Energy-Efficient Matching for Resource Allocation in D2D Enabled Cellular Networks

Energy-Efficient Matching for Resource Allocation in D2D Enabled Cellular Networks

Zhenyu Zhou, *Member, IEEE,* Kaoru Ota, *Member, IEEE,* Mianxiong Dong, *Member, IEEE,* and Chen Xu, *Member, IEEE*

***Abstract*—Energy-efficiency (EE) is critical for device-to-device (D2D) enabled cellular networks due to limited battery capacity and severe co-channel interference. In this paper, we address the EE optimization problem by adopting a stable matching approach. The NP-hard joint resource allocation problem is formulated as a one-to-one matching problem under two-sided preferences, which vary dynamically with channel states and interference levels. A game-theoretic approach is employed to analyze the interactions and correlations among user equipments (UEs), and an iterative power allocation algorithm is developed to establish mutual preferences based on nonlinear fractional programming. We then employ the Gale-Shapley (GS) algorithm to match D2D pairs with cellular UEs (CUs), which is proved to be stable and weak Pareto optimal. We provide a theoretical analysis and description for implementation details and algorithmic complexity. We also extend the algorithm to address scalability issues in large-scale networks by developing tie-breaking and preference deletion based matching rules. Simulation results validate the theoretical analysis and demonstrate that significant performance gains of average EE and matching satisfactions can be achieved by the proposed algorithm.**

***Index Terms*—energy-efficient matching, resource allocation, nonconvex optimization, D2D communications, game-theoretical approach.**

I. INTRODUCTION

DUE to the explosive growth of Internet of things (IoT) and cellular technology, it is predicted that billions of devices will be interconnected and the corresponding data traffic will grow more than 1000 times by 2020 [1]–[4]. Device-to-device (D2D) communication that enables ubiquitous information acquisition and exchange among devices over a direct link [5], is a key enabler to facilitate future 5G mobile systems [6]. D2D communications can be operated as an underlay to cellular networks through spectrum reusing [5], which brings numerous benefits and significant performance improvements to network capacity and user experience [7], [8].

The operation of distributed D2D communications within centralized cellular networks does give rise to new challenges in resource allocation optimization due to limited spectrum and battery capacity. One major line of works aims at maximizing the spectrum efficiency (SE) through resource allocation. A three-stage joint optimization of admission control, power allocation, and link selection was studied in [9]. An evaluation of SE performance under various resource sharing modes was performed in [10]. Resource allocation problems with queuing models and delay constraints were considered in [11]. In [12], the authors employed reverse iterative combinatorial auction (ICA) to solve the system sum-rate optimization problem. Spectrum-efficient resource allocation algorithms have been proposed to address problems under different scenarios such as relay-aided transmission [13], [14], constrained network capacity [15], wireless video networks [16], software-defined multi-tier cellular networks [17], [18], and energy harvesting [19], etc. Comprehensive surveys and overviews of spectrum-efficient resource management for D2D communications were provided in [13], [20].

Although the above works are able to achieve significant SE performance gains, energy consumption of user equipments (UEs) is completely ignored during the optimization process. Without energy-efficient resource allocation design, UEs have to continually increase transmission power to satisfy stringent quality of service (QoS) requirements in an interference-limited environment, which in turn causes more interference to other UEs and leads to rapid depletion of battery energy. By exploiting the centralized architecture of cellular networks and distributed locations of UEs, energy-efficient resource allocation problems have been addressed in both centralized and distributed ways. Centralized schemes for device-to-multi-device (D2MD) and device-cluster scenarios were studied in [21] and [22], respectively. In [23]–[25], the authors proposed auction based power allocation, channel selection, and cooperative relay selection algorithms for energy efficiency (EE) optimization, respectively. A fractional frequency reuse (FFR) based two-stage channel selection and power allocation algorithm was proposed in [26]. A joint optimization algorithm for mode selection and resource scheduling was proposed by employing a coalition game modeling approach [27]. Theoretical analysis of the tradeoff between EE and SE was developed in [28], [29], and was extended to multi-hop scenarios in [30].

However, most of the previous studies have ignored mutual preferences and satisfactions of both D2D pairs and cellular

Manuscript received January 2, 2016; revised May 16, 2016; accepted July 16, 2016. This work was partially supported by the Fundamental Research Funds for the Central Universities under Grant Number 2014MS08, 2015MS04, and 2016MS17. This work was also partially supported by JSPS KAKENHI Grant Number 26730056, 15K15976, 16K00117, and JSPS A3 Foresight Program.

Z. Zhou and C. Xu are with the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China, 102206. (E-mal: zhenyu_zhou@ncepu.edu.cn, chen.xu@ncepu.edu.cn)

K. Ota and M. Dong are with the Department of Information and Electric Engineering, Muroran Institute of Technology, Muroran, Hokkaido, Japan. M. Dong is the corresponding aurthor. (E-mail: mx.dong@csse.muroran-it.ac.jp, ota@csse.muroran-it.ac.jp)

UEs (CUs). A common assumption is that every UE is willing to accept and obey a resource allocation decision even though it can achieve a better performance by disrupting this decision. Detailed modeling of preference from the perspective of EE is missing. Several significant challenges arise when UEs' preferences and satisfactions are taken into consideration. First of all, it is difficult to model preferences of UEs because they vary dynamically with channel states and aggregate interference levels. Second, it is impossible to make every UE always feel satisfied with the same resource allocation decision because UEs may have different or even conflicting preferences. Last but not least, communication overhead and transmission delay caused by obtaining the complete knowledge of every UE's preference may lead to infeasibility and scalability issues with two-sided preferences.

To address these challenges, we propose an energy-efficient stable matching algorithm to solve the NP-hard resource allocation problem by combining advantages of game theory, matching theory, and nonlinear fractional programming. In computational complexity theory, NP-hard problem represents that the problem is at least as hard as any NP-complete problem, which cannot be solved by using polynomial-time algorithms [31]. Game theory that enables in-depth analysis of UEs with conflicting objectives has been widely applied for optimizing resource allocation in D2D communications [13], [20], [32]. Despite its popularity and potential benefits, most game-theory based approaches such as the Nash equilibrium, only validate unilateral stability notions per player by showing that any strategy deviating from the equilibrium cannot achieve better performance [33]. Such one-sided stability may be impractical when performing resource allocation between two disjoint sets of players with individualized mutual preferences.

In comparison, matching theory provides a distributed self-organizing and self-optimizing approach for solving combinatorial problems of matching resources in two disjoint sets [34]–[36]. In particular, it is suitable for wireless resource management due to its ability to handle complex objective functions related to heterogeneous UEs through generally defined preferences. Matching theory based resource allocation algorithms have been developed for cellular networks [33], [37], cognitive radios [38], D2D communications [33], and mobile energy-harvesting networks [39], etc.

Related works that employ matching theory to solve resource allocation problems for D2D communications are summarized and compared as follows. In [40], matching theory was exploited to solve the resource allocation problem in a multi-tier heterogeneous network which consists of macro UEs, small cell UEs, and D2D UEs. The work was then extended to the scenario of relay-aided D2D communications under channel uncertainties, which were modeled as ellipsoidal uncertainty sets by exploiting robust optimization theory [41]. In [42], matching theory was used for solving the relay selection problem in full duplex D2D communications. The interactions and interconnections between D2D UEs and CUs were not taken into consideration. In [43], cheating was introduced into the matching process to further improve UEs' satisfactions by falsifying certain UEs' preference profiles. However, we believe that the energy-efficient joint partner selection and power allocation problem with UEs' preferences and satisfactions considered in this paper has not been well addressed in the above mentioned works.

The main contributions of this paper are summarized as follows:

- A problem formulation for optimizing energy efficiency of any D2D pair or CU under transmission power, channel reusing, and QoS constraints is derived. The formulation obtained is an mixed integer nonlinear programming (MINLP) problem, which uses a binary variable to indicate partner selection (which UE should be selected to form a channel-reusing partnership), and a continuous variable for power allocation (how much transmission power should be allocated for the potential D2D-CU pair). To solve the MINLP problem, we introduce a *one-to-one matching* model which matches D2D pairs with CUs according to mutual preferences. In this way, the original NP-hard *joint partner selection and power allocation problem* can be decoupled into two separate subproblems and solved in a tractable manner.
- One main focus of this work is how to establish mutual preferences from the perspectives of EE. We model a D2D pair (or CU)'s preference over a CU (or D2D pair) as the maximum achievable EE under the specified matching. The power allocation problem developed for obtaining UE preference is modeled as a noncooperative game, in which each UE aims at optimizing its individual EE given the transmission power strategies of its channel-reusing partner. A nonlinear fractional programming and Lagrange dual decomposition based iterative algorithm is developed for establishing preference profiles of both D2D pairs and CUs [44], [45]. The existence and uniqueness properties of the Nash equilibrium and its relationships with optimum power allocation strategies are analyzed theoretically via mathematical proofs.
- Finally, we propose to advocate the Gale-Shapley (GS) algorithm to solve the formulated energy-efficient matching problem under established two-sided preferences and corresponding power allocation strategies. The proposed matching algorithm is also extended to address scalability issues encountered in large-scale networks. Detailed discussion and in-depth analysis of matching stability, distributed/centralized implementation, and computational complexity are presented. Simulation results show that the proposed algorithm can obtain significant EE performance gains and remarkably improve matching satisfactions for a wide range of satisfaction threshold values.

