Energy-Efficient Resource Allocation for Secure D2D Communications Underlaying UAV-Enabled Networks

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***Abstract*—In this paper, we investigate the energy-efficient resource allocation problem in device-to-device (D2D) communications underlaying unmanned aerial vehicle (UAV)-enabled networks. The UAV is deployed as a flying base station to communicate with wireless users in the presence of an eavesdropper in the cell. We consider two types of users: the ground users (GUs) served by the UAV and the D2D users that communicate directly with one another. Our aim is to maximize the total energy efficiency (TEE) of all D2D pairs while guaranteeing the quality of service (QoS) requirements and secrecy rates of all GUs and D2D users via joint power control and channel allocation. The considered TEE maximization problem is a mixed-integer nonlinear programming (MINLP) problem, which is difficult to solve. Therefore, we propose a method that consists of outer and inner loops. In the outer loop, Dinkelbach's algorithm is utilized to transform the original fractional programming problem into a subtractive form. In the inner loop, we employ the alternating optimization method and divide the equivalent optimization problem into two sub-problems: power allocation and channel allocation. Solving the two sub-problems directly using standard convex optimization software may have high complexity. Therefore, we also propose a low-complexity algorithm using the Lagrangian dual and Kuhn—Munkres algorithm to obtain the optimal power allocation in closed-form and the optimal channel allocation, respectively. Simulation results show that the proposed algorithm converges in a small number of iterations. Furthermore, the proposed approach shows its superior performance compared with other benchmark methods.**

***Index Terms*—D2D communications, energy efficiency, physical layer security, resource allocation, UAV.**

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I. Introduction

Unmanned aerial vehicles (UAVs) have gained considerable research attention during the past decade because of their low cost and high flexibility [1]. UAV is likely to have better communication channels due to the strong line-of-sight (LoS) feature of air-to-ground (ATG) communications. UAVs can serve as aerial user equipments (UEs), wireless relays, or flying base stations (BSs) to enhance the throughput and coverage. Owing to these advantages, comprehensive studies have been applied to UAV-aided wireless communication networks [2]–[6]. In [2], optimal beamforming and power allocation are jointly investigated to maximize the instantaneous data rate in a UAV enabled full-duplex relaying system. The authors in [3] study the throughput maximization problem where a UAV is deployed as a mobile relay by joint optimizing the source/relay transmit power and the relay trajectory, subject to practical mobility constraints. In [4], a joint central processing unit (CPU) frequency, offloading data amount, transmit power, and UAV's trajectory optimization method is proposed to minimize the total required energy of the UAV. In [5], the minimum average secrecy rate is maximized where a UAV BS transmits confidential information to multiple receivers with the aid of a UAV jammer in the presence of eavesdroppers. In [6], the authors propose a bandwidth design scheme, which minimizes the energy consumption of the UAV when it communicates with the ground BS using space–time line codes.

Device-to-device (D2D) communications [7] are gaining increasing research attention due to their integration in the fifth generation (5 G) mobile networks. D2D communications refer to the case that two mobile users can transmit data directly without going through the BS, which can reduce the transmission delay, improve the spectrum efficiency and increase the data rate. D2D communications have been proposed to underlay cellular networks so that D2D users can reuse the channel of cellular users (CUs), hence improving the spectrum utilization. However, such communication schemes will also cause interference between D2D users and cellular users. Therefore, dynamic power allocation techniques should be applied in such networks.

Due to the limited energy of batteries, energy efficient resource allocation has become an important research direction in D2D communications. In [8], the authors model the energy efficiency (EE) resource allocation problem as a non-cooperative game, in which each user aims to maximize its own EE rather than the system-wide EE. In [9], the authors present a cooperative D2D communication scheme. For cellular users, the D2D users act as relays in the uplink cellular network to optimize the total achievable rate. In [10], a stable matching approach is proposed to solve the EE optimization problem. The authors adopt an iterative power allocation algorithm, and a game-theoretic method is developed to analyze the interaction and correlation among user devices. In [11], the authors propose throughput maximization strategies for battery-limited networks by jointly considering the data rate and battery lifetime of each user. In [12], the authors investigate an uplink resource allocation algorithm under a general "many-to-many" scenario with the purpose of maximizing the sum data rate of D2D pairs. In [13], the authors consider a resource allocation problem in D2D-enabled vehicular networks with delayed channel state information (CSI). In those studies, the BS is fixed, which has certain limitations and is not flexible in a highly dynamic environment.

Thanks to its high flexibility and rapid deployment capabilities, UAV is an ideal platform for communication with severe shadowing, e.g., in places with urban or mountainous topography, or natural disasters areas with damaged BSs. Some research works have considered the performance of UAV-enabled D2D networks [14]–[16]. An efficient spectrum sharing method for a UAV and terrestrial D2D communications is designed by alternately optimizing the transmit power and UAV's trajectory in [14]. To control the interference and minimize the UAV-assisted file dispatching time, the authors of [15] propose a graph-based file dispatching protocol in a D2D-enhanced UAV-NOMA network. The outage probability for UAV connected users and D2D receivers is addressed and the power control design is proposed in [16].

Wireless transmission has broadcast characteristics, so it is vital to consider the interference and security of UAV-enabled networks. However, few papers have jointly taken into account energy efficient communications and secure communications underlaying UAV-enabled D2D systems, where the communication between the UAV and its connected users can be readily overheard by eavesdroppers. For example, the aim of [14] is to maximize the sum throughput satisfying the information causality and UAV's trajectory constraints, which does not consider energy efficiency. The authors of [17] study a problem of revealing the tradeoff between energy efficiency and delay in D2D communications underlaying cellular networks, where they do not consider secrecy issues. The paper [18] aims to maximize the minimum weighted energy efficiency of D2D links while guaranteeing minimum data rates for cellular links, where the security of communication is not considered either. The problem of secrecy communication is considered in [19]. However, only a single D2D pair is considered in that paper.

Motivated by the above observations, a UAV-enabled secure D2D communication scenario is considered in this paper, where a UAV acting as a flying BS provides communications for the ground network. We aim to maximize the total energy efficiency (TEE) of all D2D pairs with guaranteed quality of service (QoS) requirements and secrecy rate via joint power control and channel allocation. We first formulate the TEE maximization problem into a mathematical optimization problem, which is non-convex and difficult to solve. To overcome this challenge, we propose a method that consists of outer and inner loops. In the outer loop, Dinkelbach's algorithm is utilized to transform the original fractional programming problem into a subtractive form. In the inner loop, we employ the alternating optimization method and divide the equivalent optimization problem into two sub-problems: power allocation and channel allocation. For the power allocation problem, we can transform it into a difference of concave functions (DC) form; for the channel allocation problem, we can convert it into a convex form using relaxation. Both sub-problems can be solved using standard convex optimization software. However, directly solving them using standard convex optimization software may have high complexity. Therefore, we also propose low-complexity dual-based algorithms to solve the sub-problems. For the power control sub-problem, we derive the optimal power allocation with a closed-form solution using the Lagrangian dual. For the channel allocation sub-problem, Kuhn–Munkres algorithm is used to obtain the optimal channel allocation based on the power control strategy. We perform extensive numerical simulations to verify the effectiveness of the proposed algorithms and compare their performance with other schemes. We summarize the major contributions of this paper as follows:

- We jointly consider energy efficient communications and secure communications in a D2D communication system underlaying UAV-enabled networks. We formulate the resource allocation problem for TEE maximization as a non-convex optimization problem.
- We propose an alternating optimization based method to solve the inner-loop problem and divide the equivalent optimization problem into two sub-problems. For the sub-problems, we also propose low-complexity solution methods using the Lagrangian dual and the Kuhn–Munkres algorithm, which greatly speeds up the proposed method.
- We perform numerical simulation for the proposed iterative algorithm and compare its performance with other benchmark methods. Simulation results show that the proposed algorithm achieves higher TEE while satisfying the secrecy rate and D2D link rate constraints.

The organization of this paper is as follows: In Section II, we introduce the system model and problem formulation. Section III transforms the problem into an equivalent form and propose the alternating optimization based method. Low-complexity methods to solve the two sub-problems based on the Lagrangian dual and the Kuhn–Munkres algorithm are discussed in Section IV. Numerical simulation results are presented in Section V. Finally, the conclusion is given in Section VI.

