Energy-efficient D2D Communications with Dynamic Time-resource Allocation

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***Abstract*—In this paper, we investigate resource allocation schemes for Device-to-Device (D2D) communications, which aim to minimize the energy consumption of cellular users (CUs) and D2D pairs. Different from existing works where the resource allocation is performed in the premise that the sizes of orthogonal channels/resource blocks are given, we consider the case that the time resource can be dynamically adjusted according to the rate requirements of CUs and D2D pairs during the resource allocation. We first formulate the resource allocation as a mixed integer non-linear programming (MINLP). We then demonstrate that, given the selections of CUs for D2D pairs, the formulated energy minimization problem is conditionally convex, and the convexity condition is derived accordingly. If the convexity condition is not satisfied, we propose an iterative algorithm to minimize the energy consumption. Based on these results, we further develop a random-switch-based iterative (RSBI) algorithm to find the solution to the MINLP by improving the CU-selection for D2D pairs. Simulation results show that, compared with the equipotent and proportional-fair time allocation schemes, our approach can achieve an energy saving ratio of 17%-81% under various network settings.**

***Index Terms*—Energy efficiency, Device-to-Device (D2D) communications, Dynamic time resource allocation.**

I. INTRODUCTION

The popularity of mobile applications allows people to enjoy ubiquitous infotainment services, such as video streaming, mobile health, and online social networking. More and more applications require mobile devices to frequently exchange data with base stations (BSs), which will quickly drain the battery of mobile devices. In view of this, how to facilitate energy-efficient communications in cellular networks has been extensively studied (i.e., [1]–[5]). Unfortunately, these works are not applicable to the current/future cellular networks due to the introduction of device-to-device (D2D) communications. Generally speaking, D2D communications allow devices to communicate directly without going through BSs and are introduced to improve the capacity of cellular networks [6]–[10]. With the introduction of D2D communications, the management of cellular networks gets more complicated due to the interaction between cellular users and D2D pairs and how to achieve energy-efficient communications in cellular networks becomes more challenging because D2D communications also share the cellular spectrum.

In the current literature, the resource allocation for energy-efficient design of D2D communications is usually performed in the premise that the sizes of orthogonal channels/resource blocks are given [11]–[21]. Sheng et al. [11] investigated the energy efficiency and delay tradeoff for D2D communications. In [12], [13], the energy-efficient D2D communications with mode selection were discussed. In [14], [15], the non-cooperative game was adopted to solve the resource allocation problem that maximizes the energy efficiency of D2D networks. Hoang et al. [16] discussed how to maximize the minimum weighted energy efficiency of D2D links while guaranteeing minimum data rates for cellular links. Yin et al. [17] attempted to maximize the energy efficiency of D2D pairs in both non-cooperative and cooperative modes. In [18], [19], Jiang and Wang et al. investigated the joint resource allocation and power control for energy-efficient D2D networks by a problem-transforming method and an iterative combinatorial auction algorithm, respectively. In [20], Yang et al. discussed the energy-efficient resource allocation problem for D2D communications overlaying long-term evolution (LTE) networks with non-orthogonal and orthogonal strategies. In [21], Zhou et al. studied the deployment of D2D communications in the cloud radio access network (C-RAN) based LTE-advanced systems. Although these proposed works can significantly reduce the energy consumption of mobile devices, they have overlooked the fact that if the sizes of orthogonal channels/resource blocks can be dynamically adjusted according to the rate requirements of the occupying transmissions during the resource allocation, the system energy consumption can be further reduced.

Recently, Penda et al. [22] have discussed the energy-efficient mode selection for the communication pairs in cellular networks. They considered the dynamic time-resource allocation for the uplink and downlink transmissions when cellular mode is adopted. However, they adopted the overlay manner for the communication pairs with D2D mode, and did not consider the dynamic adjustment of time resource among different communication pairs.

To further reduce the energy consumption of the mobile devices, in this paper, we investigate the resource allocation problem for D2D communications underlaying cellular net-

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works in the case that the time resource can be adjusted according to the rate requirements of CUs and D2D pairs during the resource allocation. Obviously, by doing this, the time resource can be used more efficiently. However, the theoretical analysis becomes more complicated. In particular, we need to jointly consider the time resource adjustment, the transmit power control of D2D transmissions, and the CU-D2D pairing. The main contributions of this paper are summarized as follows:

1) We propose that the system energy consumption can be further reduced by dynamically allocating the time resource according to the rate requirements of different links. We formulate the energy consumption minimization problem of the considered network as a mixed integer non-linear programming (MINLP).
2) We prove that, when the selections of CUs for D2D pairs are given, the energy consumption minimization problem is conditionally convex, and derive the convexity condition accordingly. This condition implies that if the channel fading is neglected, the energy minimization problem is convex when each D2D pair shares the uplink resources of a CU located closer to the BS than the transmitter of the corresponding D2D pair, which is usually satisfied in practice since to protect CUs' transmission, it is often necessary to pair CUs with D2D pairs staying farther from the BS. To cover the situation where the convexity condition is not satisfied, we propose an iterative algorithm to solve the energy minimization problem effectively.
3) Based on the solution above, we propose a random-switch-based iterative (RSBI) algorithm to further improve the CU selections for D2D pairs. Our performance evaluation results show that, compared with the equipotent and proportional-fair time allocation schemes, the proposed iterative algorithm can achieve an energy saving ratio of 17%-81% under various network settings. Furthermore, the proposed RSBI algorithm achieves the close optimal solution obtained from the exhaustive search method, and can save 10%-83% of the energy compared with several other CU-selection schemes.

The rest of this paper is organized as follows. Section II presents the network and power model. In Section III, we formulate the energy minimization problem with dynamic time resource allocation. In Section IV, we discuss how to solve the formulated problem. In Section V, we carry out simulations to evaluate the performance of the proposed algorithms. Section VI concludes this paper.

II. System Description

A. Network Model

We consider a cellular network with a BS, a set of CUs and D2D pairs, where the D2D pairs share the uplink resource of CUs, as shown in Fig. 1. The role of the mobile devices has been defined when they join in the network and each device can only have one role, either a CU or a D2D node. Considering that the transmit power of the mobile devices is limited and the receiving sensitivity of the mobile devices is much lower than the BS, two mobile devices can be defined as one D2D pair only when they have data transmission requirement and are close to each other. Furthermore, the devices that communicate with the devices in another cell through the BS must be defined as CUs. Thus, the number of D2D pairs and CUs in the network is indeed determined by the communication requirements and locations of the mobile devices. In this paper, we focus on the scenario where the number of D2D pairs is smaller than the number of CUs. Usually, this scenario is called "resource-abundant" scenario and has been investigated in many existing works, i.e. [23]–[29]. Similar to [23]–[29], to avoid mutual interferences between D2D pairs, reduce the impact of D2D transmissions on the cellular transmissions, and simplify the theoretical analysis, we assume that the uplink resource of each CU can be shared by at most one D2D pair, and each D2D pair can only share the resource of one CU. For the other cases, i.e. the cases where the D2D pairs may be more than the CUs, allowing one CU to share its resource with several D2D pairs in orthogonal or non-orthogonal way, and allowing one D2D pair to share the resource of several CUs, we would be more likely to investigate them in the future works since the problem formulation process will become much more complicated and we need new efficient approach to obtain the solution.

Centralized resource allocation is adopted and the BS is responsible for allocating the resource. In LTE cellular system, the resource is usually divided into resource blocks in both time and frequency domains. In this paper, we focus on the dynamic resource allocation in time domain, and thus when a CU transmits, it occupies all the sub-channels in frequency domain. That is, time is divided into frames of fixed length. In each frame, each CU is allocated a dedicated time period (a dedicated number of time slots), as shown in Fig. 2. Furthermore, since we do not consider the resource allocation in frequency domain, frequency flat-fading channel is adopted and for each device, the transmit power in all frequency sub-channels is set to the same value. In this paper, we focus on the energy-efficient design, that is, minimizing the energy consumption of the CUs and D2D pairs while satisfying their transmission rate requirements[1]. We need to jointly consider the time resource allocation for CUs, transmit power optimization for the D2D transmissions, and the pairing between CUs and D2D pairs.

We further assume that all the D2D nodes are in the coverage of the BS and thus the BS can use the control channel to implement the network synchronization among all devices in the system. In the literature, network synchronization problem of D2D networks has been carefully investigated in many existing papers, i.e. [30], [31]. In [30], Abedini et al. provided a distributed synchronization scheme for D2D networks based on broadcasting specific physical layer signals, which addressed both time and frequency synchronization (resolving clock offset and skew) and incorporated various impairments factors, including the propagation delay, and the

[1]Since the transmission rates of all the devices are satisfied, the network throughput and the fairness among users have been guaranteed in some sense. In this paper, we do not consider the queuing details of the packets of different users and thus the delay metric is not involved.

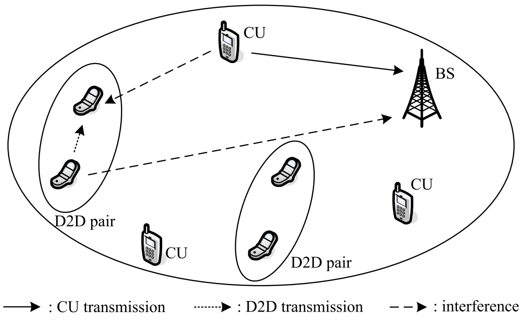

Fig. 1. The considered cellular network.

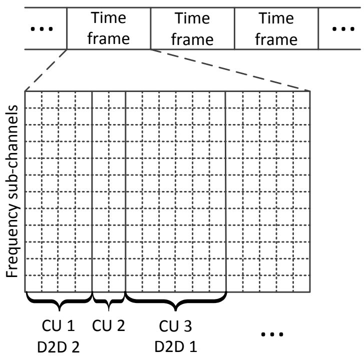

Fig. 2. The frame architecture.

errors in measuring the time and frequency offsets. In [31], Sun et al. proposed a low-complexity timestamp-based adaptive distributed network synchronization (ARES) algorithm for mobile D2D systems. The overhead of these two network synchronization schemes is not too high since they only need to transmit some short synchronization messages. Although the schemes proposed in [30] and [31] focus on solving the synchronization problem of D2D networks in the partial-coverage and out-of-coverage scenarios where part of the D2D nodes or all the D2D nodes are out of the coverage of the BS, they indeed can be trimmed for the application in the considered all-in-coverage scenario in this paper by using the reliable cellular control channel to transmit the synchronization messages.