The remaining parts of this paper are outlined as follows. Section II provides a detailed description of the objective functions and preference modeling for the formulated resource allocation problems. Section III develops the proposed energy-efficient matching algorithm. Simulation results are presented and discussed in section IV. Section V concludes the paper and presents future research directions.

II. Energy-Efficient Resource Allocation Problem Formulation

In this section, we firstly provide a detailed description of the system model of D2D communications underlaying cellular networks with UE preferences, and then present the formulation of the energy-efficient resource allocation problem.

A. System Model

We consider uplink spectrum sharing in D2D communications underlaying cellular networks, which is shown in Fig. 1. Uplink spectrum sharing is considered in particularly because firstly, uplink spectrum resources are usually under-utilized compared to the downlink in frequency division duplexing (FDD) based cellular systems [27]; secondly, co-channel interference caused by D2D UEs can be handled more easily by a powerful base station (BS) than CUs. We assume that each CU is allocated with an orthogonal channel (e.g., an orthogonal resource block in LTE), i.e., K active CUs occupy a total of K orthogonal channels and there is no co-channel interference among CUs. A pair of D2D transmitter and receiver that meet D2D communication requirements form a D2D pair, and are allowed to reuse at most one CU's channel for transmission. The scenario that each D2D pair reuses more than one channel is equivalent to a *one-to-many matching* problem, which is out of the scope of this paper and left to future works.

As a result, all of active D2D transmitters cause co-channel interference to the BS, and a CU causes co-channel interference to the D2D receiver that operates in the same channel. QoS requirements are imposed for both CUs and D2D pairs. In this paper, we assume that the D2D mode and peer selection process has already been finished, and we mainly focus on the resource allocation part. The joint optimization of mode selection, peer selection, and resource allocation is a completely new problem, which is out of the scope of this paper and will be treated in our future works. Regarding how to perform mode selection and peer selection, interested readers may refer to [7], [11], [46] and references therein for more details.

There are a total of N D2D pairs and K CUs. Throughout the paper, the index sets of active D2D pairs and CUs are denoted as $\mathcal{D} = \{d_1, \cdots, d_i, \cdots, d_N\}$, and $\mathcal{C}$ $=\{c_1, \cdots, c_k, \cdots, c_K\}$, respectively.

Definition 1. The partner selection matrix of D2D pairs is denoted as $\mathbf{X}_{N\times K}$, where the (i,k)-th element $x_{i,k} \in \{0,1\}$ indicates the selection decision of the D2D-CU partnership (d_i, c_k) for the D2D pair d_i, $\forall d_i \in \mathcal{D}$, $\forall c_k \in \mathcal{C}$. If $x_{i,k} = 1$, d_i prefers to forming a partnership with c_k, and if $x_{i,k} = 0$, otherwise.

Definition 2. The partner selection matrix of CUs is denoted as $\mathbf{Y}_{K\times N}$, where the (k,i)-th element $y_{k,i} \in \{0,1\}$ indicates the selection decision of the D2D-CU partnership (c_k, d_i) for the CU c_k, $\forall c_k \in \mathcal{C}$, $\forall d_i \in \mathcal{D}$. If $y_{k,i} = 1$, c_k prefers to forming a partnership with d_i, and if $y_{k,i} = 0$, otherwise.

Remark 1. Due to the individualized and differentiated preferences of d_i and c_k, it is very possible to have conflicting partner selection decisions, i.e., $x_{i,k} \neq y_{k,i}$. A D2D-CU partnership (d_i, c_k) can be formed if and only if $x_{i,k} = y_{k,i} = 1$.

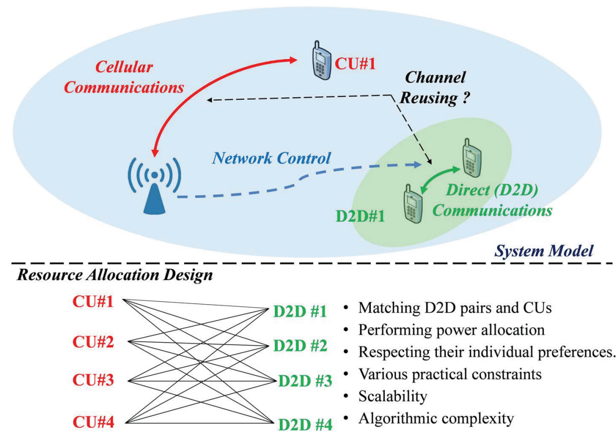


Fig. 1. Practical implementation and resource allocation design for D2D communications underlaying cellular networks with UE preferences.

Regarding channel models, both fast fading and slow fading which are caused by multi-path propagation, shadowing, and pathloss are taken into consideration [9]. The channel gain of the interference from c_k to d_i is given by

$$g_{k,i}^c = \varpi \beta_{k,i}^c \zeta_{k,i}^c d_{k,i}^{-\alpha}, \tag{1}$$

where ϖ is the pathloss constant, $\beta_{k,i}^c$ is the fast-fading gain with exponential distribution, $\zeta_{k,i}^c$ is the slow-fading gain with log-normal distribution, α is the pathloss exponent, and $d_{k,i}$ is the transmission distance. In a similar way, we can define the channel gain of d_i as g_i^d, the interference channel gain between the transmitter of d_i and the BS as $g_{i,B}^d$, and define the channel gain between c_k and the BS as $g_{k,B}^c$.

The achievable SE (defined as bits/s/Hz) of d_i is given by

$$U_i^d = \sum_{c_k \in \mathcal{C}} \log_2 \left(1 + \frac{x_{i,k} y_{k,i} p_i^d g_i^d}{N_0 + x_{i,k} y_{k,i} p_k^c g_{k,i}^c} \right), \tag{2}$$

where p_i^d and p_k^c represent the transmission power of d_i and c_k, respectively. N_0 is the noise power on each channel. The achievable SE of c_k is given by

$$U_k^c = \log_2 \left(1 + \frac{p_k^c g_{k,B}^c}{N_0 + \sum_{d_i \in \mathcal{D}} x_{i,k} y_{k,i} p_i^d g_{i,B}^d} \right). \tag{3}$$

The total power consumptions of d_i and c_k are given by

$$E_i^d = \sum_{c_k \in \mathcal{C}} \frac{1}{\eta} x_{i,k} y_{k,i} p_i^d + 2p_{cir}, \tag{4}$$

$$E_k^c = \frac{1}{\eta} p_k^c + p_{cir}. \tag{5}$$

p_{cir} is the total circuit power consumption which includes values of mixer, frequency synthesizer, digital-to-analog converter (DAC)/analog-to-digital converter (ADC), etc. η is the power amplifier (PA) efficiency, i.e., $0 < \eta < 1$. The power consumption of the BS is not considered because it is powered by external grid power.

B. Problem Formulation

Eventually better channel conditions and proper transmission power strategies can improve the EE performance more efficiently. Therefore, for any D2D pair or CU, the following questions need to be answered before reaching a decision:

- How to select a partner to form a D2D-CU channel-reusing pair for optimizing EE performance?
- How to perform power allocation for the expected D2D-CU pair?
- How to satisfy various practical resource allocation constraints such as maximum transmission power levels, QoS requirements, and channel-reusing rules, etc?
- How to avoid disruptions from other D2D pairs or CUs which also wish to be matched with the preferred D2D pair or CU?