II. System Model and Problem Formulation

A. System Model

We consider secure D2D communications underlaying a UAV-enabled network where a UAV is deployed at a low altitude above the center of the virtual cell with a radius R. As shown in Fig. 1, the considered model consists of a network where a number of wireless users are randomly distributed. A UAV acting as a flying BS serves those users and an eavesdropper

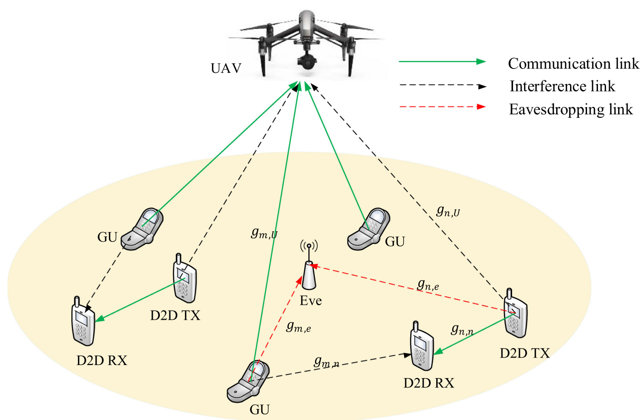

Fig. 1. Secure D2D communications underlaying a UAV-enabled network.

(Eve) is located on the ground. The altitude of the UAV is fixed to h. The wireless users are divided into two groups: ground users (GUs) that communicate with the UAV, and D2D users that communicate with each other directly. Furthermore, each pair of D2D users are distributed inside a given area with the cluster radius r. We assume that GUs communicate with the UAV using orthogonal frequency division multiple access (OFDMA) and D2D users reuse the same spectrum of the GUs in the network. So interference management plays an important role in such environment. In our model, we assume the transmit power allocations of the GUs are fixed and focus on solving the power control and channel allocation problems of the D2D users.

The considered cell consists of N pairs of D2D users and M GUs which occupy M orthogonal subchannels. The set of GUs and the set of D2D pairs are denoted as $\mathcal{M} = \{1, 2, \ldots, M\}$ and $\mathcal{N} = \{1, 2, \ldots, N\}$, respectively. We assume the subchannels have been pre-allocated to the GUs. The D2D users reuse the subchannels occupied by the GUs, and different D2D pairs should be assigned to different subchannels. Let $c_{m,n} \in \{0, 1\}$ denote whether the channel of the mth GU is reused by the nth D2D pair. We have $c_{m,n} = 1$ if the mth GU's subchannel is allocated to the nth D2D link; and $c_{m,n} = 0$, otherwise.

The communication links between the UAV and the GUs and the interference links between the UAV and the D2D transmitter (D2D TX) are regarded as air-to-ground (ATG) channels, which include LoS and NLoS signal components with different probabilities of occurrence [20]–[22]. The channel gain between the UAV and the mth GU can be given as follows:

$$g_{m,U} = Pr_{m,U}^{LoS} \cdot g_{m,U}^{LoS} + Pr_{m,U}^{NLoS} \cdot g_{m,U}^{NLoS}, \tag{1}$$

where $g_{m,U}^{LoS}$ is the channel gain for the LoS link, and $g_{m,U}^{NLoS}$ is the channel gain for the NLoS link. They can be written as

$$g_{m,U}^{LoS} = \left(\sqrt{d_{m,U}^2 + h^2}\right)^{-\alpha_u} \tag{2}$$

and

$$g_{m,U}^{NLoS} = \eta \left(\sqrt{d_{m,U}^2 + h^2}\right)^{-\alpha_u}. \tag{3}$$

Here $d_{m,U}$ denotes the horizontal distance between the UAV and GU-m, h is the altitude of the UAV, α_u is pathloss exponent for the ATG link, and η is additional attenuation factor if NLoS exists over the ATG link. The probability of the LoS connection $Pr_{m,U}^{LoS}$ depends on the environment, user location, and the angle of elevation between the UAV and its associated user, which is expressed as follows [23]:

$$Pr_{m,U}^{LoS} = \frac{1}{1 + A \exp(-B(\theta_{m,U} - A))}, \tag{4}$$

where $\theta_{m,U} = \frac{180}{\pi} \arcsin(\frac{h}{\sqrt{d_{m,U}^2 + h^2}})$ is the elevation angle between the UAV and GU-m. A and B are constants that depend on the type of environment. Furthermore, the probability of NLoS connection $Pr_{m,U}^{NLoS} = 1 - Pr_{m,U}^{LoS}$.

Similarly, the interfering channel from the nth D2D TX to the UAV is denoted as $g_{n,U}$, which is given by

$$g_{n,U} = Pr_{n,U}^{LoS} \cdot g_{n,U}^{LoS} + Pr_{n,U}^{NLoS} \cdot g_{n,U}^{NLoS}. \tag{5}$$

Both fast fading and slow fading are considered in the communication links between users. Thus, the channel gain between the nth D2D transmitter and its associated D2D receiver (D2D RX) can be written as

$$g_{n,n} = G \beta_{n,n} \gamma_{n,n} d_{n,n}^{-\alpha}, \tag{6}$$

where G is the path loss constant, α is the path loss exponent, $\beta_{n,n}$ is the fast fading gain with exponential distribution related to the nth D2D pair, $\gamma_{n,n}$ is the slow fading gain with log-normal distribution, and $d_{n,n}$ is the distance between the nth D2D pair. Similarly, the interfering channel from the mth GU to the nth D2D receiver is denoted as $g_{m,n}$, which can be modeled as

$$g_{m,n} = G \beta_{m,n} \gamma_{m,n} d_{m,n}^{-\alpha}. \tag{7}$$

The eavesdropping channel gain between the mth GU and Eve and the eavesdropping channel gain between the nth D2D TX and Eve are denoted as $g_{m,e}$ and $g_{n,e}$, respectively. They can be expressed similarly to (7), where both fast fading and slow fading are considered in the eavesdropping links. Therefore, the achievable data rate of the mth GU can be expressed as

$$R_m^c = \log_2 \left(1 + \frac{P_m^c g_{m,U}}{\sum_{n=1}^{N} c_{m,n} P_n^d g_{n,U} + N_0}\right), \tag{8}$$

where P_m^c and P_n^d denote the transmit power of the mth GU and that of the nth D2D transmitter, respectively. The variance of the additive white Gaussian noise at the receiver is denoted as N_0. Similarly, the achievable data rate of the nth D2D pair can be written as

$$R_n^d = \log_2 \left(1 + \frac{P_n^d g_{n,n}}{\sum_{m=1}^{M} c_{m,n} P_m^c g_{m,n} + N_0}\right). \tag{9}$$

Furthermore, the secrecy rate of the nth D2D link is given by [24]

$$R_{ns}^d = \log_2 \left(1 + \frac{P_n^d g_{n,n}}{\sum_{m=1}^{M} c_{m,n} P_m^c g_{m,n} + N_0}\right) - \log_2 \left(1 + \frac{P_n^d g_{n,e}}{\sum_{m=1}^{M} c_{m,n} P_m^c g_{m,e} + N_0}\right). \tag{10}$$

Similarly, the secrecy rate of the mth GU link can be expressed as

$$R_{ms}^c = \log_2\left(1 + \frac{P_m^c g_{m,U}}{\sum_{n=1}^N c_{m,n} P_n^d g_{n,U} + N_0}\right) - \log_2\left(1 + \frac{P_m^c g_{m,e}}{\sum_{n=1}^N c_{m,n} P_n^d g_{n,e} + N_0}\right). \quad (11)$$