B. Power Model

Generally speaking, three types of power consumption are involved in an active RF transmission process: the power consumption of the power amplifier (PA) at the transmitter, namely, P_{PA}, the power consumption of the circuitry blocks at the transmitter except the PA, termed P_{ct}, and the power consumption of the circuitry blocks at the receiver, say, P_{cr}. Let θ denote the drain efficiency of the PA. Then, P_{PA} can be calculated by $\frac{P_{tr}}{\theta}$, where P_{tr} is the transmit power of the transmitting device. When a device is idle, it does not transmit or receive packets. In this case, it consumes power due to the leakage current [3], denoted by P_{id}.

III. Problem Formulation

Let $\mathcal{C} = \{c_i, 1 \le i \le |\mathcal{C}|\}$ and $\mathcal{D} = \{d_j, 1 \le j \le |\mathcal{D}|\}$ denote a set of CUs and D2D pairs, respectively. The transmitter and the receiver of D2D pair d_j are denoted as d_j^1 and d_j^2. The rate requirements of CU c_i and D2D pair d_j are denoted as R_{c_i} and R_{d_j}. We employ $y_{i,j} \in \{0,1\}$ to indicate whether D2D pair d_j shares the uplink resource of CU c_i. That is, $y_{i,j} = 1$ when d_j shares the uplink resource of c_i; otherwise, $y_{i,j} = 0$. According to Section II-A, we have $\sum_{d_j \in \mathcal{D}} y_{i,j} \le 1, \forall c_i \in \mathcal{C}$ and $\sum_{c_i \in \mathcal{C}} y_{i,j} = 1, \forall d_j \in \mathcal{D}$. Based on Shannon's capacity formula, the achievable rate of c_i, r_{c_i}, equals

$$r_{c_i} = W \log \left(1 + \frac{P_{tr}^{c_i} g_{c_i}^{BS}}{\sum_{d_j \in \mathcal{D}} y_{i,j} P_{tr}^{d_j^1} g_{d_j^1}^{BS} + N} \right), \quad (1)$$

where P_{tr}^u denotes the transmit power of device u, g_u^v represents the channel gain from device u to device v, N is the noise power, and W is the total bandwidth of all the frequency sub-channels. The unit of r_{c_i} is "nats/s" since the natural logarithm is adopted.

To fulfill the transmission rate requirement of CU c_i, the fraction of time[2] allocated to c_i, say, t_{c_i}, should satisfy

$$t_{c_i} = \frac{R_{c_i}}{r_{c_i}} = \frac{R_{c_i}}{W \log \left(1 + \frac{P_{tr}^{c_i} g_{c_i}^{BS}}{\sum_{d_j \in \mathcal{D}} y_{i,j} P_{tr}^{d_j^1} g_{d_j^1}^{BS} + N} \right)}. \quad (2)$$

The system idle time, t_{idle}, equals

$$t_{idle} = 1 - \sum_{c_i \in \mathcal{C}} t_{c_i}. \quad (3)$$

According to the power model described in Section II-B, the energy consumption of active and inactive mobile devices during the transmission of CU c_i, $E_{t_{c_i}}^{act}$ and $E_{t_{c_i}}^{nact}$, can be written as

$$\begin{aligned} E_{t_{c_i}}^{act} = t_{c_i} \Bigg(& \frac{1}{\theta} \left(P_{tr}^{c_i} + \sum_{d_j \in \mathcal{D}} y_{i,j} P_{tr}^{d_j^1} \right) + P_{ct}^{c_i} \\ & + \sum_{d_j \in \mathcal{D}} \left(y_{i,j} \left(P_{ct}^{d_j^1} + P_{cr}^{d_j^2} \right) \right) \Bigg), \end{aligned} \quad (4)$$

$$\begin{aligned} E_{t_{c_i}}^{nact} = t_{c_i} \Bigg(& \sum_{c_{i'} \in \mathcal{C} \setminus \{c_i\}} P_{id}^{c_{i'}} \\ & + \sum_{d_j \in \mathcal{D}} \left((1 - y_{i,j}) \left(P_{id}^{d_j^1} + P_{id}^{d_j^2} \right) \right) \Bigg), \end{aligned} \quad (5)$$

where P_{ct}^u, P_{cr}^u, and P_{id}^u denote P_{ct}, P_{cr}, and P_{id} for device u. Then, the energy consumption of mobile devices during the

[2]In LTE cellular systems, time is divided into time frames and each time frame contains a number of time slots. In this paper, similar to [1]–[5], to facilitate the analysis, the time in each frame is normalized to "1", and we use a continuous variable "the fraction of time" to approximately represent the number of time slots used by each device in each frame. For example, if there are 10 time slots in each frame, "$t_{c_i} = 0.2$" represents that CU c_i occupies two time slots in each frame. Obviously, this approximation is more precise when the number of time slots in each frame is larger.

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transmission of c_i, namely $E_{t_{c_i}}$, equals

$$\begin{aligned}E_{t_{c_i}} &= E^{act}_{t_{c_i}} + E^{nact}_{t_{c_i}} \\ &= t_{c_i}\left(\tfrac{1}{\theta}P^{c_i}_{tr} + \sum_{d_j\in\mathcal{D}}\left(y_{i,j}\left(\tfrac{1}{\theta}P^{d_j^1}_{tr} + P^{d_j^1}_{ct} + P^{d_j^2}_{cr}\right) + \right.\right. \\ &\left.\left.(1-y_{i,j})\left(P^{d_j^1}_{id} + P^{d_j^2}_{id}\right)\right) + P^{c_i}_{ct} + \sum_{c_{i'}\in\mathcal{C}\setminus\{c_i\}} P^{c_{i'}}_{id}\right).\end{aligned} \tag{6}$$

When the system is idle, all the mobile devices consume idle power. The energy consumption during the system idle time t_{idle}, namely E_{idle}, equals

$$E_{idle} = t_{idle}\left(\sum_{c_i\in\mathcal{C}} P^{c_i}_{id} + \sum_{d_j\in\mathcal{D}}\left(P^{d_j^1}_{id} + P^{d_j^2}_{id}\right)\right). \tag{7}$$

The energy consumption of all the mobile devices, E_{total}, can then be calculated by

$$E_{total} = \sum_{c_i\in\mathcal{C}} E_{t_{c_i}} + E_{idle}. \tag{8}$$

Furthermore, the transmission rate of D2D pair d_j, i.e., r_{d_j}, equals

$$r_{d_j} = W\log\left(1 + \frac{P^{d_j^1}_{tr} g^{d_j^2}_{d_j^1}}{\sum_{c_i\in\mathcal{C}} y_{i,j}P^{c_i}_{tr} g^{d_j^2}_{c_i} + N}\right). \tag{9}$$

Therefore, the energy consumption minimization problem for the D2D communications underlaying cellular networks can be formulated as follows.

$$\begin{aligned}\min\ & E_{total}, \\ \text{s.t.}\ & \sum_{c_i\in\mathcal{C}} t_{c_i} \le 1, && \text{(10a)}\\ & r_{d_j} \ge R_{d_j}, \forall d_j\in\mathcal{D}, && \text{(10b)}\\ & \sum_{d_j\in\mathcal{D}} y_{i,j} \le 1, \forall c_i\in\mathcal{C}, && \text{(10c)}\\ & \sum_{c_i\in\mathcal{C}} y_{i,j} = 1, \forall d_j\in\mathcal{D}, && \text{(10d)}\\ & 0 < P^{c_i}_{tr} \le P^{\max}_c, \forall c_i\in\mathcal{C}, && \text{(10e)}\\ & 0 < P^{d_j^1}_{tr} \le P^{\max}_d, \forall d_j\in\mathcal{D}, && \text{(10f)}\\ \text{var.}\ & P^{c_i}_{tr}, c_i\in\mathcal{C}, \\ & P^{d_j^1}_{tr}, d_j\in\mathcal{D}, \\ & y_{i,j}\in\{0,1\}, c_i\in\mathcal{C}, d_j\in\mathcal{D}.\end{aligned}$$

Here, $P^{\max}_c$ and $P^{\max}_d$ are the maximum allowable transmit power of cellular transmissions and D2D transmissions. Constraint (10a) implies that, in each cell, the normalized transmission time of CUs cannot be longer than 1. Constraint (10b) ensures that the transmission rate of each D2D pair should satisfy its minimum rate requirement[3]. Constraints (10c) and (10d) are due to the fact that the uplink resource of each CU can be shared by at most one D2D pair and each D2D pair should share the uplink resource of one CU. Constraints (10e) and (10f) represent that the transmit power of each device should not be higher than the corresponding maximum allowable transmit power. We assume that admission control has been adopted such that a new device is allowed to enter the system only if all the constraints can be satisfied. In particular, when a new device wants to enter the network, it sends a request signal with the necessary information for resource allocation (i.e., rate requirements, locations) to the BS. The BS then starts a new problem solution process to determine whether the system can accommodate this new device. If an effective solution can be found, the BS broadcasts a signal with the new resource allocation results to the new device for allowance and the devices that have existed in the system to renew the scheduling. Otherwise, the BS sends back a rejecting signal to the new device. When a device leaves the system, the BS restarts a new problem solution process, and after the problem solution process finishes, it broadcasts the new resource allocation results to all the devices in the system.

[3]Note that the minimum rate requirements of CUs have been considered in the object function and thus we do not need an additional constraint for the minimum rate of CUs.

Applying equations (2), (3), (6), (7), (8), and (9), after some simplifications, Problem (10) can be reformulated as

$$\begin{aligned}\min\ & \sum_{c_i\in\mathcal{C}}\left(\frac{R_{c_i}}{W\log\left(1+\frac{P^{c_i}_{tr}g^{BS}_{c_i}}{\sum_{d_j\in\mathcal{D}} y_{i,j}P^{d_j^1}_{tr}g^{BS}_{d_j^1}+N}\right)}\left(\frac{1}{\theta}P^{c_i}_{tr} + \right.\right.\\ & \sum_{d_j\in\mathcal{D}}\left(y_{i,j}\left(\frac{1}{\theta}P^{d_j^1}_{tr} + P^{d_j^1}_{ct} + P^{d_j^2}_{cr} - P^{d_j^1}_{id} - P^{d_j^2}_{id}\right)\right)\\ & \left.\left.+P^{c_i}_{ct} - P^{c_i}_{id}\right)\right), \\ \text{s.t.}\ & \sum_{c_i\in\mathcal{C}}\frac{R_{c_i}}{W\log\left(1+\frac{P^{c_i}_{tr}g^{BS}_{c_i}}{\sum_{d_j\in\mathcal{D}} y_{i,j}P^{d_j^1}_{tr}g^{BS}_{d_j^1}+N}\right)} \le 1, && \text{(11a)}\\ & W\log\left(1+\frac{P^{d_j^1}_{tr}g^{d_j^2}_{d_j^1}}{\sum_{c_i\in\mathcal{C}} y_{i,j}P^{c_i}_{tr}g^{d_j^2}_{c_i}+N}\right) \ge R_{d_j}, \forall d_j\in\mathcal{D}, && \text{(11b)}\\ & (10c), (10d), (10e), (10f), \\ \text{var.}\ & P^{c_i}_{tr}, c_i\in\mathcal{C}, \\ & P^{d_j^1}_{tr}, d_j\in\mathcal{D}, \\ & y_{i,j}\in\{0,1\}, c_i\in\mathcal{C}, d_j\in\mathcal{D}.\end{aligned}$$

Obviously, Problem (11) is an MINLP, which may be difficult to solve in general. In the next section, we will discuss how to solve this problem.

