28)$$

where $\nabla f_4(\mathbf{p}_0)$ is the gradient of $f_4(\mathbf{p})$ at the initial value $\mathbf{p}_0$

$$\begin{aligned} &\nabla f_4(\mathbf{p}_0)(\mathbf{p} - \mathbf{p}_0)^{\mathrm{T}} \\ &= \frac{1}{\ln 2} \sum_{k=1}^{K} \sum_{j=1, j\ne k}^{K} \frac{\left(M_2 g_{k,j^*}^c + g_{k,j}^d \right)\left(p_k - p_0 \right)}{M_1 + \sum_{m=1,\ne k}^{K} p_m g_{m,k}^d} \end{aligned} \quad (29)$$

where

$$M_1 = M_2 \sum_{k=1}^{K} p_k g_{k,i^*}^c + (M_2 + 1)\sigma^2, \; M_2 = \gamma_{\text{th}} g_{c,k}^d / g_{c,i^*}^c.$$

The optimization problem can be given as

$$\max_{\mathbf{p}} J_2 = \frac{f_3(\mathbf{p}) - f_4(\mathbf{p}_0) - \nabla f_4(\mathbf{p}_0)(\mathbf{p}-\mathbf{p}_0)^{\mathrm{T}}}{F(\mathbf{p})} \quad (30)$$
$$\text{s.t.} \quad R_d^* \ge R_{\min,d}, \, 6(\mathrm{d}).$$

We adopt the FP theory to reform the above objective function J_2 into a concave one and it becomes

$$\max_{\mathbf{p}} J_3 = f_3(\mathbf{p}) - f_4(\mathbf{p}_0) - \nabla f_4(\mathbf{p}_0)(\mathbf{p}-\mathbf{p}_0)^{\mathrm{T}} - \omega_2 F(\mathbf{p}) \quad (31)$$
$$\text{s.t.} \quad R_d^* \ge R_{\min,d}, \, 6(\mathrm{d})$$

where ω_2 is non-negative FP factor

$$\omega_2 = \frac{f_3(\mathbf{p}) - f_4(\mathbf{p}_0) - \nabla f_4(\mathbf{p}_0)(\mathbf{p}-\mathbf{p}_0)^{\mathrm{T}}}{F(\mathbf{p})}. \quad (32)$$

The optimization problem (31) is convex, thus the optimal solution can be obtained by GD method. Similar to the near-optimal PA scheme, we derive the partial derivative of J_3 with respect to p_k as

$$\begin{aligned}\nabla J_3(\mathbf{p}) &= \frac{\partial J_3}{\partial p_k} \\ &= \frac{1}{\ln 2}\sum_{j=1}^{K} \frac{M_2 g_{k,j^*}^c + g_{k,j}^d}{M_1 + \sum_{m=1}^{K} p_m g_{m,k}^d} \\ &\quad - \frac{1}{\ln 2}\sum_{j=1,\neq k}^{K} \frac{M_2 g_{k,j^*}^c + g_{k,j}^d}{M_1 + \sum_{m=1,\neq k}^{K} p_m g_{m,k}^d} - \omega_2.\end{aligned} \quad (33)$$

Therefore, we can attain the sub-optimal PA

$$\mathbf{p}_{\mathrm{sub}}^{(v+1)} = \mathbf{p}_{\mathrm{sub}}^{(v)} - \zeta * \nabla J_3(\mathbf{p}) \quad (34)$$

where $\mathbf{p}_{\mathrm{sub}}^{(v)}$ is the v-th iteration of $\mathbf{p}$, ζ is the step size.

The sub-optimal power allocation algorithm is summarized in Algorithm 2.

Algorithm 2 Sub-optimal Power Allocation Algorithm

1: **Initialize** iterative index $l = 0$, initial point $\mathbf{p}_0^{(l)}$
2: Utilize (24) to compute p_c^*
3: **Repeat**
4: **Initialize** tolerance $\varepsilon > 0$, $\omega_2 = 0$
5: **Repeat**
6: $v = v + 1$
7: Update $\mathbf{p}_{\mathrm{sub}}^{(v)}$, compute J_3 and ω_2
8: **Until** $J_3 < \varepsilon$
9: $l = l + 1$
10: Update $\mathbf{p}_0^{(l)} = \mathbf{p}_{\mathrm{sub}}^{(v)}$
11: **Until** $\mathbf{p}_0^{(l)}$ converges.