B. Problem Formulation

We aim to maximize the TEE of all D2D pairs via power control and channel allocation while guaranteeing the minimum required data rates and secrecy rates of GUs and D2D users. TEE is defined as the ratio of the sum data rate of all D2D pairs to the total power consumed by them. In our problem, it is assumed that the transmit power and channel allocation of GUs are fixed and known. Thus, the TEE optimization problem can be formulated as follows:

$$\max_{\{P_n^d\},\{c_{m,n}\}} \quad TEE \triangleq \frac{\sum_{n=1}^N \sum_{m=1}^M c_{m,n} R_n^d}{\sum_{n=1}^N \sum_{m=1}^M c_{m,n} P_n^d + P_0} \quad (12a)$$

$$s.t. \quad R_n^d \geq R_n^{min}, \quad \forall n \in \mathcal{N} \quad (12b)$$

$$R_{ns}^d \geq R_n^s, \quad \forall n \in \mathcal{N} \quad (12c)$$

$$R_m^c \geq R_m^{min}, \quad \forall m \in \mathcal{M} \quad (12d)$$

$$R_{ms}^c \geq R_m^s, \quad \forall m \in \mathcal{M} \quad (12e)$$

$$0 \leq P_n^d \leq P_{max}^d, \quad \forall n \in \mathcal{N} \quad (12f)$$

$$c_{m,n} \in \{0,1\}, \quad \forall m \in \mathcal{M}, n \in \mathcal{N} \quad (12g)$$

$$\sum_{m=1}^M c_{m,n} \leq 1, \quad \forall n \in \mathcal{N} \quad (12h)$$

$$\sum_{n=1}^N c_{m,n} \leq 1, \quad \forall m \in \mathcal{M}, \quad (12i)$$

where P_0 denotes the circuit power that is consumed by the user's circuit blocks and is considered to be static. P_{max}^d is the maximum transmit power of the D2D transmitters. R_n^{min} and R_m^{min} are the minimum rate guaranteeing the QoS of D2D users and GUs, respectively. Furthermore, R_n^s is the minimum secrecy rate requirement of the nth D2D link and R_m^s is the minimum secrecy rate requirement of the mth GU link. Constraint (12f) ensures that the transmit power allocated to the D2D transmitter does not exceed the maximum transmit power. Constraints (12h) and (12i) respectively guarantee that a D2D pair reuse at most one GU's channel and the channel of a GU can be shared by at most one D2D pair.

The proposed optimization problem is a fractional programming problem with binary variables, which is a non-convex optimization problem and generally difficult to solve. In the following, we transform the original problem into an equivalent form and propose an alternating optimization based method.

Algorithm 1: Dinkelbach's Algorithm.

1: Initialization: loop index $i = 0$, $r_i = 0$, convergence threshold ϵ, maximum iterations i_{max}
2: **while** $|F(\mathbf{P}, \mathbf{c}, r_i)| \geq \epsilon$ or $i \leq i_{max}$ **do**
3: For the given r_i, solve problem (14) to obtain the optimal $\tilde{P}_n^d$ and $\tilde{c}_{m,n}$
4: Update $r_{i+1} = \frac{\sum_{n=1}^N \sum_{m=1}^M \tilde{c}_{m,n} \tilde{R}_n^d}{\sum_{n=1}^N \sum_{m=1}^M \tilde{c}_{m,n} \tilde{P}_n^d + P_0}$ with $\tilde{P}_n^d$ and $\tilde{c}_{m,n}$
5: Set $i = i + 1$
6: **end while**

III. Alternating Optimization Based Method

The difficulties to solve the TEE maximization problem (12) lie on two aspects: first, the objective function in (12) is of a fractional form, which makes the objective function nonlinear and non-convex; second, the optimization variables in (12) are coupled. Therefore, we first transform (12) into an equivalent subtractive form using Dinkelbach's algorithm [25], and then propose an alternating optimization based method to decouple the variables.

A. Dinkelbach's Algorithm

Dinkelbach's algorithm is widely used to solve fractional programming problems. In the following discussions, we use $\mathbf{P}$ and $\mathbf{c}$ to respectively denote the power optimization and channel allocation variables of the original problem (12), and use $\mathcal{A}$ to denote the feasible set that satisfies the constraints (12b)–(12i) for the sake of brevity.

The objective function in (12) is a concave-over-convex fractional function. Its corresponding subtractive form can be written as

$$f(\mathbf{P}, \mathbf{c}, r) \triangleq \sum_{n=1}^N \sum_{m=1}^M c_{m,n} R_n^d - r\left(\sum_{n=1}^N \sum_{m=1}^M c_{m,n} P_n^d + P_0\right), \quad (13)$$

where r is an additional variable introduced for Dinkelbach's algorithm. It is obvious that $f(\mathbf{P}, \mathbf{c}, r)$ is a linear, convex and monotonically decreasing function of variable r. Dinkelbach's algorithm performs a series of iterations by choosing an initial value r_0 for the variable r. In the ith iteration, we let $r = r_i$ and solve the following problem

$$\max_{\{\mathbf{P},\mathbf{c}\}} \quad f(\mathbf{P}, \mathbf{c}, r_i) \quad (14a)$$

$$\text{s.t.} \quad \text{Constraints} \quad (12b)-(12i). \quad (14b)$$

We denote the optimal solution of (14) as $\{\tilde{P}_n^d\}$ and $\{\tilde{c}_{m,n}\}$. In the next iteration, the value of r is updated as

$$r_{i+1} = \frac{\sum_{n=1}^N \sum_{m=1}^M \tilde{c}_{m,n} \tilde{R}_n^d}{\sum_{n=1}^N \sum_{m=1}^M \tilde{c}_{m,n} \tilde{P}_n^d + P_0}. \quad (15)$$

The details of Dinkelbach's algorithm is presented in Algorithm 1.

The maximum TEE of all D2D pairs r^* for problem (12) can be written as

$$r^* = \max_{\{\mathbf{P},\mathbf{c}\}\in\mathcal{A}} \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} c_{m,n} R_n^d}{\sum_{n=1}^{N}\sum_{m=1}^{M} c_{m,n} P_n^d + P_0}. \quad (16)$$

It has been proved in [25] that the optimal value r^* for TEE in (16) should satisfy $F(r^*) = 0$, and the variable r will converge to the optimal value r^* monotonically by iteratively updating the value of r_i in Algorithm 1.

Let $F(r)$ denote the optimal objective value of problem (14), which is presented in (17), as shown at the bottom of this page. In each iteration of Dinkelbach's algorithm, for the given value of r_i, problem (14) is still a MINLP, which is difficult to solve directly. Thus we propose an alternating optimization based method to solve problem (14) for the given value of r_i. The alternating optimization based method decomposes problem (14) into two sub-problems: power control and channel allocation. For each sub-problem, we proceed by assuming the channel allocation variables or the power control variables to be given and fixed.

B. Power Control Strategy

The power allocation strategy is designed by fixing the channel allocation variables $\bar{\mathbf{c}}$. Given a set of feasible $\{\bar{c}_{m,n}\}$ which satisfy constraints (12g), (12h) and (12i), then problem (14) with fixed channel allocation $\bar{\mathbf{c}}$ can be written as

$$\max_{\{P_n^d\}} \quad f(\mathbf{P}, \bar{\mathbf{c}}, r) \quad (18a)$$

$$\text{s.t.} \quad R_n^d \geq R_n^{min}, \quad \forall n \in \mathcal{N} \quad (18b)$$

$$R_{ns}^d \geq R_n^s, \quad \forall n \in \mathcal{N} \quad (18c)$$

$$R_m^c \geq R_m^{min}, \quad \forall m \in \mathcal{M} \quad (18d)$$

$$R_{ms}^c \geq R_m^s, \quad \forall m \in \mathcal{M} \quad (18e)$$

$$0 \leqslant P_n^d \leqslant P_{max}^d, \quad \forall n \in \mathcal{N}. \quad (18f)$$

It can be easily seen that, the objective function is concave since $\bar{c}_{m,n}$ is fixed. The constraint (18b) can be transformed into the convex form as follows

$$P_n^d g_{n,n} \geq \Gamma_0 \left(P_m^c g_{m,n} + N_0\right), \quad (19)$$

where $\Gamma_0 = 2^{R_n^{min}} - 1$.

Constraint (18d) can be reformulated as

$$(2^{R_m^{min}} - 1)(P_n^d g_{n,U} + N_0) \leq P_m^c g_{m,U}. \quad (20)$$

Note that R_{ns}^d in (10) is the form of the difference of concave functions (DC), and therefore the constraint (18c) is non-convex. Therefore, we can employ the DC algorithm to transform (18c) into a convex form. The DC algorithm replaces the subtrahend concave function in (10) with its first-order approximation as the surrogate function. Denote

$$R_{neve}^d(P_n^d) = \log_2\left(1 + \frac{P_n^d g_{n,e}}{P_m^c g_{m,e} + N_0}\right). \quad (21)$$

Then we have the following result.