IV. Energy-efficient Resource Allocation

To find the solution, we represent $P^{c_i}_{tr}(c_i\in\mathcal{C})$ in problem (11) with $t_{c_i}(c_i\in\mathcal{C})$ based on (2) as

$$P_{tr}^{c_i} = \frac{1}{g_{c_i}^{BS}}\left(e^{\frac{R_{c_i}}{Wt_{c_i}}}-1\right)\left(\sum_{d_j\in\mathcal{D}} y_{i,j}P_{tr}^{d_j^1}g_{d_j^1}^{BS}+N\right). \quad (12)$$

Furthermore, according to (2), we know that t_{c_i} decreases as $P_{tr}^{c_i}$ increases. When $P_{tr}^{c_i}$ is close to 0, t_{c_i} is close to "$+\infty$"; when $P_{tr}^{c_i}$ equals $P_c^{\max}$, t_{c_i} equals $\frac{R_{c_i}}{W\log\left(1+\frac{P_c^{\max}g_{c_i}^{BS}}{\sum_{d_j\in\mathcal{D}} y_{i,j}P_{tr}^{d_j^1}g_{d_j^1}^{BS}+N}\right)}$. Thus, constraint (10e) can be expressed as

$$t_{c_i} \geq \frac{R_{c_i}}{W\log\left(1+\frac{P_c^{\max}g_{c_i}^{BS}}{\sum_{d_j\in\mathcal{D}} y_{i,j}P_{tr}^{d_j^1}g_{d_j^1}^{BS}+N}\right)}, \forall c_i\in\mathcal{C}, \quad (13)$$

which is equivalent to

$$\left(e^{\frac{R_{c_i}}{Wt_{c_i}}}-1\right)\left(\sum_{d_j\in\mathcal{D}} y_{i,j}P_{tr}^{d_j^1}g_{d_j^1}^{BS}+N\right) \leq P_c^{\max}g_{c_i}^{BS}, \forall c_i\in\mathcal{C}. \quad (14)$$

In addition, constraint (11b) can be rewritten as

$$\frac{\sum_{c_i\in\mathcal{C}} y_{i,j}P_{tr}^{c_i}g_{c_i}^{d_j^2}+N}{P_{tr}^{d_j^1}g_{d_j^1}^{d_j^2}} \leq \frac{1}{e^{\frac{R_{d_j}}{W}}-1}, \forall d_j\in\mathcal{D}. \quad (15)$$

Then, by applying (12), Problem (11) can be reformulated as

$$\begin{aligned}
\min \sum_{c_i\in\mathcal{C}} &\left(t_{c_i}\left(\frac{\left(e^{\frac{R_{c_i}}{Wt_{c_i}}}-1\right)}{\theta g_{c_i}^{BS}}\left(\sum_{d_j\in\mathcal{D}} y_{i,j}P_{tr}^{d_j^1}g_{d_j^1}^{BS}+N\right)\right.\right.\\
&+\sum_{d_j\in\mathcal{D}}\left(y_{i,j}\left(\tfrac{1}{\theta}P_{tr}^{d_j^1}+P_{ct}^{d_j^1}+P_{cr}^{d_j^2}-P_{id}^{d_j^1}-P_{id}^{d_j^2}\right)\right)\\
&\left.\left.+P_{ct}^{c_i}-P_{id}^{c_i}\right)\right),
\end{aligned}$$

$$\text{s.t.} \sum_{c_i\in\mathcal{C}} t_{c_i} \leq 1, \quad (16a)$$

$$\frac{\sum_{c_i\in\mathcal{C}}\left(\frac{y_{i,j}g_{c_i}^{d_j^2}\left(e^{\frac{R_{c_i}}{Wt_{c_i}}}-1\right)\left(\sum_{d_j\in\mathcal{D}} y_{i,j}P_{tr}^{d_j^1}g_{d_j^1}^{BS}+N\right)}{g_{c_i}^{BS}}\right)}{P_{tr}^{d_j^1}g_{d_j^1}^{d_j^2}} + \frac{N}{P_{tr}^{d_j^1}g_{d_j^1}^{d_j^2}} \leq \frac{1}{e^{\frac{R_{d_j}}{W}}-1}, \forall d_j\in\mathcal{D}, \quad (16b)$$

$$\left(e^{\frac{R_{c_i}}{Wt_{c_i}}}-1\right)\left(\sum_{d_j\in\mathcal{D}} y_{i,j}P_{tr}^{d_j^1}g_{d_j^1}^{BS}+N\right) \leq P_c^{\max}g_{c_i}^{BS}, \forall c_i\in\mathcal{C}, \quad (16c)$$

$$(10c), (10d), (10f),$$

$$\text{var. } t_{c_i}, c_i\in\mathcal{C}, \quad P_{tr}^{d_j^1}, d_j\in\mathcal{D}, \quad y_{i,j}\in\{0,1\}, c_i\in\mathcal{C}, d_j\in\mathcal{D}.$$

Next, we first solve the resource allocation problem by optimizing t_{c_i} and $P_{tr}^{d_j^1}$, when $y_{i,j}$ is given. Then, based on the resource allocation results in the first step, we propose a RSBI algorithm to obtain the final solution.

A. Resource Allocation Given $y_{i,j}$

In this section, we show that, given $y_{i,j}$, Problem (16) is conditionally convex and derive the corresponding condition that guarantees Problem (16) to be convex. When the convexity condition is satisfied, we can obtain the optimal t_{c_i} and $P_{tr}^{d_j^1}$ by employing the traditional solution techniques for convex optimization [33]. When it is not, we propose an iterative algorithm to solve it.

1) Convexity condition for Problem (16) given $y_{i,j}$: The convexity condition can be derived based on the following lemma where the constraint set of Problem (16), given $y_{i,j}$, is shown to be convex.

Lemma 1: The constraint set of Problem (16), given $y_{i,j}$, is convex.

Proof: For the feasible $y_{i,j}$, constraints (10c) and (10d) are satisfied. Noting that the constraint sets described by constraints (16a) and (10f) are obviously convex, we only need to prove that constraints (16b) and (16c) are convex.

(a) Proof of convexity for constraint (16b).

Noticing that the right-hand side of constraint (16b) is a constant, the constraint set of (16b) is a sublevel set of the function $H_j\left(t_{c_1},...,t_{c_i},...,t_{c_{|\mathcal{C}|}},P_{tr}^{d_j^1}\right)$, where

$$H_j\left(t_{c_1},...,t_{c_i},...,t_{c_{|\mathcal{C}|}},P_{tr}^{d_j^1}\right) \triangleq \frac{\sum_{c_i\in\mathcal{C}}\left(\frac{y_{i,j}g_{c_i}^{d_j^2}}{g_{c_i}^{BS}}\left(e^{\frac{R_{c_i}}{Wt_{c_i}}}-1\right)\left(\sum_{d_j\in\mathcal{D}} y_{i,j}P_{tr}^{d_j^1}g_{d_j^1}^{BS}+N\right)\right)+N}{P_{tr}^{d_j^1}g_{d_j^1}^{d_j^2}}. \quad (17)$$

From [33], to prove the convexity of constraint (16b), we only need to prove that $H_j\left(t_{c_1},...,t_{c_i},...,t_{c_{|\mathcal{C}|}},P_{tr}^{d_j^1}\right)$ is convex.

We know that for a D2D pair (i.e. d_j), it should share the uplink resource of one CU. Without loss of generality, we assume that d_j shares the uplink resource of CU c_{i^0}. That is, $y_{i^0,j}=1$ and $y_{i,j}=0, \forall c_i \in \mathcal{C}\backslash\{c_{i^0}\}$. Then, equation (17) can be simplified to

$$H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)=\frac{\frac{g_{c_{i^0}}^{d_j^2}}{g_{c_{i^0}}^{BS}}\left(e^{\frac{R_{c_{i^0}}}{Wt_{c_{i^0}}}}-1\right)\left(P_{tr}^{d_j^1}g_{d_j^1}^{BS}+N\right)+N}{P_{tr}^{d_j^1}g_{d_j^1}^{d_j^2}}. \tag{18}$$

Next, we show that the Hessian Matrix of $H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)$ is positive semi-definite. The second partial derivatives of $H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)$ can be derived as

$$\frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial^2 t_{c_{i^0}}}=\frac{\frac{R_{c_{i^0}}g_{c_{i^0}}^{d_j^2}}{Wg_{c_{i^0}}^{BS}}\left(P_{tr}^{d_j^1}g_{d_j^1}^{BS}+N\right)e^{\frac{R_{c_{i^0}}}{Wt_{c_{i^0}}}}\left(\frac{R_{c_{i^0}}}{Wt_{c_{i^0}}}+2\right)}{P_{tr}^{d_j^1}g_{d_j^1}^{d_j^2}t_{c_{i^0}}^3},$$

$$\frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial t_{c_{i^0}}\partial P_{tr}^{d_j^1}}=\frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial P_{tr}^{d_j^1}\partial t_{c_{i^0}}}=\frac{NR_{c_{i^0}}g_{c_{i^0}}^{d_j^2}e^{\frac{R_{c_{i^0}}}{Wt_{c_{i^0}}}}}{Wt_{c_{i^0}}^2\left(P_{tr}^{d_j^1}\right)^2g_{d_j^1}^{d_j^2}g_{c_{i^0}}^{BS}},$$

$$\frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial^2 P_{tr}^{d_j^1}}=\frac{\frac{2Ng_{c_{i^0}}^{d_j^2}}{g_{c_{i^0}}^{BS}}\left(e^{\frac{R_{c_{i^0}}}{Wt_{c_{i^0}}}}-1\right)+2N}{\left(P_{tr}^{d_j^1}\right)^3g_{d_j^1}^{d_j^2}}.$$

Since $\frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial^2 t_{c_{i^0}}}\geq 0$, $\frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial t_{c_{i^0}}\partial P_{tr}^{d_j^1}}=\frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial P_{tr}^{d_j^1}\partial t_{c_{i^0}}}\geq 0$, and $\frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial^2 P_{tr}^{d_j^1}}\geq 0$, we have

$$\begin{pmatrix} t_{c_{i^0}} & P_{tr}^{d_j^1}\end{pmatrix}\begin{bmatrix}\frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial^2 t_{c_{i^0}}} & \frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial t_{c_{i^0}}\partial P_{tr}^{d_j^1}}\\ \frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial P_{tr}^{d_j^1}\partial t_{c_{i^0}}} & \frac{\partial^2 H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)}{\partial^2 P_{tr}^{d_j^1}}\end{bmatrix}\begin{pmatrix} t_{c_{i^0}}\\ P_{tr}^{d_j^1}\end{pmatrix}\geq 0.$$

That is, the Hessian Matrix of $H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)$ is positive semi-definite. According to [33], $H_j\left(t_{c_{i^0}},P_{tr}^{d_j^1}\right)$ is convex. Therefore, constraint (16b) is convex.