3.3 Computational Complexity Analysis

This subsection exhibits the computational complexity analysis of our proposed algorithms. In Algorithm 1, the computational complexity is mainly from optimizing **p** by outer and inner iteration, respectively. Therefore, the complexity based on Algorithm 1 can be denoted by $\mathcal{O}\left(2KL_0L_1L_2 \log(1/\varepsilon_1)\right)$, where L_0 is the number of outer iterations, L_1 and L_2 are the numbers of inner iterations, ε_1 is the computational accuracy of the GD method. Accordingly, the computational complexity for Algorithm 2 is consisted with $\mathcal{O}\left(KL_3L_4 \log(1/\varepsilon_2)\right)$, where L_3 and L_4 are the numbers of outer and inner iterations in sub-optimal scheme, ε_2 is computational accuracy of GD method. In addition, $\mathcal{O}\left((1/\varepsilon_3)^{K+1}\right)$ is the complexity of the exhaustive search scheme and ε_3 is the search accuracy.

4. Simulation Results

This section presents the simulation results to demonstrate the EE performance of our proposed energy-efficient PA algorithms. We consider the uplink communication scenario in DAS and there are N RAUs. The polar coordinate of RAU1 is (0,0), the $(N-1)$ RAU's polar coordinates are $\left(\sqrt{3/7}r, \pi i/3\right), i = 1,\cdots,N-1$. The cellular user and D2D pairs are randomly distributed in the cell. The transmitter and receiver of the D2D pairs are close enough to meet the communication distance requirements. The simulation parameters are summarized in Tab. 1.

Parameters	Value
Cellular radius r	1000 m
Path loss exponent	3
Noise power	–104 dBm
Circuit power	1.5 W
Number of RAUs N	7
Number of channel realization	1000
Minimum rate requirement of CU	3 bit/s/Hz

Tab. 1. Simulation parameters.

In Fig. 2, the EE performances under different PA schemes are compared. We also give the comparison of baseline scheme in previous work [18], while assuming only one D2D pair. We can find that both EE of our proposed PA schemes are increasing firstly and then stay to be a constant with the increase of $P_{\max,d}$, which confirms the effectiveness of both proposed schemes. The uplink EE with the near-optimal PA scheme is shown to be quite close to the exhaustive search. Besides, the sub-optimal algorithm only has a little EE performance loss within the near-optimal algorithm, but the sub-optimal PA algorithm has lower complexity since the fewer iteration are computed and the closed-form PA can be derived.

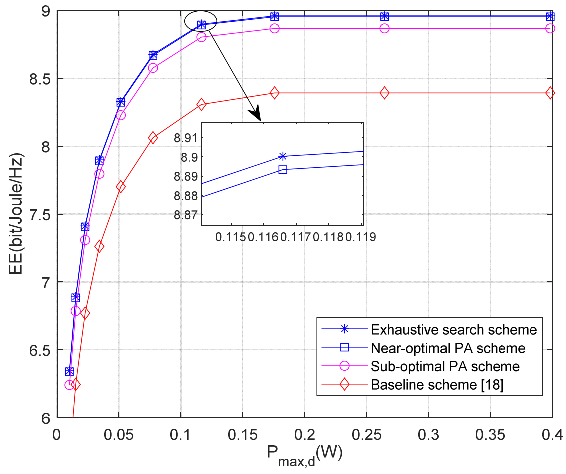

Fig. 2. EE with different PA schemes.

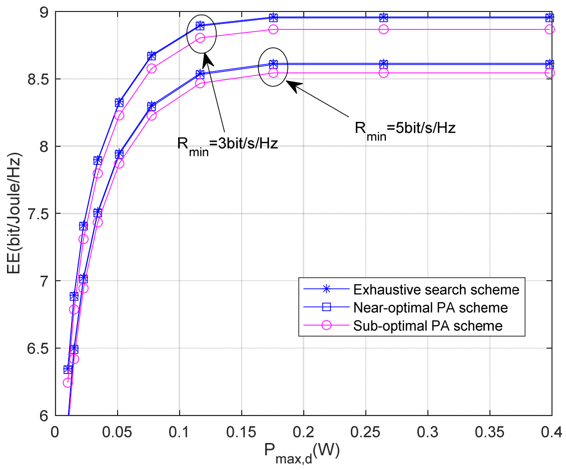

Fig. 3. EE with different rate requirements.