Lemma 1: Given a feasible D2D transmit power $P_n^{d(l)}$, the first-order approximation of the transmission rate can be expressed as follows

$$\begin{aligned} R_{ns}^d(P_n^d) &\geq R_{ns}^d(P_n^d, P_n^{d(l)}) \\ &= R_n^d(P_n^d) - R_{neve}^d(P_n^{d(l)}) \\ &\quad - \nabla R_{neve}^d(P_n^{d(l)})\left(P_n^d - P_n^{d(l)}\right), \end{aligned} \quad (22)$$

where $\nabla R_{neve}^d(P_n^{d(l)})$ can be expressed as

$$\nabla R_{neve}^d(P_n^{d(l)}) = \frac{g_{n,e}}{\ln 2(g_{n,e}P_n^{d(l)} + P_m^c g_{m,e} + N_0)}. \quad (23)$$

Proof: Bacause $R_n^d(P_n^d)$ and $R_{neve}^d(P_n^d)$ are concave, based on the first-order condition of concave functions, there is $R_{neve}^d(P_n^d) \leq R_{neve}^d(P_n^{d(l)}) + \nabla R_{neve}^d(P_n^{d(l)})(P_n^d - P_n^{d(l)})$. Thus $R_{ns}^d(P_n^d) = R_n^d(P_n^d) - R_{neve}^d(P_n^d) \geq R_n^d(P_n^d) - R_{neve}^d(P_n^{d(l)}) - \nabla R_{neve}^d(P_n^{d(l)})(P_n^d - P_n^{d(l)}) = R_{ns}^d(P_n^d, P_n^{d(l)})$. Therefore, $R_{ns}^d(P_n^d, P_n^{d(l)})$ provides a tight low bound for $R_{ns}^d(P_n^d)$ at $P_n^d(l)$. □

The secrecy rate R_{ms}^c in (11) also has a DC form. Given a feasible D2D transmit power $P_n^{d(l)}$, the first-order approximation of the secrecy rate R_{ms}^c in (18e) can be expressed as

$$\begin{aligned} R_{ms}^c(P_n^d) &\geq R_{ms}^c(P_n^d, P_n^{d(l)}) \\ &= R_m^c(P_n^{d(l)}) + \nabla R_m^c(P_n^{d(l)})\left(P_n^d - P_n^{d(l)}\right) \\ &\quad - R_{meve}^c(P_n^d) \end{aligned} \quad (24)$$

where $\nabla R_m^c(P_n^{d(l)})$ is

$$\begin{aligned} F(r) &\triangleq \max_{\{\mathbf{P},\mathbf{c}\}\in\mathcal{A}} f(\mathbf{P}, \mathbf{c}, r) \\ &= \max_{\{\mathbf{P},\mathbf{c}\}\in\mathcal{A}} \sum_{n=1}^{N}\sum_{m=1}^{M} c_{m,n} R_n^d - r\left(\sum_{n=1}^{N}\sum_{m=1}^{M} c_{m,n} P_n^d + P_0\right) \\ &= \max_{\{\mathbf{P},\mathbf{c}\}\in\mathcal{A}} \sum_{n=1}^{N}\sum_{m=1}^{M} c_{m,n} \log_2\left(1 + \frac{P_n^d g_{n,n}}{\sum_{m=1}^{M} c_{m,n} P_m^c g_{m,n} + N_0}\right) - r\left(\sum_{n=1}^{N}\sum_{m=1}^{M} c_{m,n} P_n^d + P_0\right) \end{aligned} \quad (17)$$

$$\nabla R_m^c(P_n^{d(l)}) = -\frac{P_m^c g_{m,U} g_{n,U}}{\ln 2 (g_{n,U} P_n^{d(l)} + N_0)(g_{n,U} P_n^{d(l)} + N_0 + P_m^c g_{m,U})} \tag{25}$$

and $R_{meve}^c(P_n^d)$ is

$$R_{meve}^c(P_n^d) = \log_2 \left(1 + \frac{P_m^c g_{m,e}}{P_n^d g_{n,e} + N_0}\right). \tag{26}$$

Thus problem (18) can be reformulated as

$$\max_{\{P_n^d\}} \quad f(\mathbf{P}, \bar{\mathbf{c}}, r) \tag{27a}$$

$$\text{s.t.} \quad R_n^d \geq R_n^{min}, \quad \forall n \in \mathcal{N} \tag{27b}$$

$$R_{ns}^d(P_n^d, P_n^{d(l)}) \geq R_n^s, \quad \forall n \in \mathcal{N} \tag{27c}$$

$$(2^{R_m^{min}} - 1)(P_n^d g_{n,U} + N_0) \leq P_m^c g_{m,U}, \forall m \in \mathcal{M} \tag{27d}$$

$$R_{ms}^c(P_n^d, P_n^{d(l)}) \geq R_m^s, \quad \forall m \in \mathcal{M} \tag{27e}$$

$$0 \leqslant P_n^d \leqslant P_{max}^d, \quad \forall n \in \mathcal{N}. \tag{27f}$$

Now (27) becomes a convex optimization problem. Standard convex optimization software, such as CVX, can be adopted to obtain the optimal solution of (27) for the given channel allocation $\bar{\mathbf{c}}$.

C. Channel Allocation Strategy

When the optimal power is obtained, the optimal channel allocation with the given power can be achieved in the next iteration by solving the following problem.

$$\max_{\{c_{m,n}\}} \quad f(\bar{\mathbf{P}}, \mathbf{c}; r) \tag{28a}$$

$$\text{s.t.} \quad c_{m,n} \in \{0, 1\}, \quad \forall m \in \mathcal{M} \quad \forall n \in \mathcal{N} \tag{28b}$$

$$\sum_{m=1}^{M} c_{m,n} \leq 1, \quad \forall n \in \mathcal{N} \tag{28c}$$

$$\sum_{n=1}^{N} c_{m,n} \leq 1, \quad \forall m \in \mathcal{M}, \tag{28d}$$

where $\bar{\mathbf{P}}$ denotes the given power allocation. To deal with the binary variables, we first relax $c_{m,n}$ to continuous form between 0 and 1. Then problem (28) can be rewritten as

$$\max_{\{c_{m,n}\}} \quad f(\bar{\mathbf{P}}, \mathbf{c}; r) \tag{29a}$$

$$\text{s.t.} \quad 0 \leq c_{m,n} \leq 1, \quad \forall m \in \mathcal{M} \quad \forall n \in \mathcal{N} \tag{29b}$$

$$\sum_{m=1}^{M} c_{m,n} \leq 1, \quad \forall n \in \mathcal{N} \tag{29c}$$

$$\sum_{n=1}^{N} c_{m,n} \leq 1, \quad \forall m \in \mathcal{M}, \tag{29d}$$

Algorithm 2: Alternating Optimization Method to Solve (14) Using CVX.

Initialization: loop index $l = 0$, feasible power $\{P_n^{d(0)}\}$, convergence threshold ϵ.
while $|R_{ns}^d(P_n^{d(l+1)}) - R_{ns}^d(P_n^{d(l)})| \geq \epsilon$ **do**
  Set $j = 0$, initial feasible set $\{c_{m,n}^{(0)}\}$.
  while $|f(\mathbf{P}, \mathbf{c}; r)^{j+1} - f(\mathbf{P}, \mathbf{c}; r)^{j}| \geq \epsilon$ **do**
    Solve (27) for $\mathbf{c} = \mathbf{c}^{(j)}$ to generate $\mathbf{P}^{(j+1)}$ using CVX;
    Solve (29) for $\mathbf{P} = \mathbf{P}^{(j+1)}$ to determine channel allocation $\mathbf{c}^{(j+1)}$ using CVX and (30);
    $j = j + 1$;
  end while
  Update $\mathbf{P}_n^{d(l)} = \mathbf{P}^{(j+1)}$;
  $l = l + 1$;
end while
Return the solution $\mathbf{P}_n^{d*}$ and $\mathbf{c}^*$.

which is a convex optimization problem and can be solved by standard convex optimization software, such as CVX. Then the optimal channel allocation strategy with given power allocation $\bar{\mathbf{P}}$ can be obtained as

$$c_{m,n}^* = \begin{cases} 1, & \text{if } c_{m,n} = \arg\max_{c_{m,n}} f(\bar{\mathbf{P}}, \mathbf{c}; r) \\ 0, & \text{otherwise.} \end{cases} \tag{30}$$

Now we have transformed the power allocation and channel allocation sub-problems into convex optimization problems. Alternating optimization method solves the original problem (14) by alternately solving the power allocation and channel allocation sub-problems. The details of the alternating optimization method to solve problem (14) using CVX is summarized in Algorithm 2.

IV. Dual-Based Algorithm

In each iteration of Dinkelbach's algorithm, for the given r_i, Using Algorithm 2 to solve problem (14) with CVX has a high complexity. In this section, we propose a dual-based algorithm to solve (14) by resorting to Lagrange dual and Kuhn–Munkres method.