(b) Proof of convexity for constraint (16c).

Similar to previous argument, to prove the convexity of constraint (16c), we only need to prove that the left-hand side of constraint (16c), denoted as $L_i\left(t_{c_i},P_{tr}^{d_1^1},...,P_{tr}^{d_j^1},...,P_{tr}^{d_{|\mathcal{D}|}^1}\right)$, is a convex function of t_{c_i} and $P_{tr}^{d_j^1}(1\leq j\leq|\mathcal{D}|)$. From constraint (16c), $L_i\left(t_{c_i},P_{tr}^{d_1^1},...,P_{tr}^{d_j^1},...,P_{tr}^{d_{|\mathcal{D}|}^1}\right)$ can be written as

$$L_i\left(t_{c_i},P_{tr}^{d_1^1},...,P_{tr}^{d_j^1},...,P_{tr}^{d_{|\mathcal{D}|}^1}\right)\triangleq \left(e^{\frac{R_{c_i}}{Wt_{c_i}}}-1\right)\left(\sum_{d_j\in\mathcal{D}}y_{i,j}P_{tr}^{d_j^1}g_{d_j^1}^{BS}+N\right). \tag{19}$$

According to constraint (10c), for a CU (i.e. c_i), there are two cases. One case is that c_i shares its uplink resource with a D2D pair, that is, $\sum_{d_j\in\mathcal{D}}y_{i,j}=1$. The other case is that c_i does not share its uplink resource with any D2D pair, that is, $\sum_{d_j\in\mathcal{D}}y_{i,j}=0$. In the following, we prove that $L_i\left(t_{c_i},P_{tr}^{d_1^1},...,P_{tr}^{d_j^1},...,P_{tr}^{d_{|\mathcal{D}|}^1}\right)$ is convex in both cases.

Case 1: $\sum_{d_j\in\mathcal{D}}y_{i,j}=1$.

Without loss of generality, we assume that c_i shares its uplink resource with d_{j^0}. That is, $y_{i,j^0}=1$ and $y_{i,j}=0, \forall d_j\in\mathcal{D}\backslash\{d_{j^0}\}$. Then, in this case, equation (19) can be simply expressed as

$$L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)=\left(e^{\frac{R_{c_i}}{Wt_{c_i}}}-1\right)\left(P_{tr}^{d_{j^0}^1}g_{d_{j^0}^1}^{BS}+N\right). \tag{20}$$

The second partial derivatives of $L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)$ respectively equal

$$\frac{\partial^2 L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)}{\partial^2 t_{c_i}}=\frac{R_{c_i}e^{\frac{R_{c_i}}{Wt_{c_i}}}\left(P_{tr}^{d_{j^0}^1}g_{d_{j^0}^1}^{BS}+N\right)\left(\frac{R_{c_i}}{Wt_{c_i}}+2\right)}{Wt_{c_i}^3},$$

$$\frac{\partial^2 L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)}{\partial t_{c_i}\partial P_{tr}^{d_{j^0}^1}}=\frac{\partial^2 L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)}{\partial P_{tr}^{d_{j^0}^1}\partial t_{c_i}}=-\frac{R_{c_i}g_{d_{j^0}^1}^{BS}}{Wt_{c_i}^2}e^{\frac{R_{c_i}}{Wt_{c_i}}},$$

$$\frac{\partial^2 L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)}{\partial^2 P_{tr}^{d_{j^0}^1}}=0.$$

Then, we have

$$\begin{pmatrix} t_{c_i} & P_{tr}^{d_{j^0}^1}\end{pmatrix}\begin{bmatrix}\frac{\partial^2 L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)}{\partial^2 t_{c_i}} & \frac{\partial^2 L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)}{\partial t_{c_i}\partial P_{tr}^{d_{j^0}^1}}\\ \frac{\partial^2 L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)}{\partial P_{tr}^{d_{j^0}^1}\partial t_{c_i}} & \frac{\partial^2 L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)}{\partial^2 P_{tr}^{d_{j^0}^1}}\end{bmatrix}\begin{pmatrix} t_{c_i}\\ P_{tr}^{d_{j^0}^1}\end{pmatrix}$$
$$=e^{\frac{R_{c_i}}{Wt_{c_i}}}\frac{R_{c_i}}{Wt_{c_i}}\left(\frac{R_{c_i}}{Wt_{c_i}}\left(P_{tr}^{d_{j^0}^1}g_{d_{j^0}^1}^{BS}+N\right)+2N\right),$$

which is always non-negative. That is, when $\sum_{d_j\in\mathcal{D}}y_{i,j}=1$, the Hessian Matrix of $L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)$ is positive semi-definite. According to [33], $L_i\left(t_{c_i},P_{tr}^{d_{j^0}^1}\right)$ is convex when $\sum_{d_j\in\mathcal{D}}y_{i,j}=1$.

Case 2: $\sum_{d_j\in\mathcal{D}}y_{i,j}=0$.

In this case, equation (19) can be simplified to

$$L_i\left(t_{c_i}\right)=N\left(e^{\frac{R_{c_i}}{Wt_{c_i}}}-1\right), \tag{21}$$

which is the function of t_{c_i} only. The second derivative of $L_i\left(t_{c_i}\right)$ equals

$$\frac{d^2 L_i\left(t_{c_i}\right)}{d^2 t_{c_i}} = \frac{N R_{c_i} e^{\frac{R_{c_i}}{W t_{c_i}}} \left(\frac{R_{c_i}}{W t_{c_i}} + 2\right)}{W t_{c_i}^3}. \tag{22}$$

Since $\frac{d^2 L_i\left(t_{c_i}\right)}{d^2 t_{c_i}}$ is always non-negative, $L_i\left(t_{c_i}\right)$ is convex when $\sum\limits_{d_j \in \mathcal{D}} y_{i,j} = 0$.

Thus, in both cases, $L_i\left(t_{c_i}, P_{tr}^{d_1^1}, ..., P_{tr}^{d_j^1}, ..., P_{tr}^{d_{|\mathcal{D}|}^1}\right)$ is convex. That is, constraint (16c) is convex. Together with part (a) of this proof, we can conclude that, when $y_{i,j}$ is given, the constraint set of Problem (16) is a convex set. ■

Based on Lemma 1, the convexity condition of Problem (16), given $y_{i,j}$, can be derived as shown in Theorem 1.

Theorem 1: When $y_{i,j}$ is given, Problem (16) is a convex optimization problem if

$$y_{i,j} g_{d_j^1}^{BS} \leq g_{c_i}^{BS}, \forall c_i \in \mathcal{C}, \forall d_j \in \mathcal{D}. \tag{23}$$

Proof: According to Lemma 1, when $y_{i,j}$ is given, the constraint set of Problem (16) is a convex set. Thus, we only need to prove that, when $y_{i,j}$ is given, the objective function of Problem (16) is convex if condition (23) is satisfied.

To proceed, let

$$\begin{aligned} U_i \triangleq\, & t_{c_i} \left(\frac{1}{\theta g_{c_i}^{BS}} \left(e^{\frac{R_{c_i}}{W t_{c_i}}} - 1 \right) \left(\sum_{d_j \in \mathcal{D}} y_{i,j} P_{tr}^{d_j^1} g_{d_j^1}^{BS} + N \right) \right. \\ & + \sum_{d_j \in \mathcal{D}} \left(y_{i,j} \left(\frac{1}{\theta} P_{tr}^{d_j^1} + P_{ct}^{d_j^1} + P_{cr}^{d_j^2} - P_{id}^{d_j^1} - P_{id}^{d_j^2} \right) \right) \\ & \left. + P_{ct}^{c_i} - P_{id}^{c_i} \right). \end{aligned} \tag{24}$$

Obviously, the objective function of Problem (16) is convex when, for each $c_i \in \mathcal{C}$, U_i is convex. From constraint (10c), $y_{i,j}$'s satisfy either $\sum\limits_{d_j \in \mathcal{D}} y_{i,j} = 1$ or $\sum\limits_{d_j \in \mathcal{D}} y_{i,j} = 0$. In the following, we will separately derive the condition that guarantees U_i to be convex for these two cases.

Case 1: $\sum\limits_{d_j \in \mathcal{D}} y_{i,j} = 1$.

When $\sum\limits_{d_j \in \mathcal{D}} y_{i,j} = 1$, we know that there is a D2D pair in $\mathcal{D}$ sharing the resource of c_i. Without loss of generality, we assume that d_{j^0} shares the resource of c_i. That is, $y_{i,j^0} = 1$ and $y_{i,j} = 0, \forall d_j \in \mathcal{D} \backslash \left\{d_{j^0}\right\}$. Then, equation (24) can be simplified as

$$\begin{aligned} U_i = t_{c_i} & \left(\frac{1}{\theta g_{c_i}^{BS}} \left(e^{\frac{R_{c_i}}{W t_{c_i}}} - 1 \right) \left(P_{tr}^{d_{j^0}^1} g_{d_{j^0}^1}^{BS} + N \right) \right. \\ & \left. + \frac{P_{tr}^{d_{j^0}^1}}{\theta} + P_{ct}^{c_i} + P_{ct}^{d_{j^0}^1} + P_{cr}^{d_{j^0}^2} - P_{id}^{d_{j^0}^1} - P_{id}^{d_{j^0}^2} - P_{id}^{c_i} \right). \end{aligned} \tag{25}$$