Figure 3 reveals EE performance with different minimum rate constraints of CU. The curves indicate that both proposed schemes are effective and meaningful within different rate requirements. The EE performance gradually increases and then remains stable as $P_{max,\,d}$ increases. It is due to the powers of D2D pairs being limited when $P_{max,\,d}$ is small. As the increase of $P_{max,\,d}$, the powers of D2D pairs can reach a larger value and the EE will increase correspondingly. However, the EE increases finally to a certain value due to the limitation of power constraints. From Fig. 3, it also can be concluded that the EE with a lower minimum rate outperforms the other higher minimum rate. This is because when the minimum rate constraint is high, there is a limitation for the transmit powers of D2D pairs to prevent interference with CU communication, which causes a reduction in energy efficiency.

Table 2 exhibits the total running time of our proposed algorithms. As illustrated in Tab. 2, we can find that the near-optimal PA algorithm and sub-optimal PA algorithm run in less time than the exhaustive search because of low complexity. Meanwhile, the sub-optimal PA algorithm runs less time than the near-optimal scheme, as expected. In addition, the comparison of the running time is also consistent with the complexity analysis which further demonstrates the effectiveness of the proposed algorithms.

Scheme	Near-optimal scheme	Sub-optimal scheme	Exhaustive search
Runtime	2577.68 s	93.26 s	14626.63 s

Tab. 2. Comparison of running time.

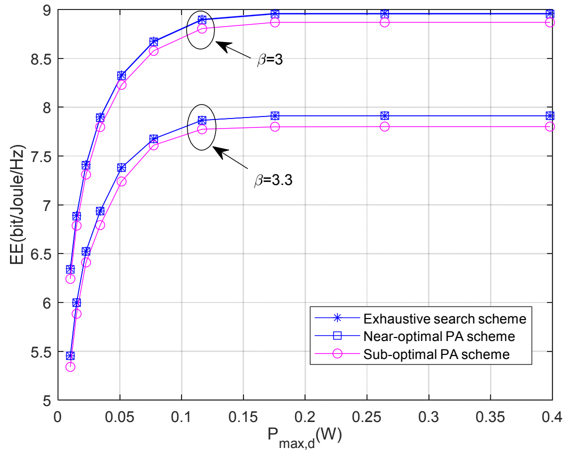

Fig. 4. EE performance vs. different path loss exponents.

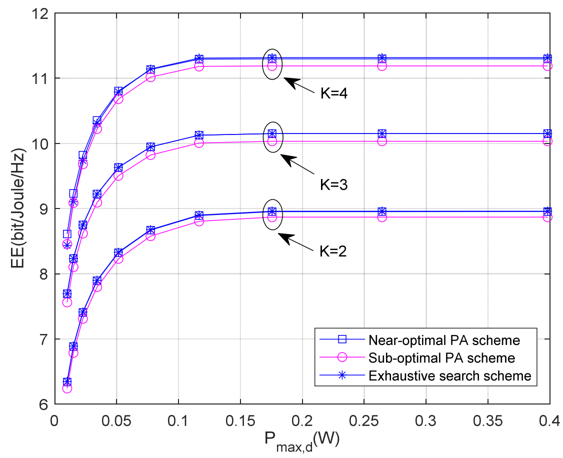

Fig. 5. EE with different numbers of D2D pairs.

In Fig. 4, we compare the EE performance under different path loss exponents for the proposed power allocation schemes. Figure 4 illustrates that both EE of the near-optimal PA scheme and sub-optimal PA scheme are improved when the path loss exponent decreases. This phenomenon can be explained as the fact that the increase of exponent leads to the increase of path loss and signal attenuation, which expands the reduction on the energy efficiency. This corresponds to the actual communication scenario and further proves the effectiveness and rationality of the proposed schemes.