The above questions indicate that the optimization of EE involves solving a *joint partner selection and power allocation problem*. To be more general, denoting $\mathbf{x_i} = \{x_{i,1}, \cdots, x_{i,k}, \cdots, x_{i,K}\}$ and $\mathbf{y_k} = \{y_{k,1}, \cdots, y_{k,i}, \cdots, y_{k,N}\}$ as d_i's and c_k's binary partner selection strategy sets, respectively, and denoting p_i^d and p_k^c as d_i's and c_k's continuous power allocation strategies, respectively, the objective function in terms of EE (bits/J/Hz) is defined as the SE (bits/s/Hz) divided by the total power consumption (W) [47]. The EE objective functions of d_i (including both the transmitter and receiver) and c_k are given by

$$U_{i,EE}^d(\mathbf{x_i}, p_i^d) = \frac{U_i^d(\mathbf{x_i}, p_i^d)}{E_i^d(\mathbf{x_i}, p_i^d)} = \frac{\sum_{c_k \in \mathcal{C}} \log_2\left(1 + \frac{x_{i,k} y_{k,i} p_i^d g_i^d}{N_0 + x_{i,k} y_{k,i} p_k^c g_{k,i}^c}\right)}{\sum_{c_k \in \mathcal{C}} \frac{1}{\eta} x_{i,k} y_{k,i} p_i^d + 2p_{cir}}, \quad (6)$$

$$U_{k,EE}^c(\mathbf{y_k}, p_k^c) = \frac{U_k^c(\mathbf{y_k}, p_k^c)}{E_k^c(p_k^c)} = \frac{\log_2\left(1 + \frac{p_k^c g_{k,B}^c}{N_0 + \sum_{d_i \in \mathcal{D}} x_{i,k} y_{k,i} p_i^d g_{i,B}^d}\right)}{\frac{1}{\eta} p_k^c + p_{cir}}. \quad (7)$$

The joint partner selection and power allocation problem for d_i can be formulated as

$$\begin{aligned} \max_{(\mathbf{x_i}, p_i^d)} \quad & U_{i,EE}^d(\mathbf{x_i}, p_i^d) \\ \text{s.t.} \quad & C_{i,1}^d : 0 \le p_i^d \le p_{i,max}^d, \\ & C_{i,2}^d : U_i^d(\mathbf{x_i}, p_i^d) \ge U_{i,min}^d, \\ & C_{i,3}^d : x_{i,k} = \{0,1\}, \forall c_k \in \mathcal{C}, \\ & C_{i,4}^d : \sum_{c_k \in \mathcal{C}} x_{i,k} \le 1. \end{aligned} \quad (8)$$

$C_{i,1}^d$ ensures that the power allocation of d_i should not exceed the maximum allowed transmission power $p_{i,max}^d$. $C_{i,2}^d$ specifies the QoS requirement which represents that the minimum SE should not fall below $U_{i,min}^d$. $C_{i,3}^d$ and $C_{i,4}^d$ are the channel-reusing constraints which make sure that at most one channel can be shared simultaneously by d_i and one existing CU.

The problem formulation for c_k is given by

$$\begin{aligned} \max_{(\mathbf{y_k}, p_k^c)} \quad & U_{k,EE}^c(\mathbf{y_k}, p_k^c) \\ \text{s.t.} \quad & C_{k,1}^c : 0 \le p_k^c \le p_{k,max}^c, \\ & C_{k,2}^c : U_k^c(\mathbf{y_k}, p_k^c) \ge U_{k,min}^c, \\ & C_{k,3}^c : y_{k,i} = \{0,1\}, \forall d_i \in \mathcal{D}, \\ & C_{k,4}^c : \sum_{d_i \in \mathcal{D}} y_{k,i} \le 1. \end{aligned} \quad (9)$$

$C_{k,1}^c$ and $C_{k,2}^c$ specify the transmission power and QoS constraints. $C_{k,3}^c$ and $C_{k,4}^c$ ensure that at most one D2D pair can share the same channel with c_k simultaneously.

Remark 2. By observing (8) and (9), we find that the partner selection problem is coupled with the power allocation problem. The formulation obtained is an NP-hard MINLP problem, which involves both binary and continuous variables for resource allocation optimization. Thus, the formulations obtained in neither (8) nor (9) cannot be solved directly by using either nonlinear fractional programming or integer programming. Furthermore, neither of the two programming approaches has taken UEs' preferences and satisfactions into consideration, which may lead to unstable and unsatisfied resource allocation decision.

To solve (8) and (9), we introduce a *one-to-one matching* model to match D2D pairs with CUs according to their mutual preferences. In this fashion, the original NP-hard MINLP problem can be decoupled into two separate subproblems and solved in a tractable manner. We use the triple $(\mathcal{C}, \mathcal{D}, \mathcal{P})$ to denote the formulated matching problem, i.e., $\mathcal{D}$, $\mathcal{C}$ represent the two finite and distinct sets of D2D pairs and CUs, respectively, and $\mathcal{P}$ is the set of mutual preferences. Both D2D pairs and CUs seek to form proper channel-reusing partnerships to maximize EE under constraints of QoS and transmission power. The definition of a matching μ is given by [35]:

Definition 3. For the matching problem $(\mathcal{C}, \mathcal{D}, \mathcal{P})$, μ is a point-by-point mapping from $\mathcal{C} \cup \mathcal{D}$ onto itself under preference $\mathcal{P}$. This is, for any $c_k \in \mathcal{C}$ and $d_i \in \mathcal{D}$, $\mu(c_k) \in \mathcal{D} \cup \{c_k\}$ and $\mu(d_i) \in \mathcal{C} \cup \{d_k\}$. $\mu(c_k) = d_i$ if and only if $\mu(d_i) = c_k$.

If $\mu(d_i) = d_i$ or $\mu(c_k) = c_k$, d_i or c_k stays single. Either d_i or c_k can send a request for forming a partnership with its preferred partner based on its preference (which is the partner selection subproblem), and demonstrate the allocated transmission power for the formed partnership (which is the power allocation subproblem). Both d_i and c_k are assumed to only care about their own matched partners and show little concerns to matching results of others. This assumption is valid because UEs are privately owned and operated by independent individuals.

III. ENERGY-EFFICIENT STABLE MATCHING FOR D2D COMMUNICATIONS

In this section, we introduce the proposed energy-efficient stable matching approach. First, we develop an iterative algorithm for preference establishment based on noncooperative game theory and nonlinear fractional programming in

Subsection III-A. Then, the derivation of the energy-efficient matching based on the GS algorithm is presented in Subsection III-B. Finally, in-depth discussions and theoretical analysis of matching stability, distributed/centralized implementation, and computational complexity are provided in Subsection III-C.

A. Preference Establishment

1) Noncooperative Game based Preference Modeling: The set of UEs' preferences $\mathcal{P}$ is necessary for developing the energy-efficient matching. We model d_i's preference over c_k as the maximum achievable EE under the matching $\mu(d_i) = c_k$ ($x_{i,k} = y_{k,i} = 1$). Thus, the partner selection decision of d_i has been already fixed, and only the power allocation strategy needs to be optimized. The formulated power allocation problem is given by

$$\begin{aligned} \max_{p_i^d} \quad & U_{i,EE}^d(p_i^d)\Big|_{\mu(d_i)=c_k} \\ \text{s.t.} \quad & C_{i,1}^d, C_{i,2}^d. \end{aligned} \tag{10}$$

The power allocation problem for c_k under the matching $\mu(c_k) = d_i$ is given by

$$\begin{aligned} \max_{p_k^c} \quad & U_{k,EE}^c(p_k^c)\Big|_{\mu(c_k)=d_i} \\ \text{s.t.} \quad & C_{k,1}^c, C_{k,2}^c. \end{aligned} \tag{11}$$

There are two challenges when solving the above optimization problems. First, from (6) and (7), $U_{i,EE}^d$ and $U_{k,EE}^c$ are inter-correlated through the interference terms, i.e., $p_k^c g_{k,i}^c$ and $p_i^d g_{i,B}^d$. Second, the problems formulated in (10) and (11) are still nonconvex due to the fractional form of $U_{i,EE}^d$ and $U_{k,EE}^c$.

In order to study the inter-connections between D2D pairs and CUs (to solve the first challenge), we adopt a game-theoretic approach to model the distributed power allocation problem as a noncooperative game $\mathcal{G}$. UEs are assumed as rational and selfish [48], i.e., each $d_i \in \mathcal{D}$ (or $c_k \in \mathcal{C}$) cares about its individual objective $U_{i,EE}^d$ (or $U_{k,EE}^c$), but is not otherwise concerned with $U_{j,EE}^d, \forall d_j \in \mathcal{D}\backslash\{d_i\}$ (or $U_{m,EE}^c, \forall c_m \in \mathcal{C}\backslash\{c_k\}$). The game $\mathcal{G}$ can be described as $\mathcal{G} = (\mathcal{C}, \mathcal{D}, \mathcal{A}, \mathcal{U})$, wherein $\mathcal{A} = \{A_1^d, \cdots, A_N^d, A_1^c, \cdots, A_K^d\}$ is the set of possible strategies that a UE can take, and $\mathcal{U} = \{U_{1,EE}^d, \cdots, U_{N,EE}^d, U_{1,EE}^c, \cdots, U_{K,EE}^c\}$ is the set of UEs' utilities. For example, if $A_i^d = \{[0, p_{i,max}^d]\}$, then d_i is allowed to select p_i^d from the interval $[0, p_{i,max}^d]$.