The second partial derivatives of U_i equal

$$\frac{\partial^2 U_i}{\partial^2 t_{c_i}} = \frac{R_{c_i}^2 e^{\frac{R_{c_i}}{W t_{c_i}}}}{\theta W^2 g_{c_i}^{BS} t_{c_i}^3} \left(P_{tr}^{d_{j^0}^1} g_{d_{j^0}^1}^{BS} + N \right), \tag{26}$$

$$\begin{aligned} \frac{\partial^2 U_i}{\partial t_{c_i} \partial P_{tr}^{d_{j^0}^1}} = \frac{\partial^2 U_i}{\partial P_{tr}^{d_{j^0}^1} \partial t_{c_i}} = \frac{g_{d_{j^0}^1}^{BS}}{\theta g_{c_i}^{BS}} \left(e^{\frac{R_{c_i}}{W t_{c_i}}} - 1 \right) \\ - \frac{R_{c_i} g_{d_{j^0}^1}^{BS}}{\theta W g_{c_i}^{BS} t_{c_i}} e^{\frac{R_{c_i}}{W t_{c_i}}} + \frac{1}{\theta}, \end{aligned} \tag{27}$$

$$\frac{\partial^2 U_i}{\partial^2 P_{tr}^{d_{j^0}^1}} = 0. \tag{28}$$

With (26), (27), and (28), we have

$$\begin{aligned} & \begin{pmatrix} t_{c_i} & P_{tr}^{d_{j^0}^1} \end{pmatrix} \begin{bmatrix} \frac{\partial^2 U_i}{\partial^2 t_{c_i}} & \frac{\partial^2 U_i}{\partial t_{c_i} \partial P_{tr}^{d_{j^0}^1}} \\ \frac{\partial^2 U_i}{\partial P_{tr}^{d_{j^0}^1} \partial t_{c_i}} & \frac{\partial^2 U_i}{\partial^2 P_{tr}^{d_{j^0}^1}} \end{bmatrix} \begin{pmatrix} t_{c_i} \\ P_{tr}^{d_{j^0}^1} \end{pmatrix} \\ & = t_{c_i} \left(\frac{P_{tr}^{d_{j^0}^1} g_{d_{j^0}^1}^{BS} e^{\frac{R_{c_i}}{W t_{c_i}}}}{\theta g_{c_i}^{BS}} \left(\left(\frac{R_{c_i}}{W t_{c_i}} - 1 \right)^2 + 1 \right) \right. \\ & \left. + \frac{N R_{c_i}^2 e^{\frac{R_{c_i}}{W t_{c_i}}}}{\theta W^2 g_{c_i}^{BS} t_{c_i}^2} + \frac{2 P_{tr}^{d_{j^0}^1}}{\theta} \left(1 - \frac{g_{d_{j^0}^1}^{BS}}{g_{c_i}^{BS}} \right) \right). \end{aligned} \tag{29}$$

If $g_{d_{j^0}^1}^{BS} \leq g_{c_i}^{BS}$, then, $1 - \frac{g_{d_{j^0}^1}^{BS}}{g_{c_i}^{BS}} \geq 0$. Thus, it follows

$$\begin{pmatrix} t_{c_i} & P_{tr}^{d_{j^0}^1} \end{pmatrix} \begin{bmatrix} \frac{\partial^2 U_i}{\partial^2 t_{c_i}} & \frac{\partial^2 U_i}{\partial t_{c_i} \partial P_{tr}^{d_{j^0}^1}} \\ \frac{\partial^2 U_i}{\partial P_{tr}^{d_{j^0}^1} \partial t_{c_i}} & \frac{\partial^2 U_i}{\partial^2 P_{tr}^{d_{j^0}^1}} \end{bmatrix} \begin{pmatrix} t_{c_i} \\ P_{tr}^{d_{j^0}^1} \end{pmatrix} \geq 0.$$

That is, when $\sum\limits_{d_j \in \mathcal{D}} y_{i,j} = 1$, the Hessian Matrix of U_i is positive semi-definite if $g_{d_{j^0}^1}^{BS} \leq g_{c_i}^{BS}$. Thus, when $\sum\limits_{d_j \in \mathcal{D}} y_{i,j} = 1$, U_i is convex if $g_{d_{j^0}^1}^{BS} \leq g_{c_i}^{BS}$, which can be rewritten as $y_{i,j} g_{d_j^1}^{BS} \leq g_{c_i}^{BS}, \forall d_j \in \mathcal{D}$.

Case 2: $\sum\limits_{d_j \in \mathcal{D}} y_{i,j} = 0$.

When $\sum\limits_{d_j \in \mathcal{D}} y_{i,j} = 0$, we know that c_i does not share its resource with any D2D pair. In this case, equation (24) can be simplified to

$$U_i = t_{c_i} \left(\frac{N}{\theta g_{c_i}^{BS}} \left(e^{\frac{R_{c_i}}{W t_{c_i}}} - 1 \right) + P_{ct}^{c_i} - P_{id}^{c_i} \right). \tag{30}$$

Since, in this case, U_i is only the function of t_{c_i}, we can calculate the second derivative of U_i with respect to t_{c_i} as follows.

$$\frac{\partial^2 U_i}{\partial^2 t_{c_i}} = \frac{N R_{c_i}^2 e^{\frac{R_{c_i}}{W t_{c_i}}}}{\theta W^2 g_{c_i}^{BS} t_{c_i}^3}, \tag{31}$$

which is always non-negative. Thus, U_i is convex when $\sum\limits_{d_j \in \mathcal{D}} y_{i,j} = 0$. Since the objective function of Problem (16) is convex as long as U_i is convex for each $c_i \in \mathcal{C}$, the condition that guarantees the objective function of Problem (16) to be convex can be expressed as shown in (23). Together with Lemma 1, we can conclude that, when $y_{i,j}$ is given, Problem (16) is a convex optimization problem if condition (23) is satisfied. ■

Theorem 1 implies that, if channel fading is neglected and $y_{i,j}$ is given, Problem (16) is convex only when each D2D pair shares the uplink resources of a CU located closer to the BS than the transmitter of the corresponding D2D pair. In practice, to protect CUs' uplink transmissions, it is often necessary to pair CUs with D2D pairs which stay farther from the BS. Therefore, the convexity condition can be usually satisfied in the practical scenarios. To cover the situation where the convexity condition is not satisfied, we propose an iterative algorithm to facilitate solution finding for Problem (16).

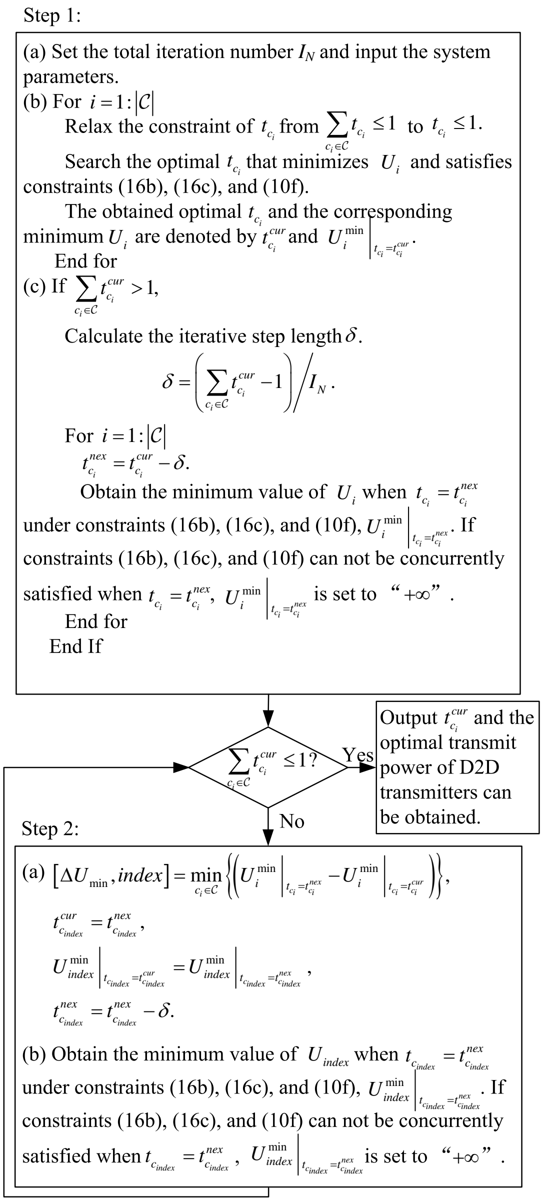

Fig. 3. The iterative algorithm.

2) The iterative algorithm when Problem (16), given $y_{i,j}$, is not convex: When the convexity condition is not satisfied, Problem (16), given $y_{i,j}$, can be solved by an iterative algorithm, as shown in Fig. 3. The iterative algorithm contains two main steps. In Step 1, after inputting the system parameters and setting the iteration number I_N, we relax the constraint of t_{c_i} from $\sum\limits_{c_i\in\mathcal{C}} t_{c_i} \le 1$ to $t_{c_i} \le 1$, and then search the optimal t_{c_i} that minimizes U_i and satisfies constraints (16b), (16c), and (10f) from 0 to 1. The obtained optimal t_{c_i} and the corresponding minimum U_i are denoted by $t_{c_i}^{cur}$ and $U_i^{\min}\big|_{t_{c_i}=t_{c_i}^{cur}}$, respectively. Note that the searching process is different when $\sum\limits_{d_j\in\mathcal{D}} y_{i,j} = 1$ and $\sum\limits_{d_j\in\mathcal{D}} y_{i,j} = 0$. When $\sum\limits_{d_j\in\mathcal{D}} y_{i,j} = 1$, CU c_i shares its resource with a D2D pair, i.e., d_{j^0}. From equation (25), given t_{c_i}, U_i increases as $P_{tr}^{d_{j^0}^1}$ increases. Thus, in the searching process, for each value (searching point) of t_{c_i}, we increase $P_{tr}^{d_{j^0}^1}$ from 0 to $P_d^{\max}$ until constraints (16b) and (16c) are satisfied for d_{j^0} and c_i. If constraints (16b) and (16c) cannot be simultaneously satisfied for d_{j^0} and c_i at the current searching point, the current value of t_{c_i} is invalid and the corresponding U_i is set to "$+\infty$". When $\sum\limits_{d_j\in\mathcal{D}} y_{i,j} = 0$, CU c_i does not share its resource with any D2D pair and U_i can be simplified to (30). In this case, constraints (16b) and (10f) are invalid. Constraint (16c) for t_{c_i} can be expressed as

$$t_{c_i} \ge \frac{R_{c_i}}{W \log\left(1+\frac{P_c^{\max} g_{c_i}^{BS}}{N}\right)}. \tag{32}$$

Then, when $\sum\limits_{d_j\in\mathcal{D}} y_{i,j} = 0$, we can search the optimal t_{c_i} that minimizes U_i from $\frac{R_{c_i}}{W \log\left(1+\frac{P_c^{\max} g_{c_i}^{BS}}{N}\right)}$ to 1. The values of $t_{c_i}^{cur}$ $(c_i \in \mathcal{C})$ are optimal, but they may not satisfy constraint (16a) "$\sum\limits_{c_i\in\mathcal{C}} t_{c_i}^{cur} \le 1$". If constraint (16a) is satisfied, the algorithm is terminated and the values of $t_{c_i}^{cur}$ $(c_i \in \mathcal{C})$ are the solution to Problem (16) under the current $y_{i,j}$. If it is not, we reduce the values of $t_{c_i}^{cur}$ $(c_i \in \mathcal{C})$ with the minimum increase in total energy consumption by repeatedly executing Step 2. Before Step 2, we need to calculate the iterative step length δ, and the values of t_{c_i} in the next iterative step $t_{c_i}^{nex}$ $(c_i \in \mathcal{C})$ as follows.

$$\delta = \frac{\left(\sum\limits_{c_i\in\mathcal{C}} t_{c_i}^{cur} - 1\right)}{I_N}, \tag{33}$$

$$t_{c_i}^{nex} = t_{c_i}^{cur} - \delta. \tag{34}$$

Then, by the similar method described above, we can obtain the minimum value of U_i when $t_{c_i} = t_{c_i}^{nex}$ under constraints (16b), (16c), and (10f), $U_i^{\min}\big|_{t_{c_i}=t_{c_i}^{nex}}$.