A. Power Control Strategy

For the power control sub-problem, we assume the channel allocation variables $\{c_{m,n}\}$ have been given. That is, we assume that the nth D2D link reuses the channel of the mth GU, i.e., $c_{m,n} = 1$, and we study the optimal power allocation for each possible D2D user and GU reuse pair. Then for the nth D2D pair, the power control subproblem can be described as follows:

$$\max_{\{P_n^d\}} \quad s_{m,n}(P_n^d) \triangleq R_n^d(P_n^d) - r\left(P_n^d + P_0\right) \tag{31a}$$

$$\text{s.t.} \quad R_n^d \geq R_n^{min}, \tag{31b}$$

$$R_{ns}^d \geq R_n^s, \tag{31c}$$

$$R_m^c \geq R_m^{min}, \tag{31d}$$

$$R_{ms}^c \geq R_m^s, \tag{31e}$$

$$0 \leqslant P_n^d \leqslant P_{max}^d. \tag{31f}$$

Using Lemma 1, the problem (31) can be transformed into the following problem

$$\max_{\{P_n^d\}} \quad s_{m,n}(P_n^d) \tag{32a}$$
$$\text{s.t.} \quad \frac{P_n^d g_{n,n}}{P_m^c g_{m,n} + N_0} \geq \Gamma_0, \tag{32b}$$
$$R_{ns}^d(P_n^d, P_n^{d(l)}) \geq R_n^s, \tag{32c}$$
$$(2^{R_m^{min}} - 1)(P_n^d g_{n,U} + N_0) \leq P_m^c g_{m,U}, \tag{32d}$$
$$R_{ms}^c(P_n^d, P_n^{d(l)}) \geq R_m^s, \tag{32e}$$
$$0 \leqslant P_n^d \leqslant P_{max}^d. \tag{32f}$$

Now that problem (32) is a convex optimization problem and satisfies Slater's conditions [26], the optimal solution can be obtained by solving the dual problem with zero duality gap.

The Lagrange function of (32) is

$$\begin{aligned}
&\mathcal{L}(P_n^d, \alpha, \beta, \gamma, \zeta, \mu, \nu) \\
&= r\left(P_n^d + P_0\right) - \log_2\left(1 + \frac{P_n^d g_{n,n}}{P_m^c g_{m,n} + N_0}\right) \\
&\quad + \alpha\left(\Gamma_0 - \frac{P_n^d g_{n,n}}{P_m^c g_{m,n} + N_0}\right) - \beta P_n^d \\
&\quad + \gamma(P_n^d - P_{max}^d) + \zeta\left(R_n^s - R_{ns}^d(P_n^d, P_n^{d(l)})\right) \\
&\quad + \mu\left[(2^{R_m^{min}} - 1)(P_n^d g_{n,U} + N_0) - P_m^c g_{m,U}\right] \\
&\quad + \nu\left(R_m^s - R_{ms}^c(P_n^d, P_n^{d(l)})\right),
\end{aligned} \tag{33}$$

where α, β, γ, ζ, μ and ν are the corresponding Lagrangian multipliers of constraints. Furthermore, $\alpha \geq 0$, $\beta \geq 0$, $\gamma \geq 0$, $\zeta \geq 0$, $\mu \geq 0$ and $\nu \geq 0$. Thus the Lagrange dual function is written as

$$\Theta_P(\alpha, \beta, \gamma, \zeta, \mu, \nu) = \min_{P_n^d} \mathcal{L}\left(P_n^d, \alpha, \beta, \gamma, \zeta, \mu, \nu\right). \tag{34}$$

Furthermore, the Lagrange dual problem is given by

$$\max_{\alpha,\beta,\gamma,\zeta,\mu,\nu} \quad \Theta_P(\alpha, \beta, \gamma, \zeta, \mu, \nu) \tag{35a}$$
$$\text{s.t.} \quad \alpha \geq 0, \beta \geq 0, \gamma \geq 0, \zeta \geq 0, \mu \geq 0, \nu \geq 0. \tag{35b}$$

We use Karush-Kuhn-Tucker (KKT) conditions [26] to find the problem's optimal solution. Let us denote $P_n^{d^*}$ as the optimal power of problem (32), which satisfies the following condition:

$$\left.\frac{\partial \mathcal{L}(P_n^d, \alpha, \beta, \gamma, \zeta, \mu, \nu)}{\partial P_n^d}\right|_{P_n^d = P_n^{d^*}} = 0, \tag{36}$$

where we have

$$\begin{aligned}
&\frac{\partial \mathcal{L}(P_n^d, \alpha, \beta, \gamma, \zeta, \mu, \nu)}{\partial P_n^d} \\
&= r - \alpha \frac{g_{n,n}}{P_m^c g_{m,n} + N_0} - \beta + \gamma \\
&\quad - (1 + \zeta)\frac{g_{n,n}}{\ln 2\left(P_m^c g_{m,n} + N_0 + g_{n,n} P_n^d\right)} \\
&\quad + \zeta \nabla R_{neve}^d(P_n^{d(l)}) + \mu(2^{R_m^{min}} - 1) g_{n,U} \\
&\quad - \nu \frac{P_m^c g_{m,e} g_{n,e}}{\ln 2(g_{n,e} P_n^d + N_0)(g_{n,e} P_n^d + N_0 + P_m^c g_{m,e})} \\
&\quad - \nu \nabla R_m^c(P_n^{d(l)}) = 0.
\end{aligned} \tag{37}$$

Let us denote

$$\begin{aligned}
\Phi &= r - \alpha \frac{g_{n,n}}{P_m^c g_{m,n} + N_0} - \beta + \gamma \\
&\quad + \zeta \nabla R_{neve}^d\left(P_n^{d(l)}\right) + \mu\left(2^{R_m^{min}} - 1\right) g_{n,U} \\
&\quad - \nu \nabla R_m^c\left(P_n^{d(l)}\right).
\end{aligned} \tag{38}$$

Equation (37) is a cubic equation, which can be rewritten as

$$A P_n^{d^3} + B P_n^{d^2} + C P_n^d + D = 0, \tag{39}$$

where

$$A = -g_{n,n} g_{n,e}^2 \, \Phi \ln 2, \tag{40}$$

$$\begin{aligned}
B = &- g_{n,e}\left[\Phi \ln 2\left(g_{n,e} P_m^c g_{m,n} + (g_{n,e} + 2g_{n,n}) N_0\right.\right. \\
&\left.\left. + P_m^c g_{m,e} g_{n,n}\right) - g_{n,n} g_{n,e}\left(1 + \zeta\right)\right],
\end{aligned} \tag{41}$$

$$\begin{aligned}
C = &-\left[(2g_{n,e} N_0 + P_m^c g_{m,e} g_{n,e}) P_m^c g_{m,n}\right. \\
&\left. + (2g_{n,e} + g_{n,n}) N_0^2 + P_m^c g_{m,e} N_0 (g_{n,e} + g_{n,n})\right] \Phi \ln 2 \\
&+ \nu P_m^c g_{m,e} g_{n,n} g_{n,e} + g_{n,n} g_{n,e} (2N_0 + P_m^c g_{m,e})\left(1 + \zeta\right),
\end{aligned} \tag{42}$$

$$\begin{aligned}
D = &\, g_{n,n} N_0 \left(1 + \zeta\right)\left(N_0 + P_m^c g_{m,e}\right) \\
&+ \nu g_{n,e} P_m^c g_{m,e}(N_0 + P_m^c g_{m,n}) \\
&- \Phi \ln 2 N_0 (N_0 + P_m^c g_{m,e})(N_0 + P_m^c g_{m,n}).
\end{aligned} \tag{43}$$

Let

$$p = \frac{C}{3A} - \frac{B^2}{9A^2},$$
$$q = \frac{D}{2A} + \frac{B^3}{27A^3} - \frac{BC}{6A^2},$$
$$\Delta = q^2 + p^3.$$

If $\Delta > 0$, there is one real root, i.e.,

$$x_{11} = \left(-q + \sqrt{\Delta}\right)^{\frac{1}{3}} + \left(-q - \sqrt{\Delta}\right)^{\frac{1}{3}}. \tag{44}$$

If $\Delta = 0$, there are two real roots, i.e.,

$$x_{21} = -2q^{\frac{1}{3}}, \tag{45}$$
$$x_{22} = q^{\frac{1}{3}}. \tag{46}$$

If $\Delta < 0$, there are three real roots, i.e.,

$$x_{31} = 2\sqrt{-p}\cos\phi, \tag{47}$$

$$x_{32} = 2\sqrt{-p}\cos\left(\phi + \frac{2}{3}\pi\right), \tag{48}$$

$$x_{33} = 2\sqrt{-p}\cos\left(\phi + \frac{4}{3}\pi\right), \tag{49}$$

where $\phi = \frac{1}{3}\arccos\frac{-q\sqrt{-p}}{p^2}$. Therefore, for a given set of Lagrange multipliers, the optimal power $P_n^{d^*}$ can be obtained with the candidate power values by solving problem (39) in the three cases mentioned above.