2) Objective Function Transformation: To overcome the second challenge, nonlinear fractional programming is employed to transform the nonconvex problem in the fractional form to equivalent convex ones. The optimum result of (10) is defined as

$$q_i^{d*} = \max_{p_i^d} U_{i,EE}^d(p_i^d)\Big|_{\mu(d_i)=c_k} = \frac{U_i^d(p_i^{d*})}{E_i^d(p_i^{d*})}, \tag{12}$$

where p_i^{d*} is the optimum power allocation strategy of d_i. Based on [44], we have

Theorem 1: q_i^{d*} is achieved if and only if

$$\max_{p_i^d} U_i^d(p_i^d) - q_i^{d*} E_i^d(p_i^d) = U_i^d(p_i^{d*}) - q_i^{d*} E_i^d(p_i^{d*}) = 0. \tag{13}$$

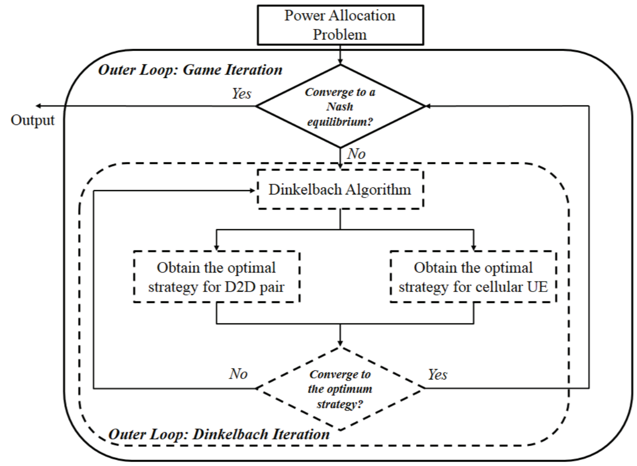


Fig. 2. The relationship between inner loop and outer loop iterations of the iterative power allocation algorithm.

Theorem 1 reveals that there exists an equivalent transformed problem with an objective function in subtractive form, which leads to the same maximum EE obtained by directly solving (10). The equivalent optimization problem in subtractive form is given by

$$\begin{aligned} \max_{p_i^d} \, & U_i^d(p_i^d) - q_i^{d*} E_i^d(p_i^d) \\ \text{s.t.} \quad & C_{i,1}^d, C_{i,2}^d. \end{aligned} \tag{14}$$

(14) is actually a multi-objective convex optimization problem where the variable q_i^{d*} can be regarded as a negative weight of E_i^d. In the same way, defining q_k^{c*} and p_k^{c*} as the optimum EE and the corresponding strategy of c_k, respectively, the transformed problem that is equivalent to (11) is given by

$$\begin{aligned} \max_{p_k^c} \, & U_k^c(p_k^c) - q_k^{c*} E_k^c(p_k^c) \\ \text{s.t.} \quad & C_{k,1}^c, C_{k,2}^c. \end{aligned} \tag{15}$$

3) Distributed Iterative Power Allocation: Both (14) and (15) are standard convex optimization problems and can be solved efficiently. However, the specific values of q_i^{d*} and q_k^{c*} are required to solve (14) and (15), respectively. In order to obtain q_i^{d*} and q_k^{c*}, an iterative algorithm is developed based on Dinkelbach's method and is given in Algorithm 1 [44]. The iterative Algorithm 1 consists of two loops: the outer loop with the iteration index l represents iterations of the noncooperative game, and the inner loop with the iteration index n represents iterations of Dinkelbach's algorithm. The relationship between inner loop and outer loop iterations is shown in Fig. 2. For each round of the game, the inner loop is executed to find the corresponding optimum power allocation strategy for each player, which stops if either the iteration stopping criteria or the maximum loop number N_{max} is reached. The game iteration continues until the achieved power allocation strategy converges to a Nash equilibrium, i.e., none player is capable of unilaterally achieving better performance by deviating from it.

Algorithm 1 Distributed Iterative Power Allocation Algorithm for Obtaining q_i^{d*} and q_k^{c*}

Input: g_i^d, $\hat{p}_i^d g_{i,B}^d$, $g_{k,B}^c$, $\hat{p}_k^c g_{k,i}^c$, $p_{i,max}^d$, $p_{k,max}^d$, $C_{i,min}^d$, $C_{k,min}^c$.
Output: q_i^{d*}, q_k^{c*}, p_i^{d*}, p_k^{c*}.
Initialize: q_i^d, q_k^c, N_{max}, Δ_g, Δ_d, Δ_c, $\hat{p}_k^c$, $\hat{p}_i^d$
while $\mid \mathbf{q}_i^{d*}(l) - \mathbf{q}_i^{d*}(l-1) \mid \leq \Delta_g$,
  & $\mid \mathbf{q}_k^{c*}(l) - \mathbf{q}_k^{c*}(l-1) \mid \leq \Delta_g$ **do**
  while $n < N_{max}$ **do**
    obtain $\hat{p}_i^d(n)$ using (20)
    if $U_i^d[\hat{p}_i^d(n)] - q_i^d(n) E_i^d[\hat{p}_i^d(n)] > \Delta_d$ **then**
      Update: $q_i^d(n+1) = U_i^d[\hat{p}_i^d(n)] / E_i^d[\hat{p}_i^d(n)]$
    else
      $p_i^{d*} = \hat{p}_i^d(n)$, and $q_i^{d*} = U_i^d(p_i^{d*}) / E_i^d(p_i^{d*})$
    end if
    obtain $\hat{p}_k^c(n)$ using (23)
    if $U_k^c[\hat{p}_k^c(n)] - q_k^c(n) E_k^c[\hat{p}_k^c(n)] > \Delta_c$ **then**
      Update: $q_k^c(n+1) = U_k^c[\hat{p}_k^c(n)] / E_k^c[\hat{p}_k^c(n)]$
    else
      $p_k^{c*} = \hat{p}_k^c(n)$, and $q_k^{c*} = U_k^c(p_k^{c*}) / E_k^c(p_k^{c*})$
    end if
    Update the Dinkelbach iteration index: $n \to n+1$
  end while
  Update: $\mathbf{q}_i^d(l) = q_i^{d*}$, $\mathbf{q}_k^{c*}(l) = q_k^{c*}$
  Update the game iteration index : $l \to l+1$
end while

At the n-th iteration of the l-th round game, $p_i^d(n)$ and $p_k^c(n)$ are obtained by solving the following problems with $q_i^d(n)$ and $q_k^c(n)$ obtained from the $(n-1)$-th iteration:

$$\begin{aligned} &\max_{p_i^d} U_i^d[p_i^d(n)] - q_i^d(n) E_i^d[p_i^d(n)] \\ &\text{s.t.} \qquad C_{i,1}^d, C_{i,2}^d. \end{aligned} \tag{16}$$

$$\begin{aligned} &\max_{p_k^c} U_k^c[p_k^c(n)] - q_k^c(n) E_k^c[p_k^c(n)] \\ &\text{s.t.} \qquad C_{k,1}^c, C_{k,2}^c. \end{aligned} \tag{17}$$

The augmented Lagrangian of (16) is given by

$$\begin{aligned} &\mathcal{L}_i^{EE}(p_i^d, \delta_i^d, \theta_i^d) = U_i^d[p_i^d(n)] - q_i^d(n) E_i^d[p_i^d(n)] \\ &-\delta_i^d(n)[p_i^d(n) - p_{i,max}^d] + \theta_i^d(n)\left(U_i^d[p_i^d(n)] - U_{i,min}^d\right), \end{aligned} \tag{18}$$

where δ_i^d and θ_i^d are the Lagrange multipliers for constraints $C_{i,1}^d$ and $C_{i,2}^d$, respectively. By using Lagrange dual decomposition, (18) is decomposed as [45]

$$\min_{(\delta_i^d, \theta_i^d \geq 0)} \max_{(p_i^d)} \mathcal{L}_i^{EE}(p_i^d, \delta_i^d, \theta_i^d). \tag{19}$$

By exploiting Karush-Kuhn-Tucker (KKT) conditions, the optimal value $\hat{p}_i^d(n)$ corresponding to $q_i^d(n)$ is given by

$$\hat{p}_i^d(n) = \left[\frac{\eta[1+\theta_i^d(n)]\log_2 e}{q_i^d(n) + \eta\delta_i^d(n)} - \frac{\hat{p}_k^c g_{k,i}^c(n) + N_0}{g_i^d}\right]^+, \tag{20}$$

Algorithm 2 Iterative Preference Establishment Algorithm for Obtaining $\mathcal{P}$

Input: the set of CUs and D2D pairs, $\mathcal{C}$, $\mathcal{D}$.
Output: the set of preference profiles $\mathcal{P}$.
for $d_i \in \mathcal{D}$ **do**
  for $c_k \in \mathcal{C}$ **do**
    calculate maximum achievable $q_i^{d*}\Big|_{\mu(d_i)=c_k}$ and $q_k^{c*}\Big|_{\mu(c_k)=d_i}$ for the D2D-CU pair (d_i, c_k) by employing Algorithm 1.
  end for
end for
for $d_i \in \mathcal{D}$ **do**
  sort all of CUs $c_k \in \mathcal{C}$ in a descending order according to $q_i^{d*}\Big|_{\mu(d_i)=c_k}$.
end for
for $c_k \in \mathcal{C}$ **do**
  sort all of D2D pairs $d_i \in \mathcal{D}$ in a descending order according to $q_k^{c*}\Big|_{\mu(c_k)=d_i}$.
end for

where $[x]^+ = \max\{0, x\}$. Then, by employing the gradient method [49], we update the Lagrange multipliers as

$$\delta_i^d(n, \tau+1) = \left[\delta_i^d(n,\tau) + \epsilon_{i,\delta}(n,\tau)\left(\hat{p}_i^d(n,\tau) - p_{i,max}^d\right)\right]^+, \tag{21}$$

$$\theta_i^d(n, \tau+1) = \left[\theta_i^d(n,\tau) - \epsilon_{i,\theta}(n,\tau)\left(U_i^d(n,\tau) - U_{i,min}^d\right)\right]^+, \tag{22}$$

where τ is the iteration index of Lagrange multiplier updating, $\epsilon_{i,\delta}$ and $\epsilon_{i,\theta}$ are the step sizes. The step sizes should be carefully chosen to guarantee convergence and optimality.