The details of Step 2 are as follows. First, we calculate the energy consumption increment when the value of t_{c_i} decreases from $t_{c_i}^{cur}$ to $t_{c_i}^{nex}$, $\Delta U_i^{\min}$, which equals $\left(U_i^{\min}\big|_{t_{c_i}=t_{c_i}^{nex}} - U_i^{\min}\big|_{t_{c_i}=t_{c_i}^{cur}}\right)$. If $\Delta U_{index}^{\min} = \min\limits_{c_i\in\mathcal{C}} \{\Delta U_i^{\min}\}$, the value of $t_{c_{index}}^{cur}$ and $t_{c_{index}}^{nex}$ are changed to $t_{c_{index}}^{nex}$ and $\left(t_{c_{index}}^{nex} - \delta\right)$, respectively. Then, we update the values of $U_{index}^{\min}\big|_{t_{c_{index}}=t_{c_{index}}^{cur}}$ and $U_{index}^{\min}\big|_{t_{c_{index}}=t_{c_{index}}^{nex}}$. By executing Step 2 repeatedly, the value of $\sum\limits_{c_i\in\mathcal{C}} t_{c_i}^{cur}$ can finally be decreased to "1" with the minimum increase in the total energy consumption.

B. RSBI Algorithm for Energy-efficient Selections of CUs

In this section, based on the resource allocation solutions developed in Section IV-A, we introduce a RSBI algorithm to improve the selections of CUs for D2D pairs, which solves the MINLP in (16). The RSBI algorithm contains two main steps: the initial step and the adjusting step, as shown in Fig.

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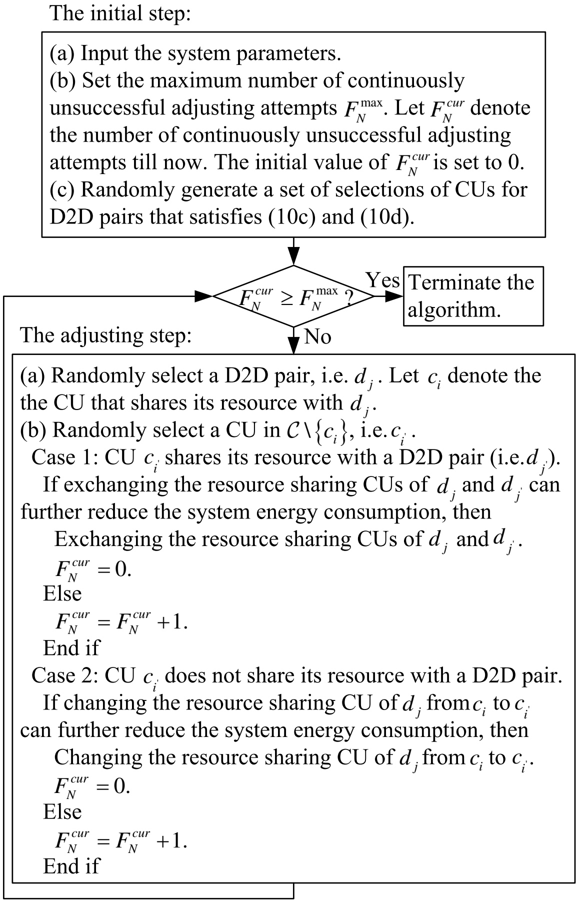

Fig. 4. The RSBI algorithm.

4. In the initial step, we input the system parameters, set the maximum number of continuously unsuccessful adjusting attempts $F_N^{\max}$, and initialize a variable F_N^{cur} that denotes the number of continuously unsuccessful adjusting attempts till now. The initial value of F_N^{cur} is set to 0. Furthermore, we randomly generate a set of selections of CUs for D2D pairs that satisfies (10c) and (10d). In the adjusting step, we try to relocate resources by exchanging the sharing CUs of two D2D pairs, or reassign a D2D pair from its sharing CU to another CU which does not share its resource with any D2D pair, to further reduce the total energy consumption. The details of the adjusting step are as follows. First, we randomly select a D2D pair from $\mathcal{D}$, i.e., d_j. Let c_i denote the CU that shares its resource with d_j. Then, we randomly select a CU from $\mathcal{C}\setminus\{c_i\}$, i.e., $c_{i'}$. In the case that $c_{i'}$ shares its resource with a D2D pair (i.e., $d_{j'}$), if reassigning d_j and $d_{j'}$ to $c_{i'}$ and c_i, respectively, can further reduce the total energy consumption, we reassign d_j to $c_{i'}$ and $d_{j'}$ to c_i, and reset F_N^{cur} to 0; otherwise, F_N^{cur} is increased by 1. In the case where $c_{i'}$ does not share its resource with any D2D pair, if pairing d_j with $c_{i'}$ instead of c_i can further reduce the total energy consumption, we reassign d_j to share the uplink resource of $c_{i'}$, and reset F_N^{cur} to 0; otherwise, F_N^{cur} is increased by 1. The RSBI algorithm is terminated when F_N^{cur} reaches the given maximum value $F_N^{\max}$.

V. Performance Evaluations

In this section, we conduct simulation study to validate the theoretical analysis and evaluate the performance of the proposed algorithms. In the simulation, the cell radius is set to 300 m, and the CUs and D2D pairs are uniformly distributed. The channel gain is obtained from log-distance path-loss model with path-loss exponent of 4 [4], [5]. The maximum transmit power of CUs and D2D nodes, the distance of D2D transmissions, the noise power density, and the channel bandwidth are set to 23 dBm, 13 dBm, 10 m, -174 dBm/Hz, and 1 MHz, respectively. Since we use normalized time in this paper, the energy consumption in a unit time is equivalent to the average power consumption.

A. Convexity Condition Validation

To validate the convexity condition, we generate random cases (random positions for CUs and D2D pairs, random CU-D2D pairings) that satisfy the convexity condition under random power parameters and rate requirements, and compare the solutions obtained from both the Karush-Kuhn-Tucher (KKT) conditions and the numerical search in Fig. 5. Since the running time of the numerical search method increases exponentially as the number of CUs and D2D pairs, we can only consider the cases with small number of CUs and D2D pairs. In particular, the numbers of CUs and D2D pairs are set to 3 and 2, respectively. The random range of the circuitry power at the transmitter and the receiver, the idle power, the drain efficiency of the PA, and the rate requirement of all the devices are set to 50 mW-200 mW, 10 mW-50 mW, 0.1-0.7, and 50 $knats/s$-700 $knats/s$, respectively. In the numerical search method, the searching step length of t_{c_i} and $P_{tr}^{d_j^1}$ is set to 0.005 and 0.1 mW, respectively. From Fig. 5, we can see that the solutions obtained from the KKT conditions and the numerical search are almost the same. The slight difference is because usually, the point obtained from KKT conditions is not one of the searching points in the numerical search method.

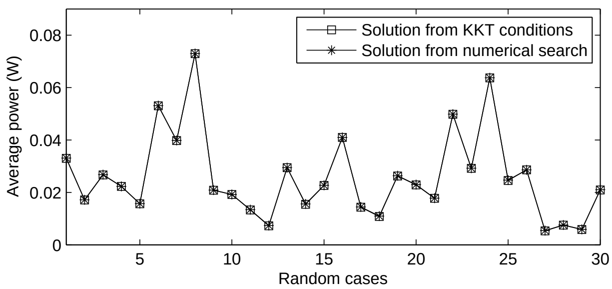

Fig. 5. Validation of the convexity condition.

B. Performance of The Iterative Algorithm

To examine the effectiveness of the proposed iterative algorithm for dynamic resource allocation, we compare it with two state-of-the-art time allocation schemes. One is the equipotent time allocation scheme in which all the time resource in a frame is uniformly allocated to each CU; the other one is the proportional-fair time allocation scheme in which all the time resource in a frame is proportionally allocated to each CU according to the total rate requirement of the device(s) that use the CU's spectrum. In these two schemes, we search the minimum transmit power that satisfies all the constraints of Problem (16) for each D2D transmission. Fig. 6, Fig. 7, and Fig. 8 show the comparison of the iterative algorithm (denoted as "Dynamic"), and the equipotent and proportional-fair time allocation schemes under different rate requirements, different numbers of CUs, and different numbers of D2D pairs when the selections of CUs for D2D pairs are given, respectively. In particular, for each point of simulation, we randomly select 10 CU-D2D pairing cases and calculate their average value. The power related parameters are set as the same as in [3] and [32]. That is, the circuitry power at the transmitter and the receiver, the idle power, and the drain efficiency of the PA are set to 106.4 mW, 121.85 mW, 25 mW, and 0.2, respectively. The iteration number I_N is set to 1000. In Fig. 6, the rate requirement of all the devices varies from 50 $knats/s$ to 320 $knats/s$ when the number of CUs and D2D pairs is respectively set to 20 and 10. In Fig. 7, the number of CUs varies from 20 to 40 when the number of D2D pairs is 10 and the rate requirement of all the devices is set to 170 $knats/s$. In Fig. 8, the number of D2D pairs varies from 12 to 32 when the number CUs is 35 and the rate requirement of all the devices is set to 120 $knats/s$.

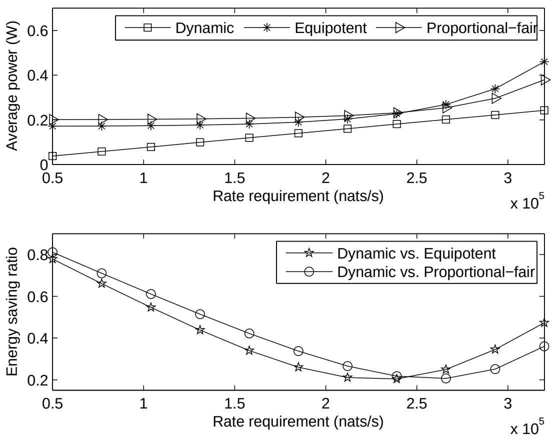

Fig. 6. The iterative algorithm vs. the equipotent and proportional-fair time allocation schemes under different rate requirements.