After $P_n^{d^*}$ is obtained, the dual variables of (35) can be updated according to the subgradients with the following formulas:

$$\alpha^{k+1} = \left[\alpha^k - \delta\left(\Gamma_0 - \frac{P_n^d g_{n,n}}{P_m^c g_{m,n} + N_0}\right)\right]^+, \tag{50}$$

$$\beta^{k+1} = \left[\beta^k + \xi P_n^d\right]^+, \tag{51}$$

$$\gamma^{k+1} = \left[\gamma^k - \theta\left(P_n^d - P_{max}^d\right)\right]^+, \tag{52}$$

$$\zeta^{k+1} = \left[\zeta^k - \kappa\left(R_n^s - R_{ns}^d(P_n^d, P_n^{d(l)})\right)\right]^+, \tag{53}$$

$$\mu^{k+1} = \left[\mu^k - \tau\left((2^{R_m^{min}} - 1)(P_n^d g_{n,U} + N_0) - P_m^c g_{m,U}\right)\right]^+, \tag{54}$$

$$\nu^{k+1} = \left[\nu^k - \sigma\left(R_m^s - R_{ms}^c(P_n^d, P_n^{d(l)})\right)\right]^+, \tag{55}$$

where $[x]^+ = \max\{0, x\}$. The parameters $\delta, \xi, \theta, \kappa, \tau$ and σ are the corresponding step-sizes in each iteration of the updates.

B. Channel Allocation Strategy

After the power control strategy is obtained as described in Section IV-A, the remaining task is to find the optimal channel allocation to maximize the TEE of D2D pairs. The channel allocation subproblem can be shown as follows:

$$\max_{\{c_{m,n}\}} \quad \sum_{n=1}^{N}\sum_{m=1}^{M} c_{m,n} s_{m,n}(P_n^{d^*}) \tag{56a}$$

$$\text{s.t.} \quad c_{m,n} \in \{0,1\}, \quad \forall m \in \mathcal{M} \quad \forall n \in \mathcal{N} \tag{56b}$$

$$\sum_{m=1}^{M} c_{m,n} \le 1, \quad \forall n \in \mathcal{N} \tag{56c}$$

$$\sum_{n=1}^{N} c_{m,n} \le 1, \quad \forall m \in \mathcal{M}. \tag{56d}$$

The channel allocation subproblem (56) is a binary linear sum assignment problem. Therefore, we propose to use Kuhn–Munkres algorithm [27] to solve it. The basic idea of Kuhn–Munkres algorithm for solving the assignment problem is to continuously modify the benefit matrix until there is at least one zero element in different rows and different columns of the matrix, and these zero elements correspond to the best allocation strategy. Kuhn–Munkres algorithm has low complexity and can converge to the best allocation in a limited number of iterations. The detailed steps of the Kuhn–Munkres algorithm to solve the assignment problem can be found in [28]. For the sake of brevity, we do not provide further details here.

Algorithm 3: Dual-Based Algorithm to Solve (14).

```
Initialization: loop index l = 0, feasible power {P_n^{d(0)}}, convergence threshold ε.
while |R_ns^d(P_n^{d(l+1)}) − R_ns^d(P_n^{d(l)})| ≥ ε do
  Set loop index k = 0, given maximum iterations k_max, initial dual variables α, β, γ, ζ, μ, ν.
  repeat
    Obtain the optimal power {P_n^{d'}} for given {P_n^{d(l)}} by solving (39) according to (44)–(49);
    Update the dual variables using (50)–(55);
    k = k + 1;
  until The dual variables converge or k ≥ k_max
  Update {P_n^{d(l)}} = {P_n^{d'}};
  l = l + 1;
end while
Return the optimal power {P_n^{d*}} = {P_n^{d(l)}}
Determine channel allocation strategy c* by solving problem (56) using Kuhn–Munkres algorithm.
Return the solution P_n^{d*} and c*.
```

By combining the power control strategy and the channel allocation strategy, the dual-based algorithm for solving problem (14) is summarized in Algorithm 3.

C. Summary of Dual-Based Algorithm

The proposed dual-based algorithm framework for solving energy efficiency resource allocation problem consists of Dinkelbach's algorithm, the DC algorithm, Lagrangian dual theory, and Kuhn–Munkres algorithm. Firstly, Dinkelbach's algorithm is used to transform the original fractional programming problem into an equivalent subtractive form. In the innner loop of Dinkelbach's algorithm, the equivalent problem is divided into two subproblems: power control subproblem and channel allocation subproblem. We use the DC algorithm to transform the power control subproblem into a convex optimization problem. Then Lagrangian dual is applied to solve the converted problem, which provides a closed-form solution and reduces the computational load. Moreover, the channel allocation subproblem is a classical bipartite graph matching problem, which is solved by Kuhn–Munkres algorithm. Fig. 2 shows the overall procedure of our algorithm.

We guarantee the convergence of our proposed dual-based algorithm. As mentioned in [29], Dinkelbach's algorithm ensure to converge with a super-linear rate. Furthermore, our power control subproblem has a closed-form solution, which can converge efficiently in the inner loop.

D. Computational Complexity Analysis

With the proposed solutions to the two sub-problems, the overall algorithm for solving the original problem is depicted

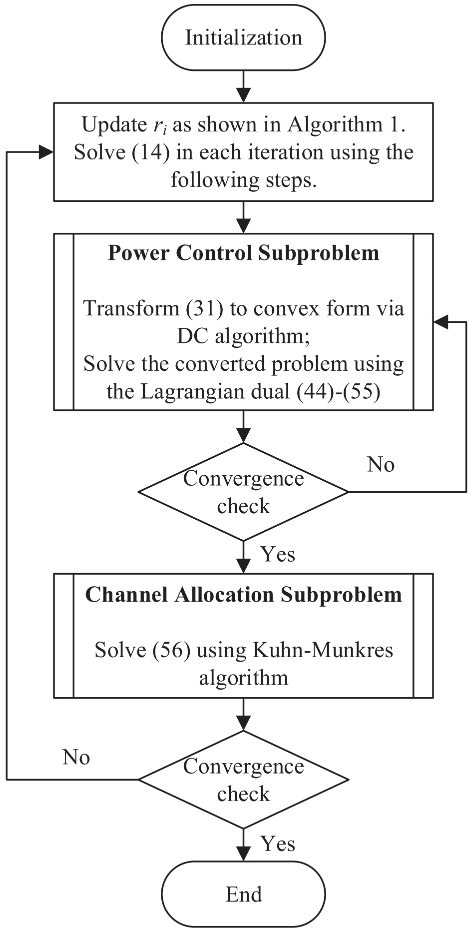

Fig. 2. Flowchart of the proposed dual-based algorithm.

in Fig. 2. The complexity of the proposed algorithm mainly concentrates on the DC-based algorithm and Kuhn-Munkres algorithm. The power control subproblem is solved by CVX which is based on the standard interior-point method, which computational complexity scale as $O((N+KN)^{3.5}\log(1/\varepsilon_c))$ and the Kuhn–Munkres algorithm complexity is $O(N^3\log(1/\varepsilon_c))$. Therefore, the complexity of the proposed overall algorithm is $O(((N+KN)^{3.5}+N^3)\log(1/\varepsilon_c))$, where ε_c denotes the accuracy of convergence.

For the dual-based algorithm, we obtain the closed-form power allocation according to (44)–(49) and update the six dual variables using (50)–(55) with maximum k_{max} iterations. Therefore, the computational complexity is $O(6Nk_{max})$. Together with the Kuhn–Munkres algorithm, the total complexity is $O(6Nk_{max}+N^3\log(1/\varepsilon_c))$.