Then, $\hat{p}_i^d(n)$ obtained in (20) is used to update $q_i^d(n+1)$ for the $(n+1)$-th iteration as $q_i^d(n+1) = U_i^d[\hat{p}_i^d(n)] / E_i^d[\hat{p}_i^d(n)]$. In the final iteration of the inner loop, setting $p_i^{d*} = \hat{p}_i^d$, q_i^{d*} can be obtained by using (12) and saved as the l-th element of the vector $\mathbf{q}_i^d$, i.e., $\mathbf{q}_i^d(l) = q_i^{d*}$. The optimization problem (17) is solved in the same way. The optimal value $\hat{p}_k^c(n)$ corresponds to $q_k^c(n)$ is given by

$$\hat{p}_k^c(n) = \left[\frac{\eta[1+\xi_k^c(n)]\log_2 e}{q_k^c(n) + \eta\rho_k^c(n)} - \frac{\hat{p}_i^d(n) g_{i,B}^d + N_0}{g_{k,B}^c}\right]^+. \tag{23}$$

Details for how to obtain q_k^{c*} are omitted due to space restrictions. The outer loop stops if the maximum EE (q_i^{d*}, q_k^{c*}) obtained in the l-th round of the game varies little from the optimization result achieved in the previous round, where the corresponding optimum strategy set (p_i^{d*}, p_k^{c*}) has converged to a Nash equilibrium.

4) Preference Profile Establishment: Algorithm 2 presents how to establish the set of preference profiles $\mathcal{P}$. For every $d_i \in \mathcal{D}$, the maximum achievable q_i^{d*} under the matching $\mu(d_i) = c_k, \forall c_k \in \mathcal{C}$, is denoted as $q_i^{d*}\Big|_{\mu(d_i)=c_k}$, and can be obtained by using Algorithm 1. We write $c_k \succ_{d_i} c_m$ to mean d_i prefers c_k to c_m, which is defined as

$$c_k \succ_{d_i} c_m \Leftrightarrow q_i^{d*}\Big|_{\mu(d_i)=c_k} > q_i^{d*}\Big|_{\mu(d_i)=c_m}, \tag{24}$$

where $\succ$ is a complete, reflexive, and transitive binary preference relation [35]. In addition, we write $c_k \succeq_{d_i} c_m$ to mean d_i likes c_k at least as well as c_m, which is defined as

$$c_k \succeq_{d_i} c_m \Leftrightarrow q_i^{d*}\Big|_{\mu(d_i)=c_k} \geq q_i^{d*}\Big|_{\mu(d_i)=c_m}. \quad (25)$$

Similarly, we write $d_i \succ_{c_k} d_j$ to mean c_k prefers d_i to d_j, which is defined as

$$d_i \succ_{c_k} d_j \Leftrightarrow q_k^{c*}\Big|_{\mu(c_k)=d_i} > q_k^{c*}\Big|_{\mu(c_k)=d_j}. \quad (26)$$

After obtaining $q_i^{d*}\Big|_{\mu(d_i)=c_k}$, $\forall c_k \in \mathcal{C}$, the preference profile $P(d_i) = \{\cdots, c_k, c_m \cdots\}$ is obtained by sorting all of CUs in a descending order according to the criteria of $q_i^{d*}\Big|_{\mu(d_i)=c_k}$, $\forall c_k \in \mathcal{C}$. The preference profile of c_k is denoted as $P(c_k)$, which is obtained by sorting all of available D2D pairs according to $q_k^{c*}\Big|_{\mu(c_k)=d_i}$, $\forall d_i \in \mathcal{D}$. The total set $\mathcal{P}$ is constructed as $\mathcal{P} = \{P(d_1), \cdots, P(d_N), P(c_1), \cdots, P(c_K)\}$.

B. Energy-Efficient Stable Matching

After obtaining $P(d_i)$ and $P(c_k)$ for each $d_i \in \mathcal{D}$ and $c_k \in \mathcal{C}$, we propose Algorithm 3 to match D2D pairs with CUs by employing the GS algorithm [34]. In the first iteration, every $d_i \in \mathcal{D}$ sends a partner request to its most preferred CU $\max\{q_i^{d*}\Big|_{\mu(d_i)=c_k}, \forall c_k \in \mathcal{C}\}$. Then, every $c_k \in \mathcal{C}$ receives the request and rejects the D2D pair if it already holds a better candidate. Any $d_i \in \mathcal{D}$ that is not rejected by the CUs at this step is held as a candidate. In the next step, any $d_i \in \mathcal{D}$ that has been already rejected sends a new request to its most preferred choice from the set of CUs that have not yet issued a rejection. If a D2D pair is rejected by all of its preferred CUs, it will give up and send no further request. Each $c_k \in \mathcal{C}$ compares all of the received requests including the candidate that was held from previous steps and only accepts the most preferred D2D pair. The request sending and rejection process finishes when every $d_i \in \mathcal{D}$ has already found a partner or has been rejected by all of CUs to which it has sent requests. Algorithm 3 has the property of *deferred acceptance* due to the fact that the best candidate kept at any step can be rejected later on if a better candidate appears.

C. Discussion and Analysis

In this subsection, we provide an in-depth theoretical analysis for the proposed energy-efficient matching algorithm.

1) Nash Equilibrium Analysis: ***Theorem 2:*** Under the matching $\mu(d_i) = c_k$, $\forall i \in \mathcal{N}, \forall k \in \mathcal{K}$, the power allocation strategy set (p_i^{d*}, p_k^{c*}) obtained by the iterative algorithm constitutes a Nash equilibrium, which exists but is not unique. Furthermore, none individual UE is able to unilaterally get better performance by deviating from the Nash equilibrium.

Proof: Please see Appendix A. ■

Algorithm 3 Energy-Efficient Stable Matching Algorithm

Input: $\mathcal{C}, \mathcal{D}, \mathcal{P}$.
Output: μ.
Initialize: $\mu = \phi$, $\Phi = \mathcal{D}$.
while $\Phi \neq \phi$ **do**
  for $d_i \in \Phi$ **do**
    d_i chooses the CU with the highest ranking from $P(d_i)$.
  end for
  for $c_k \in \mathcal{C}$ **do**
    if c_k receives a request from d_i, and prefers d_i to its current candidate d_j held from previous steps, i.e., $d_i \succ_{c_k} d_j$ **then**
      d_i is held as a new candidate, while c_k issues a rejection to d_j, i.e., $\mu(c_k) = d_i$;
      add d_j into Φ, remove d_i from Φ, and remove c_k from $P(d_j)$.
    else
      c_k issues a rejection to d_i, and holds d_j continually as its candidate, i.e., $\mu(c_k) = d_j$.
      remove c_k from $P(d_i)$.
    end if
  end for
end while

2) Stability and Optimality: The stability and optimality properties can be easily proved due to the structures of the GS algorithm. A short version of proofs are provided here for reference and more details can be found in [35], [50].

Assuming that d_i and c_k are not matched with each other under μ, i.e., $\mu(d_i) \neq c_k$ and $\mu(c_k) \neq d_i$, (d_i, c_k) can form a blocking pair that *blocks* μ if $d_i \succ_{c_k} \mu(c_k)$, and $c_k \succ_{d_i} \mu(d_i)$. μ is said to be *unstable* if there exists a blocking pair [35].

Theorem 3: The proposed energy-efficient matching μ is stable for every $d_i \in \mathcal{D}$ and $c_k \in \mathcal{C}$.

Proof: Please see Appendix B.

Theorem 4: For every $d_i \in \mathcal{D}$ and $c_k \in \mathcal{C}$ under $\mu(d_i) = c_k$, $\hat{q}_i^d\Big|_{\mu(d_i)=c_k}$ and $\hat{q}_k^c\Big|_{\mu(d_i)=c_k}$ obtained by Algorithm 1 converges to unique $q_i^{d*}\Big|_{\mu(d_i)=c_k}$ and $q_k^{c*}\Big|_{\mu(d_i)=c_k}$ in finite iterations, respectively [44], [49].