From Fig. 6 and Fig. 7, we can observe that: 1) Compared with the equipotent and proportional-fair time allocation schemes, the iterative algorithm can achieve an energy saving ratio of 17%-81% under all considered configurations. 2) In the iterative algorithm, the system energy consumption increases as the rate requirement or the number of CUs increases. 3) In the equipotent and proportional-fair time allocation schemes, the system energy consumption increases at an increasing growth rate as the rate requirement increases; while it decreases first and then increases as the number of CUs increases. 4) The energy saving ratio of the iterative algorithm to the equipotent and proportional-fair time allocation schemes decreases first and then increases as the rate requirement or the number of CUs increases. The reasons are as follows. When the rate requirement or the number of CUs is small, we do not need to allocate all the time resource to the devices in order to satisfy the rate requirements with minimum energy consumption. However, in the equipotent and proportional-fair time allocation schemes, all the time resource is uniformly or proportionally allocated to the devices. That is, as the rate requirement or the number of CUs increases from a small value, the total time resource in the equipotent and proportional-fair time allocation schemes is more close to the optimal total time resource. On the other hand, as the rate requirement or the number of CUs increases, the total traffic load increases, which leads to the increase of the system energy consumption. Since these two factors have opposite effects on energy consumption, in the equipotent and proportional-fair time allocation schemes, the system energy consumption increases slowly as the rate requirement increases in the low rate-requirement region, and decreases first as the number of CUs increases. Therefore, the energy saving ratio of the iterative algorithm to the equipotent and proportional-

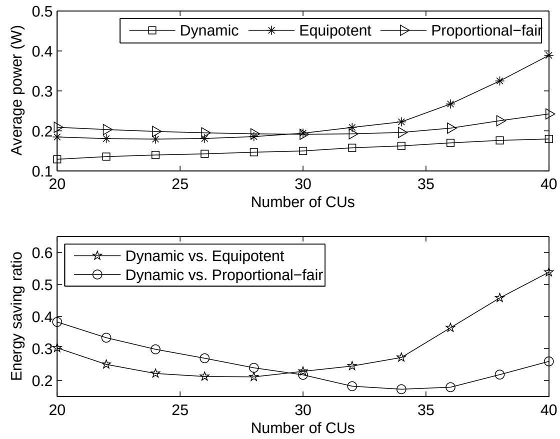

Fig. 7. The iterative algorithm vs. the equipotent and proportional-fair time allocation schemes under different numbers of CUs.

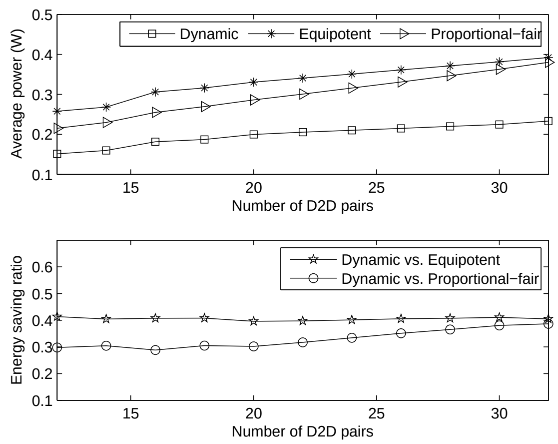

Fig. 8. The iterative algorithm vs. the equipotent and proportional-fair time allocation schemes under different numbers of D2D pairs.

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fair time allocation schemes decreases as the rate requirement or the number of CUs increases from a small value. When the rate requirement is high or the number of CUs is large, all the time resource should be used in order to minimize the energy consumption. That is, for the equipotent and proportional-fair time allocation schemes, the first factor becomes ineffective. Thus, the system energy consumption increases fast as the rate requirement increases in the high rate-requirement region, and grows as the number of CUs increases from a large value. Furthermore, as the total traffic load increases, we need to allocate the time resource more carefully. Since the equipotent and proportional-fair time allocation schemes just simply allocate the time resource in equipotent or proportional manners, the energy saving ratio of the iterative algorithm to these two schemes increases as the rate requirement or the number of CUs increases from a large value.

From Fig. 8, we can observe that, the system energy consumption in all the schemes increases, and the energy saving ratio of the iterative algorithm to the equipotent and proportional-fair time allocation schemes does not change too much, as the number of D2D pairs increases. The reason is as follows. According to the objective function of Problem (16), the transmit powers of D2D pairs can be treated as the multipliers of the functions of t_{c_i}, which have little impact on the shape of the sum of t_{c_i} functions. Thus, the energy saving ratio of the iterative algorithm to the equipotent and proportional-fair time allocation schemes does not change too much as the number of D2D pairs increases.

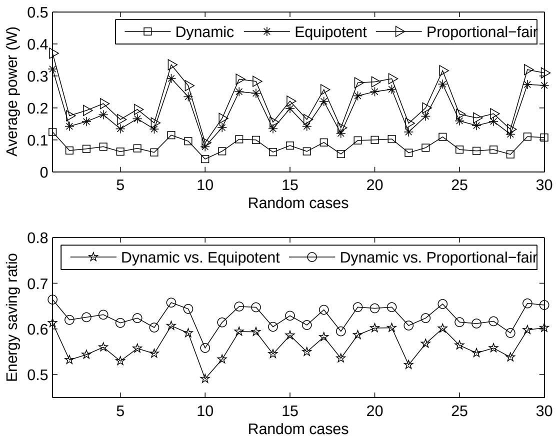

Fig. 9. The iterative algorithm vs. the equipotent and proportional-fair time allocation schemes under random power parameters.

Fig. 9 shows the comparison of the iterative algorithm and the equipotent and proportional-fair time allocation schemes under random power parameters when the number of CUs, the number of D2D pairs, the rate requirement of all the devices, and the iteration number are set to 20, 10, 100 $knats/s$, and 1000, respectively. The random ranges of power parameters are set to the same values as those in Fig. 5. From Fig. 9, we can see that, compared with the equipotent and proportional-fair time allocation schemes, the iterative algorithm achieves an energy saving ratio of 49%-66% under all configurations of power parameters.

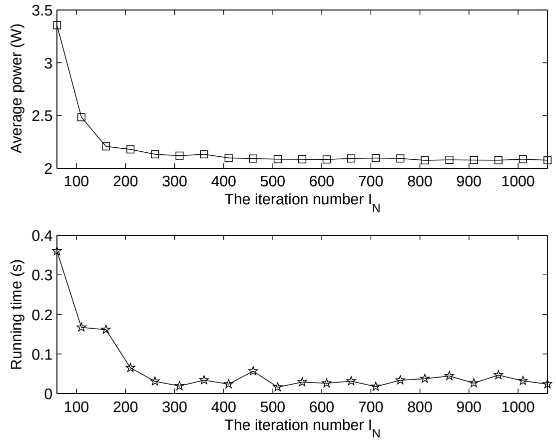

Fig. 10. The system energy consumption and the running time of the iterative algorithm vs. the iteration number.

Fig. 10 shows the effect of the iteration number I_N when the number of CUs, the number of D2D pairs, and the rate requirement of all the devices are set to 30, 20, and 340 $knats/s$, respectively. The power parameters are set to the same values as those in Fig. 6-Fig. 8. The running time of the iterative process is evaluated on a laptop with i7 CPU working at the frequency of 2.8 GHz and 4 GB RAM. From Fig. 10, we can see that in the mass, both the system energy consumption and the running time of the iterative process decrease as the iteration number I_N increases. Thus, we can select a large enough I_N to reduce the system energy consumption. The reason is as follows. As the iteration number I_N increases, the iterative step length decreases. That is, in the iterative process, the time resource can be adjusted more carefully. Thus, the system energy consumption decreases as the iteration number I_N increases. Furthermore, for a smaller iterative step length, $t^{nex}_{c_{index}}$ is bigger. According to the expressions in the left-hand side of constraints (16b) and (16c), it is easier to find the smallest value of $P^{d^1_{j0}}_{tr}$ that satisfies these two constraints for a bigger $t_{c_{index}}$. That is, the searching time for the optimal transmit power of the D2D pair is shorter when $t_{c_{index}} = t^{nex}_{c_{index}}$. Thus, although the iteration number increases, the running time of the iterative process still decreases.

C. Performance of The RSBI Algorithm

To evaluate the effectiveness of the proposed RSBI algorithm in solution finding, we first compare it with the exhaustive search method under random configurations of device numbers and rate requirements, as shown in Fig. 11. Since the computation complexity of the exhaustive search method increases exponentially with the network size, we can only obtain the solution for small networks. That is, $|\mathcal{C}|$ is randomly set in the range $[4, 8]$, and $|\mathcal{D}|$ is randomly set in the range $[1, |\mathcal{C}|]$. The rate requirement of all the devices randomly varies from 50 $knats/s$ to 500 $knats/s$. From Fig. 11, we can see that the performance of RSBI algorithm is close to the exhaustive search method.

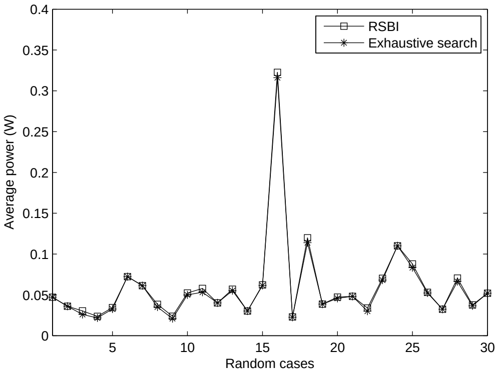

Fig. 11. The RSBI algorithm vs. the exhaustive search method.

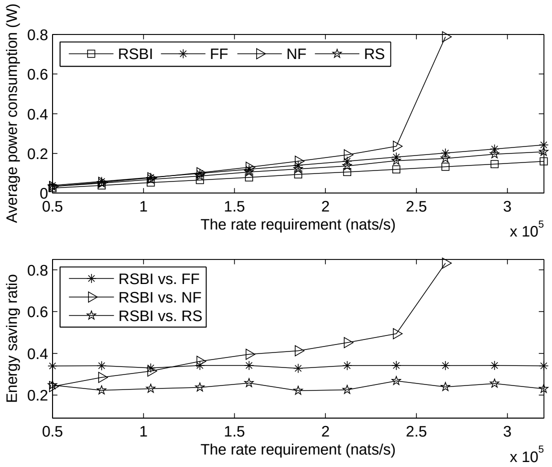

Fig. 12. The RSBI algorithm vs. the FF, NF, and RS schemes under different rate requirements.