V. Simulation Results

To verify the proposed resource allocation schemes for TEE maximization, we perform numerical simulations. In our simulation, we consider a UAV in a single-cell scenario, where $M=16$ GUs randomly distributed in the cell and the maximum D2D pair distance is denoted as r. The eavesdropper is deployed in a semi-remote location. The rest of system parameters are shown in Table I. The simulation results are performed in a MATLAB

TABLE I
Simulation Parameters

System Parameter	Value
UAV altitude h	100 m
Cell radius R	500 m
Maximum D2D pair distance r	25 m
Noise power N_0	-120 dBm
Maximum D2D user transmit power P^d_{max}	23 dBm
Circuit power P_0	0.5 W
Minimum QoS requirement R_n^{min}, R_m^{min}	8 b/s/Hz
Secrecy rate threshold R_n^s, R_m^s	3 b/s/Hz
Pathloss exponent for the ATG link α_u	3
Parameters for urban environment A, B	$10.98, 0.05$
Pathloss constant for D2D link G	10^{-2}
Pathloss exponent for D2D link α	3
Parameters of Dinkelbach's Algorithm	**Value**
Maximum iterations i_{max}	100
Convergence threshold ϵ	10^{-4}
Lagrange Dual's Parameter	**Value**
Maximum iterations k_{max}	300
Update step-sizes δ, ξ, θ, κ, τ and σ	10^{-6}

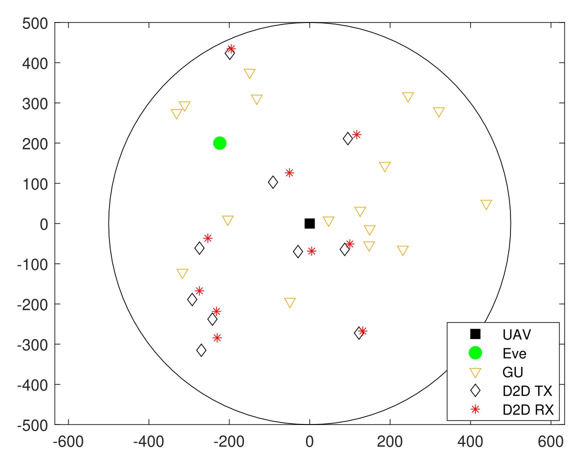

Fig. 3. The user location scenario.

environment and done by averaging over 1000 random realizations of users' locations and channels. Fig. 3 shows the location of the UAV, Eve, GUs and D2D users in one random problem realization of the system.

In Fig. 4, we show the Dinkelbach iterations of the proposed iterative algorithm with different number of D2D pairs. It is observed that the proposed iterative algorithm can converge very fast within a few iterations. Furthermore, the number of iterations increases with the increase of D2D pairs, which shows that the complexity of the algorithm depends on the number of users. However, the growth rate is very slow and close to linear, which is efficient and appropriate to scenario with large scale users.

To demonstrate the performance of our proposed algorithm, we also consider the following benchmark schemes:

- Partical Swarm Optimization (PSO): We model the TEE maximization problem as a particle swarm. Each particle in the particle swarm represents a possible solution of

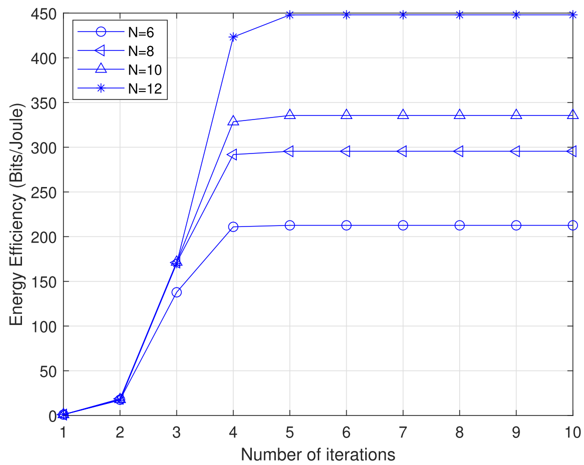

Fig. 4. The convergence performance of the proposed algorithm.

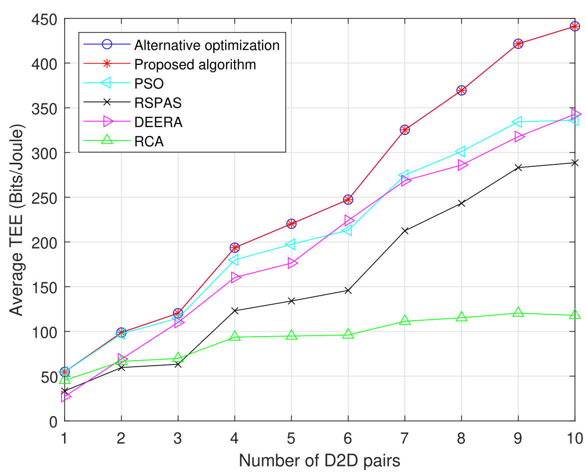

Fig. 5. Average TEE versus number of D2D pairs N.

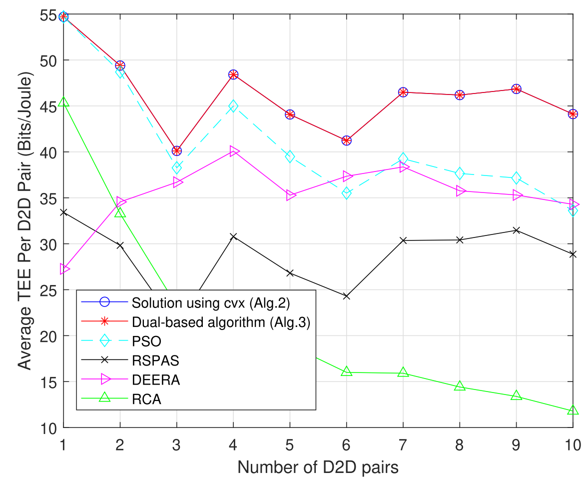

Fig. 6. Average TEE per D2D pair versus number of D2D pairs N.

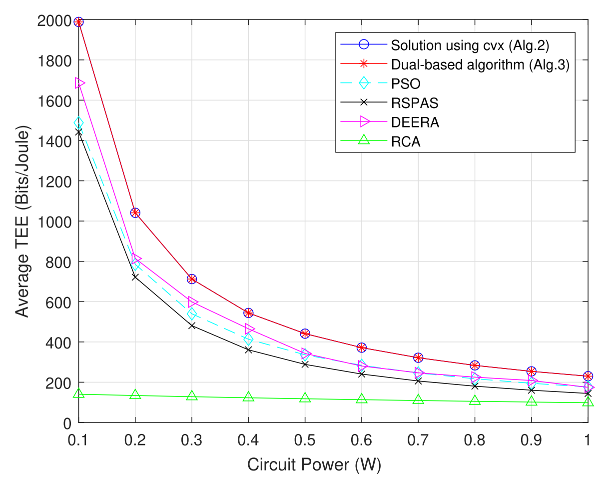

Fig. 7. Average TEE versus circuit power P_0 for 10 D2D pairs.

the problem. Based on the fitness function, each particle updates its speed and location to obtain the optimal transmit power and channel allocation.

- Robust Spectrum and Power Allocation Scheme (RSPAS) [30]: Joint spectrum and power allocation for a D2D-enabled cellular network is investigated. The goal is to maximize the sum ergodic capacity of all cellular links. However, the eavesdropper is not considered.
- Distributed Energy-Efficient Resource Allocation (DEERA): We modify the distributed energy-efficient resource allocation scheme proposed in [8] to take into account the QoS and secrecy constraints. In this method, the D2D pairs employ a distributed approach to maximize their energy efficiency while satisfying the constraints in (12).
- Random Channel Allocation (RCA): The transmit power of D2D users are distributed as maximum transmit power, and the channels are randomly allocated.

In Fig. 5, the performance of our proposed algorithm in terms of the TEE for different number of D2D pairs is illustrated. It can be observed that the energy efficiency increases with the number of D2D users. It is obvious that if the number of D2D pairs is larger, then the TEE of all D2D pairs will be larger. By comparing the results obtained from our proposed dual-based algorithm with other schemes, we can see that our proposed dual-based algorithm offers better performance. Moreover, we observe that the proposed dual-based algorithm can converge to the same optimal value as the solution using CVX. The performance of PSO is worse than our proposed iterative algorithm because the result of PSO depends on the initial parameter setting and is easy to fall into local extrema. The proposed algorithm can also achieve higher energy efficiency than RSPAS and DEERA. This is because RSPAS cannot effectively maximize the TEE and DEERA employs a distributed but selfish approach. Furthermore, the performance of RCA is the worst because of the randomness of power and channel selection.