Theorem 5: The obtained energy-efficient stable matching μ is weak Pareto optimal for every $d_i \in \mathcal{D}$.

Proof: Please see Appendix C.

3) Scalability: Implementing the proposed algorithm in cellular networks with a large number of UEs will encounter scalability problems. For example, it becomes difficult to have channel state information (CSI) of every link due to limited processing capability, increasing signalling overhead, and strict QoS requirement, etc. If d_i and c_k only have limited information about each other, Algorithm 1 is not be able to produce $q_i^{d*}\Big|_{\mu(d_i)=c_k}$ and $q_k^{c*}\Big|_{\mu(c_k)=d_i}$, which leads to the matching problem under *incomplete preference lists*. To address such challenges, we modify Algorithm 3 to handle this problem by deleting d_i and c_k from $P(c_k)$ and $P(d_i)$, respectively, if they cannot be involved in a stable matching.

$P(d_i)$ and $P(c_k)$ are *consistent* if deleting c_k from $P(d_i)$ represents that d_i is also removed from $P(c_k)$ [36]. For every $d_i \in \mathcal{D}$ and $c_k \in \mathcal{C}$, $P(d_i)$ and $P(c_k)$ are assumed to be consistent. With consistent preference profiles, the modified algorithm is able to proceed in the same fashion as Algorithm 3 and obtain a matching in polynomial time. The new matching may be partial stable due to the fact that some UEs that are deleted from preference profiles may be left unmatched.

Another frequent scalability problem is that some D2D pair or CU may have more than one best potential matching partners, e.g., a *tie* exists such that $q_i^{d*}\Big|_{\mu(d_i)=c_k} = q_i^{d*}\Big|_{\mu(d_i)=c_m}$. To break the tie, we propose some *tie-breaking* rules to force d_i to choose between c_k and c_m at any step by comparing new criteria such as the optimum SE U_i^d, or the total power consumption E_i^d. The modified algorithm can handle situations such as $q_i^{d*}\Big|_{\mu(d_i)=c_k} = q_i^{d*}\Big|_{\mu(d_i)=c_m}$ and $q_k^{c*}\Big|_{\mu(c_k)=d_i} = q_k^{c*}\Big|_{\mu(c_k)=d_j}$, $\forall d_i, d_j \in \mathcal{D}$, $\forall c_k, c_m \in \mathcal{C}$, etc. In the following, we assumes that any $c_k \in \mathcal{C}$ does not care which D2D pair would reuse its spectrum, that is, $q_k^{c*}\Big|_{\mu(c_k)=d_i} = q_k^{c*}\Big|_{\mu(c_k)=d_j, \forall d_j \neq d_i}$. This scenario can be considered as a special case of the preference tie scenario, where any potential matching partner is the best candidate. In this case, some tie-breaking rules such as "first come first serve" can be proposed to force CUs to make a decision at any step based on the new criteria. Furthermore, the time-breaking rules can be flexibly designed not only to optimize EE or SE, but also to improve miscellaneous performance metrics including reliability, security, fairness, and coverage, etc.

4) Implementation: In the distributed resource allocation algorithm, each D2D pair only needs to estimate the received interference rather than knowing the specific power allocation or partner selection strategies of interferers. The reason is that the sufficient information of strategies are contained in the form of interference. CUs also need to know the knowledge of interference, which can be estimated firstly by centralized powerful BSs and then fed back to CUs. Although the energy-efficient matching is designed in a distributed way, it is also suitable for centralized implementation to comply with the centralized architecture of existing cellular networks. A BS equipped with advanced signal processing and computation capability can operate as a matchmaker to organize the matching $(\mathcal{C}, \mathcal{D}, \mathcal{P})$. The details are given as follows.

First, the BS sends requests to every $d_i \in \mathcal{D}$ and $c_k \in \mathcal{C}$ to obtain required information for building preference profiles $P(d_i)$ and $P(c_k)$. CSI of some links such as $g_{k,B}^c, \forall c_k \in \mathcal{C}$, can be directly obtained by performing channel estimation in the BS using pilot signals. CSI of D2D links such as g_i^d has to be estimated by D2D receivers and then is fed back to the BS. CSI of interference links such as $g_{i,B}^d$ and $g_{k,i}^d, \forall d_i \in \mathcal{D}, \forall c_k \in \mathcal{C}$ is not required. After collecting enough information, the BS establishes the preference profile $P(d_i)$ for each $d_i \in \mathcal{D}$ and $P(c_k)$ for each $c_k \in \mathcal{C}$ based on Algorithm 2. Then Algorithm 3 is employed (with D2D pairs sending requests to CUs) to produce μ under the established preference profiles.

The advantages of centralized implementation can be fully exploited by future cloud radio access network (C-RAN) based mobile communication systems [51]. Preference establishment and D2D-CU matching can be realized by the powerful base band unit (BBU) pool which exploits cell cooperation and coordination among densely distributed remote radio heads (RRHs).

TABLE I
SIMULATION PARAMETERS.

Simulation Parameter	**Value**
Cell radius	500 m
Max D2D transmission distance d_{max}^d	$20 \sim 100$ m
Pathloss exponent α	4
Pathloss constant ϖ	10^{-2}
Shadowing $\zeta_{k,i}^c$ (standard deviation of a log-normal distribution)	8 dB
Multi-path fading $\beta_{i,k}^c$ (the mean of an exponential distribution)	1
Max Tx power $p_{i,max}^d, p_{k,max}^c$	23 dBm
Constant circuit power p_{cir}	20 dBm
Noise power N_0	-114 dBm
Number of D2D pairs N	$5 \sim 50$
Number of cellular UEs K	$5 \sim 50$
PA efficiency η	35%
QoS requirement $C_{k,min}^c$, $C_{i,min}^d$ (uniform distribution)	$0.5 \sim 1$ bit/s/Hz

5) Complexity: For a pair of (d_i, c_k), the computational complexity for establishing $P(d_i)$ and $P(c_k)$ mainly depends on Algorithm 1. q_i^d and q_k^c produced by Algorithm 1 increases at each iteration and converges to q_i^{d*} and q_k^{c*} at a super-linear rate [49]. With N D2D pairs and K CUs, the computational complexity of Algorithm 1 is $\mathcal{O}(NKL_{loop}L_{dual})$, where L_{loop} and L_{dual} are the numbers of iterations required for converging to the optimum EE and optimal power allocation strategies, respectively. In Algorithm 2, sorting N D2D pairs and K CUs in a descending order leads to a complexity of $\mathcal{O}\big(NK\log(NK)\big)$. In Algorithm 3, under the rule that every $d_i \in \mathcal{D}$ has only one chance to send requests to CUs in $P(d_i)$, the matching μ can be obtained with a complexity of $\mathcal{O}(KN)$ [36].

IV. NUMERICAL RESULTS

In this section, the proposed energy-efficient matching algorithm, labeled as "energy-efficient stable matching", is compared with several heuristic algorithms. The first is the power greedy algorithm, which always allocates the maximum transmission power $p_{i,max}^d$ (or $p_{k,max}^c$). The second is the random power allocation algorithm, which allocates power uniformly distributed in the range $[0, p_{i,max}^d]$ (or $[0, p_{k,max}^c]$). The third is the spectrum-efficient algorithm based on the water-filling power allocation (SINR maximization) [32], [52], [53]. The first two heuristic algorithms employ random matching which matches D2D pairs with CUs in a random way, while the third one adopts maximum-SINR based association. The values of simulation parameters are based on [9], [23], [32], and are summarized in Table I. A single cellular network is considered and the cell radius is 500 m. In each time of simulation, locations of CUs and D2D pairs are generated in a random way as shown in Fig. 3. QoS requirements in terms

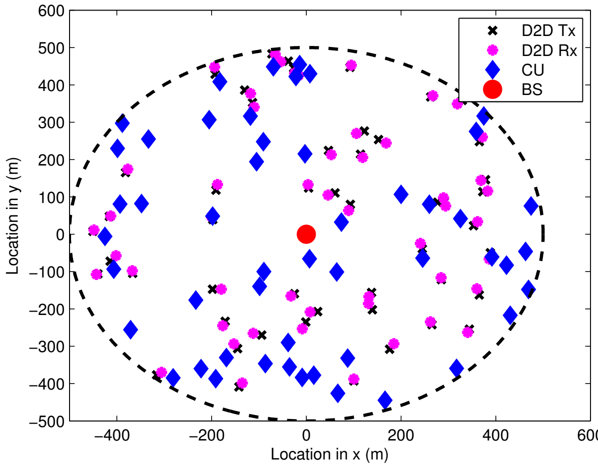


Fig. 3. A snapshot of locations of K CUs and N D2D pairs in a single cellular network ($K = N = 50$, the cell radius is 500 m).