Figure 5 gives the EE performance with different numbers of D2D pairs. It is clearly demonstrated that the EE is improved by the proposed effective PA algorithms. We present the uplink EE performance results when there are two D2D pairs, three D2D pairs, and four D2D pairs, respectively. It can be indicated that the impact of increased D2D pairs on EE is apparent and EE is significantly improved with the growth of D2D pairs. It also shows that the sum data rates are increased with the joining of more D2D pairs. The results confirm the superiority of D2D communication in enhancing system capacity and improving energy efficiency.

5. Conclusion

In this paper, we have studied the energy-efficient PA schemes to maximize EE under the constraints of data rates and transmit powers. The energy-efficient near-optimal algorithm using alternating iterative and concave-convex procedure has been applied to solve the constrained non-convex problem. Moreover, fractional programming theory has also been applied to solve the equivalent objective problem. To reduce the computational complexity, an efficient sub-optimal algorithm which can achieve the closed-form PA is proposed. The simulation results demonstrate the effectiveness of our proposed PA schemes and these schemes can obtain the beneficial EE performance of D2D communication. The above PA schemes are based on the single-CU, and we will further investigate the EE optimization performance based on multiple CUs and multiple D2D pairs in future work.

Acknowledgments

This work is supported by the Postgraduate Research and Practice Innovation Program of Jiangsu Province under Grant KYCX19-0191.

References

[1] TEHRANI, M. N., UYSAL, M., YANIKOMEROGLU, H. Device-to-device communication in 5G cellular networks: Challenges, solutions, and future directions. *IEEE Communications Magazine*, 2014, vol. 52, no. 5, p. 86–92. DOI: 10.1109/MCOM.2014.6815897

[2] GE, X., TU, S., MAO, G., et al. 5G ultra-dense cellular networks. *IEEE Wireless Communications*, 2016, vol. 23, no. 1, p. 72–79. DOI: 10.1109/MWC.2016.7422408

[3] ZHANG, S., LIU, J., GUO, H., et al. Envisioning device-to-device communications in 6G. *IEEE Network*, 2020, vol. 34, no. 3, p. 86–91. DOI: 10.1109/MNET.001.1900652

[4] YU, C., DOPPLER, K., RIBEIRO, C. B., et al. Resource sharing optimization for device-to-device communication underlaying cellular networks. *IEEE Transactions on Wireless Communications*, 2011, vol. 10, no. 8, p. 2752–2763. DOI: 10.1109/TWC.2011.060811.102120

[5] YU, X., CHU, J., YU, K., et al. Energy-efficiency optimization for iot-distributed antenna systems with SWIPT over composite fading channels. *IEEE Internet of Things Journal*, 2020, vol. 7, no. 1, p. 197–207. DOI: 10.1109/JIOT.2019.2946581

[6] HE, C., SHENG, B., ZHU, P., et al. Energy efficiency and spectral efficiency tradeoff in downlink distributed antenna systems. *IEEE Wireless Communications Letters*, 2012, vol. 1, no. 3, p. 153–156. DOI: 10.1109/WCL.2012.022812.120048

[7] ZHANG, J., ZHANG, Y., XIANG, L., et al. Robust energy-efficient transmission for wireless-powered D2D communication networks. *IEEE Transactions on Vehicular Technology*, 2021, vol. 70, no. 8, p. 7951–7965. DOI: 10.1109/TVT.2021.3095626

[8] RAMEZANI-KEBRYA, A., DONG, M., LIANG, B., et al. Joint power optimization for device-to-device communication in cellular networks with interference control. *IEEE Transactions on Wireless Communications*, 2017, vol. 16, no. 8, p. 5131–5146. DOI: 10.1109/TWC.2017.2706259

[9] FENG, D., LU, L., WU, Y., et al. Device-to-device communications underlaying cellular networks. *IEEE Transactions on Communications*, 2013, vol. 61, no. 8, p. 3541–3551. DOI: 10.1109/TCOMM.2013.071013.120787

[10] WANG, Q., SHEN, X. Power optimization in device to device communications underlying 5G cellular networks. *Radioengineering*, 2022, vol. 31, no. 1, p. 94–103. DOI: 10.13164/re.2022.0094

[11] XU, Y., LIU, Z., HUANG, C. Robust resource allocation algorithm for energy-harvesting-based D2D communication underlaying UAV-assisted networks. *IEEE Internet of Things Journal,* 2021, vol. 8, no. 23, p. 17161–17171. DOI: 10.1109/JIOT.2021.3078264