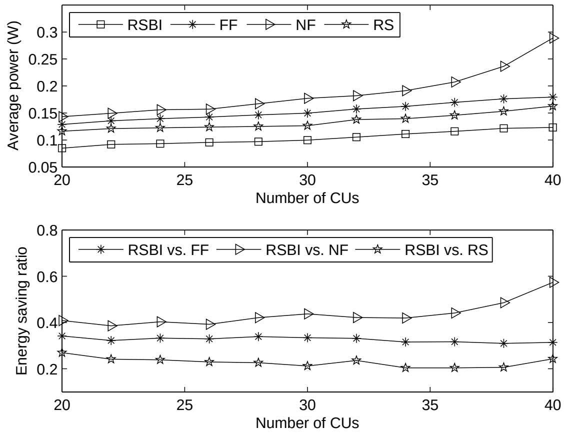

Fig. 13. The RSBI algorithm vs. the FF, NF, and RS schemes under different numbers of CUs.

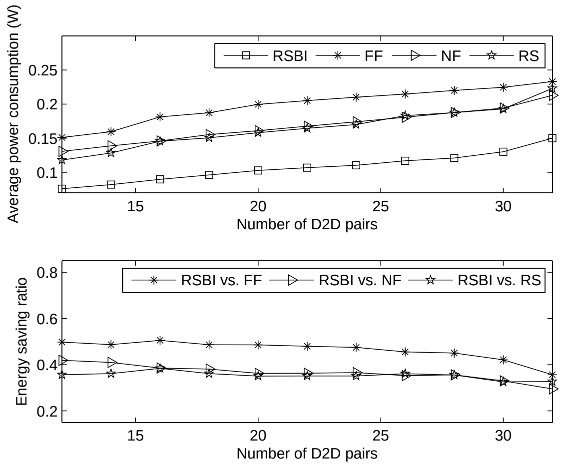

Fig. 14. The RSBI algorithm vs. the FF, NF, and RS schemes under different numbers of D2D pairs.

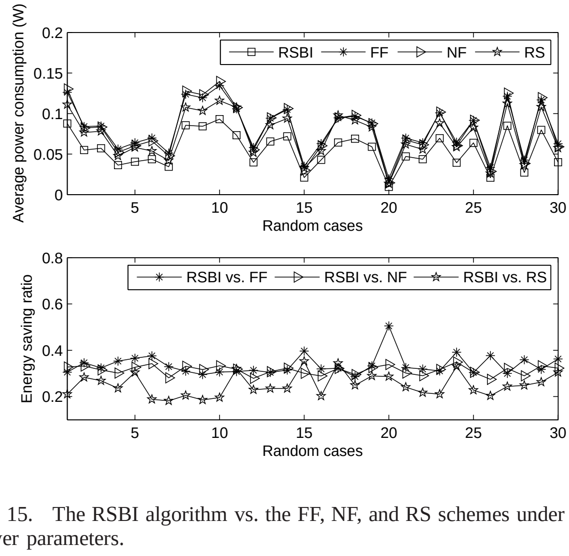

Fig. 15. The RSBI algorithm vs. the FF, NF, and RS schemes under random power parameters.

To identify the performance of RSBI algorithm in big networks, we further compare it with other CU-selection schemes, i.e., the Farthest First (FF), the Nearest First (NF), and Random Sharing (RS) schemes, in Fig. 12-Fig.15, under different rate requirements, different numbers of CUs, different numbers of D2D pairs, and random power parameters. In FF and NF schemes, each D2D pair simply shares the resource of the farthest and nearest CU away from its receiving node that satisfies (10c) and (10d), respectively. In RS scheme, we generate 20 random CU-D2D pairings that satisfy (10c) and (10d), and calculate the average system energy consumption. The configurations of simulation parameters in Fig. 12-Fig. 15 are set to the same values as those in Fig. 6-Fig. 9, respectively. For the RSBI algorithm, the maximum number of continuously unsuccessful adjusting attempts $F_N^{\max}$ is set to 80 in Fig. 14, and is set to 50 in other figures. In Fig. 12, the energy consumption of NF scheme increases dramatically when the rate requirement increases from "239 $knats/s$" to "266 $knats/s$". This is because in NF scheme, the point of "266 $knats/s$" is close to the maximum rate requirement that the system can satisfy. At this point, the optimizing space is extremely small and thus the system energy consumption increases dramatically. The simulation results of the NF scheme

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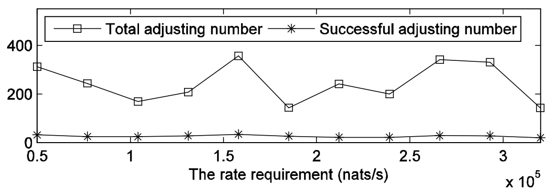
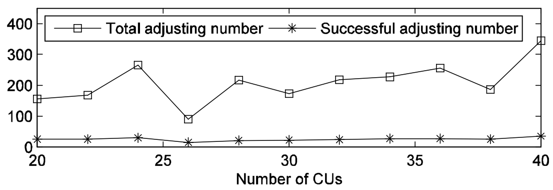
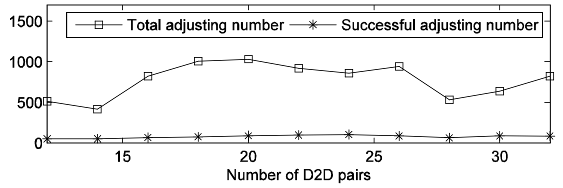


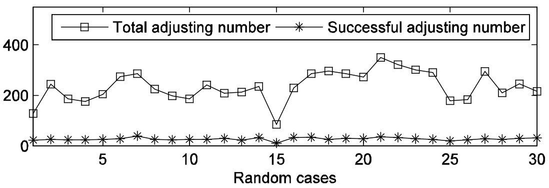
(a) The total adjusting number and the successful adjusting number in the case of Fig. 12.



(b) The total adjusting number and the successful adjusting number in the case of Fig. 13.



(c) The total adjusting number and the successful adjusting number in the case of Fig. 14.



(d) The total adjusting number and the successful adjusting number in the case of Fig. 15.

Fig. 16. The total adjusting number and the successful adjusting number of the RSBI algorithm.

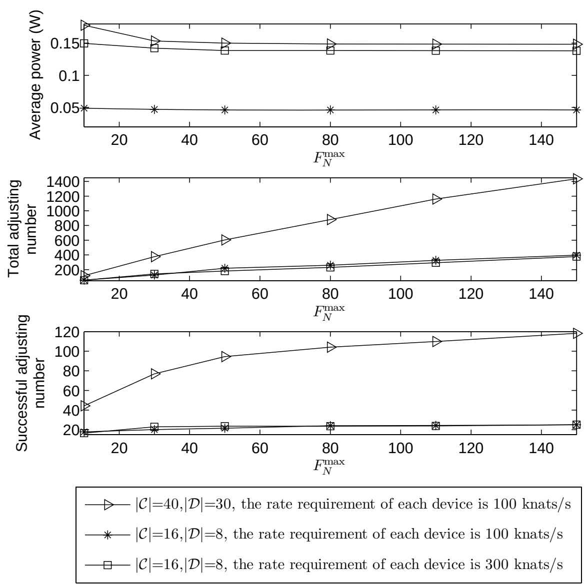


Fig. 17. The effect of $F_N^{\max}$.

at the points of "293 $knats/s$" and "320 $knats/s$" do not exist since the system cannot satisfy these rate requirements under current configurations.

From Fig. 12-Fig. 15, we can observe that, compared with the FF, NF, and RS schemes, the proposed RSBI algorithm can achieve an energy saving ratio of 10%-83%. The reasons are as follows. In FF scheme, when the farthest CU is selected, the interference from the selected CU to the D2D transmission is not the minimum one since the transmit power of the selected CU is unknown. Furthermore, the interference power received at the BS from the considered D2D transmission is not the minimum one since the transmit power of the considered D2D transmission is unknown, and the distance from the transmitting node of the considered D2D transmission to the BS is not the shortest one. The reasons for the NF and RS schemes are similar.

Fig. 16 shows the total adjusting number and the successful adjusting number of the RSBI algorithm in the cases of Fig. 12-Fig. 15. From Fig. 16, we can see that in the cases of Fig. 12-Fig. 15, only a small numbers of adjustments are needed to obtain the results. That is, the convergence rate of the RSBI algorithm is fast.

We further study the effect of the setting of $F_N^{\max}$ in Fig. 17. The power related parameters and the iteration number are set to the same values as those in Fig. 6. To reduce the randomness of the simulation results, we run ten times for each configuration and calculate the average value. From Fig. 17, we can see that by increasing the value of $F_N^{\max}$, the system energy consumption can be decreased but the computational complexity increases accordingly. That is, we can select a proper $F_N^{\max}$ according to the system requirements in practice.

VI. Conclusion

In this paper, we have studied how to minimize the energy consumption of mobile devices in the cellular networks underlaid with D2D communications through dynamic time-resource allocation. We jointly considered the time resource allocation for CUs, the transmit power control for D2D transmissions, and the selections of CUs for D2D pairs. This problem was then formulated as an MINLP. To facilitate the solution finding, we proposed a two-step approach as follows: 1) When the selections of CUs for D2D pairs are given, we showed that the energy consumption minimization problem is conditionally convex and derived the corresponding convexity condition. In the case that the convexity condition is not satisfied, we proposed an iterative algorithm to minimize the energy consumption. 2) Based on the solutions of the first step, a RSBI algorithm was further developed to improve the CU-selection for D2D pairs. Simulation results show that compared with the equipotent and proportional-fair time allocation schemes, the iterative algorithm can achieve an energy saving ratio of 17%-81% under all configurations. The RSBI algorithm can achieve close optimal solution, and save 10%-83% of the energy compared with several other CU-selection schemes.

In this paper, we mainly focused on the dynamic time resource allocation under the frequency flat-fading channel

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in the resource-abundant scenarios with the limits that the resource of one CU is at most shared by one D2D pair, and each D2D pair only shares the resource of one CU. We derived some interesting properties, i.e. conditional convexity, to accelerate the solution finding. One interesting direction in the future work is to consider the more general scenarios with less limitations, i.e. the scenarios where the D2D pairs may be more than the CUs, allowing one CU to share its resource with several D2D pairs in orthogonal or non-orthogonal way, and allowing one D2D pair to share the resource of several CUs. In these scenarios, the mutual interference becomes much more complicated. The problem formulation process will become much more difficult and we need to find new efficient algorithm for solution finding. Another interesting direction is to extend the dynamic resource allocation to both time and frequency domains. When the dynamic resource allocation in frequency domain is considered, we can adopt the frequency-selective fading channel and set distinct transmit powers for different frequency sub-channels. Obviously, by doing this, the energy-efficiency can be further improve. However, the theoretical analysis will become much more difficult since a two-dimension dynamic resource allocation is considered and many optimization variables are added.

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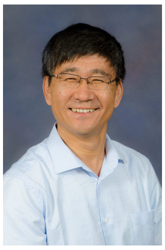

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