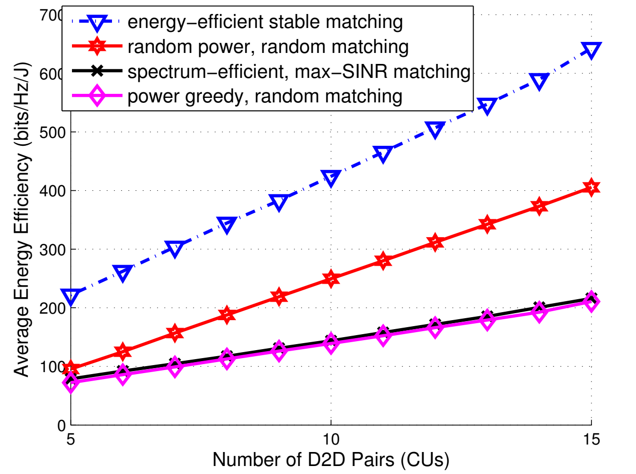


Fig. 5. Average EE of D2D pairs versus numbers of active D2D pairs and CUs ($d^d_{max} = 20$ m, $K = N = 5 \sim 15$).

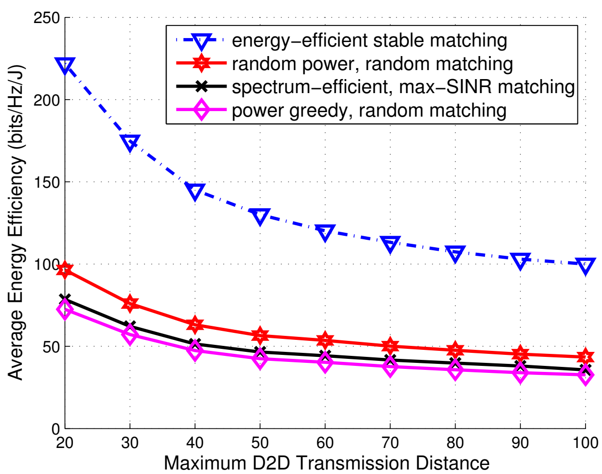


Fig. 4. Average EE of D2D pairs versus maximum D2D transmission distance ($K = N = 5$, $d^d_{max} = 20 \sim 100$ m).

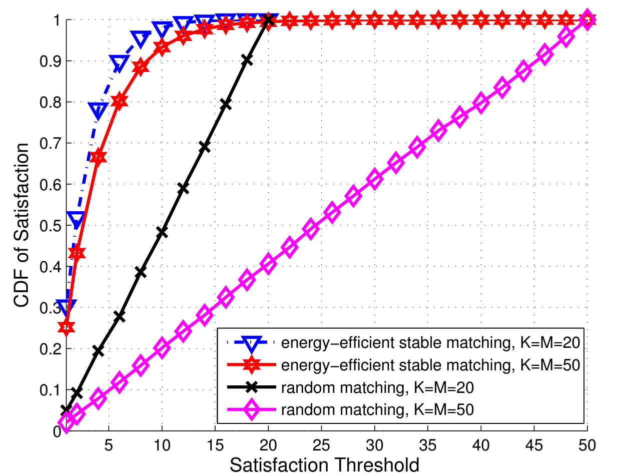


Fig. 6. CDF of D2D pairs' satisfactions versus satisfaction threshold ($N = K = 20, 50$, $d^d_{max} = 20$ m).

of SE are generated randomly from a uniform distribution in the range $[0.5, 1]$ bit/s/Hz. We average the simulation results over 10^3 times.

The average EE performance and UE satisfactions of the obtained energy-efficient stable matching is evaluated and verified. We adopt a statistical model to define a UE's satisfaction as the cumulative distribution functions (CDFs) of the matching result that is higher than its satisfaction threshold. For example, defining d_i's satisfaction threshold as c_m, the matching result $\mu(d_i)$ is compared with the threshold c_m to evaluate whether d_i is satisfied with $\mu(d_i)$. d_i is said to be satisfied with $\mu(d_i)$ if d_i prefers $\mu(d_i)$ at least as well as c_m, i.e., $\mu(d_i) \succeq_{d_i} c_m$. Otherwise, d_i is said to be unsatisfied with $\mu(d_i)$ if it is matched to a partner that is less preferred to the threshold, i.e., $c_m \succ_{d_i} \mu(d_i)$. The CDF is denoted as $Pr\{\mu(d_i) \succeq_{d_i} c_m\}$, which is the probability that d_i is matched with a partner that is more preferred to the threshold c_m.

Fig. 4 shows the average EE performance of D2D pairs versus the maximum D2D transmission distance d^d_{max} with $K = 5$ CUs and $N = 5$ D2D pairs. Simulation results demonstrate that the proposed algorithm achieves the best EE performance in the whole regime. The proposed algorithm outperforms the random power allocation algorithm, the power greedy algorithm, and the spectrum-efficient algorithm by 132%, 206%, and 248% for $d^d_{max} = 20$ m, respectively. Random allocation achieves the second best performance since there is a large probability to have a higher EE than the spectrum-efficient and power greedy algorithms which always take full advantage of any available power. It is clear that the SE gain achieved by increasing transmission power is not able to compensate for the corresponding EE loss. The power greedy algorithm has the worst EE performance among the four due to two reasons. First, power consumption is completely ignored in the resource allocation process. Second,

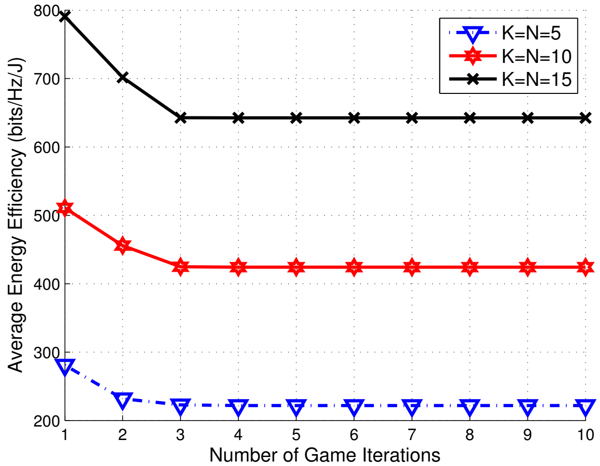


Fig. 7. Average EE versus the number of game iterations ($d^d_{max} = 20$ m, $K = N = 5, 10, 15$).

increasing transmission power beyond the point for optimum SE not only brings no SE improvement in an interference-limited environment but also causes significant EE loss. Note that, as the D2D transmission distance increases, the EE performance of all algorithms decreases because higher transmission power is required to maintain the same QoS performance than in the scenario of short distance.

Fig. 5 shows the average EE performance of D2D pairs versus the number of active CUs K and D2D pairs N with $d^d_{max} = 20$ m. The average EE performance of all algorithms increases linearly as the active number of CUs and D2D pairs increases. The reason is that as the number of CUs increases, not only the total number of available orthogonal channels increases, but also each D2D pair has a wider variety of choice in the expanded matching market than in the original one. The probability for a D2D pair to be matched with a better partner becomes higher in the expanded matching market. The proposed algorithm has the steepest slope among the four, which indicates that it can exploit more benefits from the diversity of choices than the heuristic algorithms could. Both the spectrum-efficient and the power greedy algorithms have the flattest slope since the value of choice diversity is not fully exploited and power consumption is also ignored in the resource allocation process.

Fig. 6 shows the CDF of D2D pairs' satisfactions versus various satisfaction thresholds with $K = N = 20, 50$ and $d^d_{max} = 20$ m. We adopt the Monte-Carlo method to calculate the CDF that uses repeated matching results (10^4 times) to obtain the numerical results. In the case of $K = N = 20$, the probability of being matched to the first three choices for D2D pairs is 66.4%. In contrast, the corresponding probability under random matching is only 15.4%. When the number of D2D pairs and CUs is increased from 20 to 50, there is still as high as 56.9% of D2D pairs that have been matched to the first three choices, while the corresponding probability under random matching is decreased dramatically from 15.4% to only 6.4%. Significant UE satisfaction gains can be achieved by the proposed algorithm compared to the random matching. In addition, the simulation results also reveal the fact that the proposed algorithm is able to outperform the random matching for a wide range of satisfaction values.

Fig. 7 shows the convergence of the iterative algorithm (Algorithm 1) versus the number of game iterations. It is shown that the proposed algorithm only requires $3 \sim 4$ iterations to converge to the equilibrium. In the first game iteration, higher EE performance can be achieved because CUs are not aware of the D2D pairs and transmit in lower power levels. With the entry of D2D pairs into the game, CUs have to increase their transmission power to satisfy QoS requirements, which in turn causes co-channel interference to D2D pairs and reduce their achievable EE performance until they reach a Nash equilibrium.