[12] KAI, C., WU, Y., PENG, M., et al. Joint uplink and downlink resource allocation for NOMA-enabled D2D communications. *IEEE Wireless Communications Letters*, 2021, vol. 10, no. 6, p. 1247–1251. DOI: 10.1109/LWC.2021.3063169

[13] WU, Y., WANG, J., QIAN, L., et al. Optimal power control for energy efficient D2D communication and its distributed implementation. *IEEE Communications Letters*, 2015, vol. 19, no. 5, p. 815–818. DOI: 10.1109/LCOMM.2015.2407871

[14] WANG, F., XU, C., SONG, L., et al. Energy-efficient resource allocation for device-to-device underlay communication. *IEEE Transactions on Wireless Communications*, 2015, vol. 14, no. 4, p. 2082–2092. DOI: 10.1109/TWC.2014.2379653

[15] ZHAO, W., WANG, S. Resource allocation for device-to-device communication underlaying cellular networks: An alternating optimization method. *IEEE Communications Letters*, 2015, vol. 19, no. 8, p. 1398–1401. DOI: 10.1109/LCOMM.2015.2444403

[16] WU, Q., LI, G., CHEN, W., et al. Energy-efficient D2D overlaying communications with spectrum-power trading. *IEEE Transactions on Wireless Communications*, 2017, vol. 16, no. 7, p. 4404–4419. DOI: 10.1109/TWC.2017.2698032

[17] HU, J., HENG, W., LI, X., et al. Energy-efficient resource reuse scheme for D2D communications underlaying cellular networks. *IEEE Communications Letters*, 2017, vol. 21, no. 9, p. 2097–2100. DOI: 10.1109/LCOMM.2017.2711490

[18] WANG, G., YU, X., TENG, T. Energy-efficient power allocation scheme for uplink distributed antenna system with D2D communication. *Mobile Networks and Applications*, 2021, vol. 26, p. 1225–1232. DOI: 10.1007/s11036-019-01343-2

[19] HE, C., SHENG, B., ZHU, P., et al. Energy- and spectral-efficiency tradeoff for distributed antenna systems with proportional fairness. *IEEE Journal on Selected Areas in Communications*, 2013, vol. 31, no. 5, p. 894–902. DOI: 10.1109/JSAC.2013.130508

[20] KIM, H., LEE, S., SONG, C., et al. Optimal power allocation scheme for energy efficiency maximization in distributed antenna systems. *IEEE Transactions on Communications*, 2015, vol. 63, no. 2, p. 431–440. DOI: 10.1109/TCOMM.2014.2385772

[21] LI, X., HE, C., FENG, D., et al. Power allocation criteria for distributed antenna systems with D2D communication. *AEU-International Journal of Electronics and Communications*, 2018, vol. 93, p. 109–115. DOI: 10.1016/j.aeue.2018.05.036

[22] TSENG, P., YUN, S. Block-coordinate gradient descent method for linearly constrained nonsmooth separable optimization. *Journal of Optimization Theory and Applications*, 2009, vol. 140, p. 513–535. DOI: 10.1007/s10957-008-9458-3

[23] DINKELBACH, W. On nonlinear fractional programming. *Management Science*, 1967, vol. 13, no. 7, p. 492–498. DOI: 10.1287/mnsc.13.7.492

About the Authors ...

Guangying WANG (corresponding author) was born in Shandong, China. She received her M.Sc. degree from the University of Jinan, China, in 2017. She is currently working towards Ph.D. degree at Nanjing University of Aeronautics and Astronautics, China. Her research interests include resource allocation optimization, device-to-device communication and green communication.

Arvind DHAKA received his Ph.D. degree in Computer Science and Engineering from NIT Hamirpur, India, in 2018. Since 2018, he has been working as an Assistant Professor with the Department of Computer and Communication Engineering, Manipal University Jaipur. His research interests include wireless communication, wireless sensor networks and deep learning in image processing.

Tao TENG received B.Sc. degree from Jiangsu University, China, in 2017. He is currently pursuing Ph.D. degree at Nanjing University of Aeronautics and Astronautics, China.

Kai YU received his M.Sc. degree from Dalian Maritime University, China. He is currently working towards Ph.D. degree at Nanjing University of Aeronautics and Astronautics, China.