Fig. 6 shows the average TEE per D2D pair with the number of D2D pairs. The proposed methods achieve on average TEE of 40 to 55 bits/Joule per D2D pair. The other baseline methods have lower average TEE per D2D pair. For the RCA method, its average TEE per D2D pair decreases with the number of D2D pairs.

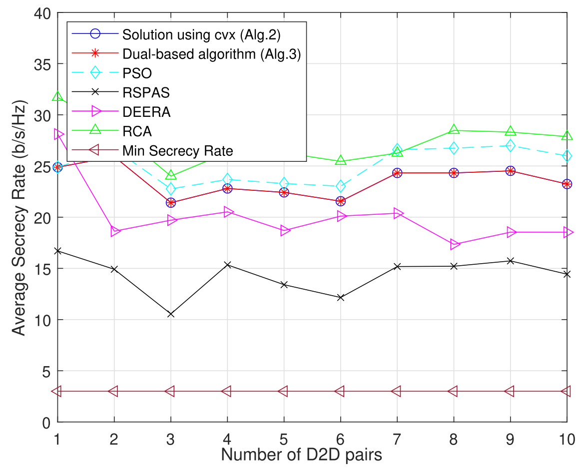

Fig. 8. Secrecy rate versus versus number of D2D pairs N.

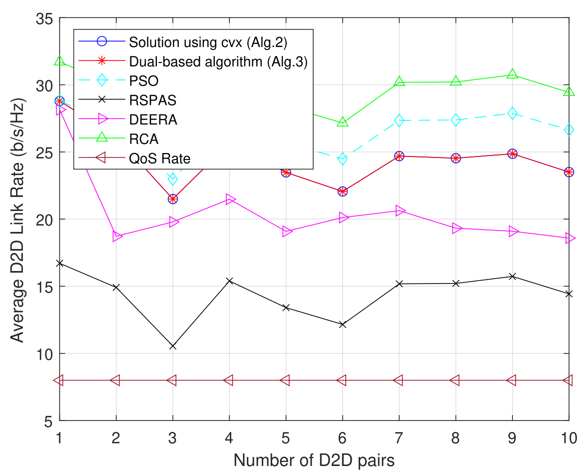

Fig. 9. D2D link communication rate versus number of D2D pairs N.

In Fig. 7, the performance of our proposed algorithm in terms of the average TEE of 10 D2D pairs for different circuit power is illustrated. It is obvious that the TEE decreases as the circuit power P_0 increases. For example, if the circuit power changes from 0.1 Watt to 0.2 Watt, the average TEE nearly halves. However, as the circuit power becomes very large, e.g., around 1 Watt, the average TEE of all schemes achieve nearly the same value. Moreover, it can be observed that our proposed methods achieve higher TEE compared with other baseline algorithms.

Fig. 8 shows the average secrecy rates of all the considered methods together with the secrecy rate threshold R_n^s and R_m^s. In our simulations, the secrecy rate constraints are satisfied by all the considered methods. Moreover, the RCA and PSO-based algorithms achieve higher secrecy rates, but at the price of lower TEE.

Fig. 9 shows the average D2D link communication rates of all the considered methods together with the minimum QoS requirements R_n^{min} and R_m^{min}. That shows the QoS constraints are satisfied by all the considered methods in our simulations.

TABLE II
TIME CONSUMPTION UNDER DIFFERENT NUMBER OF GROUND USERS AND D2D USERS

GUs	D2D users	Dual-based algorithm	Direct solution using CVX
$M = 6$	$N = 4$	1.085 s	216.406 s
$M = 8$	$N = 6$	1.111 s	550.131 s
$M = 12$	$N = 8$	1.115 s	805.166 s
$M = 16$	$N = 12$	1.215 s	1757.078 s
$M = 20$	$N = 20$	1.316 s	3780.560 s

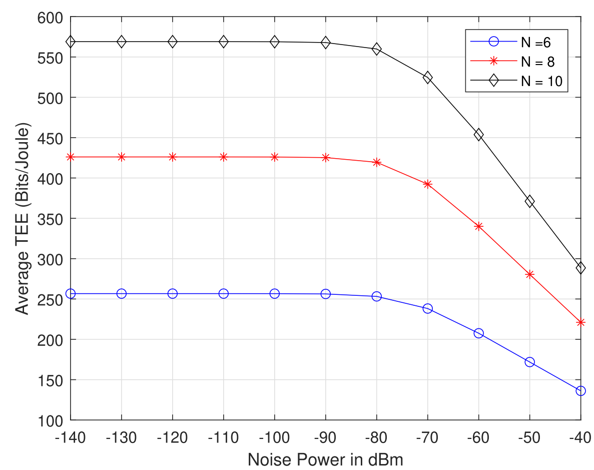

Fig. 10. Total energy efficiency versus different noise power.

In addition, in order to show the effectiveness of our proposed algorithm, we compare the required simulation time of the dual-based algorithm and that of direct solution using CVX in Table II. It is obvious that the complexity of our proposed dual-based algorithm is much lower than that of the solution using CVX. The increasing rate of time consumption using CVX is very fast with the increase of the number of users. This benefits from the fact that we derived the closed-form expressions, which reduces the computational complexity immensely.

Fig. 10 evaluates the total energy efficiency versus the noise power for our proposed dual-based algorithm. It can be observed from the figure that, the energy efficiency of all D2D users decreases with the increase of noise. This is because the higher noise power offers worse signal-to-interference-plus-noise ratio (SINR) between the UAV and D2D users, thus resulting in smaller energy efficiency. We can also see from the figure that the decrease in rate increases with the increase of noise. Within a certain noise range, the rate of decline is very slow and basically unchanged. After a certain noise is exceeded, noise becomes the dominant part of SINR. Therefore, there exist a tradeoff for the signal and noise.

VI. CONCLUSION

In this paper, we proposed an iterative scheme for energy-efficient resource allocation in D2D communications underlaying UAV-enabled networks. We considered maximizing the

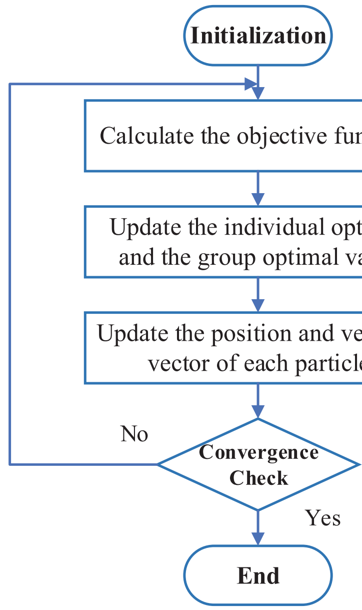

Fig. 11. Flowchart of the PSO algorithm.

total energy efficiency of all D2D pairs while guaranteeing the QoS requirements and secrecy rate of all GUs and D2D users. The proposed optimization problem is a MINLP problem. In the outer loop, Dinkelbach's algorithm is used to transform the original problem into a subtractive form. In the inner loop, Lagrangian dual and Kuhn–Munkres algorithm are employed to solve the power control sub-problem and channel allocation sub-problem, respectively. The simulation results have indicated that the proposed algorithm can converge within a few number of iterations to the optimal value. Via numerical simulations, we have also shown that the performance of the proposed scheme far exceeds other benchmark methods. For future work, we may consider a more complicated model that takes mode selection and multiple cells into consideration.

Appendix A
PSO Algorithm

In the PSO algorithm, the solution of the optimization problem is considered as a particle in the search space. All particles have a fitness value determined by a fitness function, and each particle has a velocity that determines the direction and distance they travel. The velocity and position updates depend on

$$Vid = \omega V_{id} + C_1 M_1 \left(P_{id} - X_{id}\right) + C_2 M_2 \left(P_{gd} - X_{id}\right), \quad (57)$$

$$X_{id} = X_{id} + V_{id}, \quad (58)$$

where ω, C_1, C_2 are constant which represent the inertia and the acceleration factor. When the value of ω is larger, the ability of group optimization is bigger. M_1, M_2 are random constant between [0,1]. P_{id} is individual optimal value, and P_{gd} is group optimal value.

In our problem, we set the particles as the variables to be optimized, which are the transmission power P_n^d and the channel allocation $c_{m,n}$. The fitness function is set as our objective function. Each particle updates its speed and location to obtain the optimal transmit power and channel allocation. The detailed process of PSO is shown in Fig. 11.

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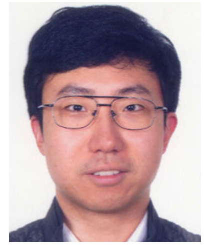

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