V. Conclusions and Future Work

In this paper, an energy-efficient stable matching algorithm was proposed for the resource allocation problem in D2D communications. Taking into account UEs' preferences and satisfactions, the joint partner selection and power allocation problem was formulated to maximize the achievable EE under maximum transmission power and QoS constraints. The resulting problem is nonconvex and computationally intractable. Inspired by the matching theory and game theory, the NP-hard problem was transformed into a one-to-one matching problem with UEs' preferences modeled as the optimum EE under a specific matching. A noncooperative game based iterative algorithm was proposed to establish mutual preferences by exploiting nonlinear fractional programming. The proposed matching algorithm was proved to be stable and weak Pareto optimal. Extensive simulation results validate the effectiveness and superiority of the proposed algorithm. The present matching approach sheds new light on the research directions for resource allocation problems in green D2D communications. Potential future works include the extension of one-to-many matching, the modeling of UE preference from a big-data perspective, and the consideration of context-aware content caching, etc.

Appendix A
Proof of Theorem 2

Proof: First, if the strategy p^{d*}_i obtained by the iterative algorithm is not the Nash equilibrium, the D2D transmitter can choose the Nash equilibrium $\hat{p}^d_i$ to obtain the maximum EE $q^{d*}_{i_m}$. However, by Theorem 1 and Theorem 4, q^{d*}_i can also be achieved by choosing p^{d*}_i, and q^{d*}_i is unique. As a result, p^{d*}_i is also part of a Nash equilibrium. A similar proof holds for p^{d*}_k.

Second, according to [48], a Nash equilibrium exists if the utility function is continuous and quasiconcave, and the set of strategies is a nonempty compact convex subset of a Euclidean space. Taking the EE objection function defined in (6) as an example, under the matching $\mu(d_i) = c_k$, the numerator U^d_i defined in (2) is a concave function of p^d_i, $\forall i \in \mathcal{N}$. The denominator defined in (4) is an affine function of p^d_i. Therefore, $U^d_{i,EE}$ is quasiconcave (Problem 4.7 in [45]).

The set of the strategies $\{[0, p^d_{i,max}]\}$ is a nonempty compact convex subset of the Euclidean space. Similarly, it is easily proved that the above conditions also hold for the cellular UE. Therefore, a Nash equilibrium exists in the noncooperative game.

Third, there may be multiple equilibria that satisfy the optimality condition. This conclusion can be directly drawn from the properties of nonlinear fractional programming as shown in page 4 of [44], which shows that the solutions p_i^{d*} of the equation $U_i^d(p_i^{d*}) - q_i^{d*} E_i^d(p_i^{d*}) = 0$, and p_k^{c*} of the equation $U_k^c(p_k^{c*}) - q_k^{c*} E_k^c(p_k^{c*}) = 0$ may not be unique. Therefore, if there exists multiple solutions, the combination of these solutions may generate multiple Nash equilibria. However, despite that there may be multiple equilibria, the maximum EE obtained by the iterative algorithm is unique. The proof is similar to the proof of Lemma 4 in [44], which proves that the optimum result obtained by nonlinear fractional programming is unique.

Finally, given a Nash equilibrium $\{p_i^{d*}, p_k^{c*}\}$, the corresponding EE $\{q_i^{d*}, q_k^{c*}\}$ produced by Algorithm 1 is unique according to Theorem 1 and Theorem 4. If d_i chooses $\tilde{p}_i^d$ rather than p_i^{d*} ($\tilde{p}_i^d \neq p_i^{d*}$) as its transmission strategy, the corresponding CU c_k will also choose $\tilde{p}_k^c$ rather than p_k^{c*} ($\tilde{p}_k^c \neq p_k^{c*}$) to improve its individual EE. The iteration process in Algorithm 1 will continue until the strategy set $\{\tilde{p}_i^d, \tilde{p}_k^c\}$ converges to a new Nash equilibrium, and the corresponding EE is denoted as $\{\tilde{q}_i^d, \tilde{q}_k^c\}$. Then, we must have $\tilde{q}_i^d = q_i^{d*}$, and $\tilde{q}_k^c = q_k^{c*}$, which otherwise contradicts with Theorem 1 and Theorem 4. Therefore, this proves that either d_i or c_k is able to unilaterally achieve better performance by deviating from the Nash equilibrium. This completes the proof.

APPENDIX B
Proof of Theorem 3

Proof: For any $d_i \in \mathcal{D}$ and any $c_k \in \mathcal{C}$ that are not matched with each other, μ is stable if (d_i, c_k) do not form a blocking pair, i.e., $d_i \succ_{c_k} \mu(c_k)$, $c_k \succ_{d_i} \mu(d_i)$. We prove the theorem by showing that the two necessary conditions $d_i \succ_{c_k} \mu(c_k)$ and $c_k \succ_{d_i} \mu(d_i)$ cannot hold at the same time.

Let us begin from the assumption that $c_k \succ_{d_i} \mu(d_i)$, then a request must have already been sent by d_i to $\mu(d_i)$ based on the defined matching rules. With the matching result $\mu(d_i) \neq c_k$, it means that d_i is less preferred by c_k compared to $\mu(c_k)$, i.e., $\mu(c_k) \succ_{c_k} d_i$. Thus, although c_k is more preferred by d_i than $\mu(d_i)$, c_k has no incentive to be matched with d_i, i.e., the condition $d_i \succ_{c_k} \mu(c_k)$ does not hold. The same proving process can be repeated with minor revision to show that the condition $c_k \succ_{d_i} \mu(d_i)$ does not hold if $d_i \succ_{c_k} \mu(c_k)$. As a result, d_i and c_k do not form a blocking pair for μ since $d_i \succ_{c_k} \mu(c_k)$ and $c_k \succ_{d_i} \mu(d_i)$ cannot hold at the same time, which proves that μ is stable.

APPENDIX C
Proof of Theorem 5

Proof: $\forall d_i \in \mathcal{D}$, we assume that there is a better matching $\mu^{'}$ such that $\mu^{'}(d_i) \succ_{d_i} \mu(d_i)$. In other words, every $d_i \in \mathcal{D}$ is matched to a better partner under $\mu^{'}$ compared to μ, that is, every $d_i \in \mathcal{D}$ is matched to some CU under $\mu^{'}$ which has rejected its request under μ. Thus, every CU in the set of $\mu^{'}(\mathcal{D})$ must have issued a rejection under μ. However, any CU which receives a request in the final step of Algorithm 3 has not issued a rejection to any D2D pair due to the matching rule. Otherwise, at least one more iteration is required to match the rejected D2D pairs with some CU. This contradicts the assumption of existing $\mu^{'}$ and proves that μ is weak Pareto optimal for D2D pairs.

REFERENCES

[1] R. Wang, H. Hu, and X. Yang, "Potentials and challenges of C-RAN supporting multi-RATs toward 5G mobile networks," *IEEE Access*, vol. 2, no. 8, pp. 1187–1194, Oct. 2014.

[2] O. Bello and S. Zeadally, "Intelligent device-to-device communications in the internet of things," *IEEE Sys. J.*, vol. PP, no. 99, pp. 1–11, Jan. 2014.

[3] S. Zhang, N. Zhang, S. Zhou, J. Gong, and Z. N. ans S Shen, "Energy-aware traffic offloading for green heterogeneous networks," *IEEE J. Sel. Areas Commun.*, vol. PP, no. 99, pp. 1–12, Jan. 2016. [Online]. Available: http://arxiv.org/abs/1409.2475

[4] N. Zhang, H. Liang, N. Cheng, Y. Tang, , J. W. Mark, and X. Shen, "Dynamic spectrum access in multi-channel cognitive radio networks," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 11, pp. 2053–2064, Sep. 2014.

[5] K. Doppler, M. Rinne, C. Wijting, C. B. Ribeiro *et al.*, "Device-to-device communication as an underlay to LTE-Advanced networks," *IEEE Comm. Mag.*, vol. 47, no. 12, pp. 42–49, Dec. 2009.

[6] M. N. Tehrani, M. Uysal, and H. Yanikomeroglu, "Device-to-device communications in 5G cellular networks: challenges, solutions, and future directions," *IEEE Comm. Mag.*, vol. 52, no. 5, pp. 86–92, May. 2014.

[7] G. Fodor, E. Dahlman, G. Mildh, S. Parkvall *et al.*, "Design aspects of network assisted device-to-device communications," *IEEE Comm. Mag.*, vol. 50, no. 3, pp. 170–177, Mar. 2012.

[8] J. Liu, Y. Kawamoto, H. Nishiyama, N. Kato, and N. Kadowaki, "Device-to-device communications achieve efficient load balancing in LTE-Advanced networks," *IEEE Wirel. Comm. Mag.*, vol. 21, no. 2, pp. 57–65, Apr. 2014.

[9] D. Feng, L. Lu, Y. Yi, G. Y. Li *et al.*, "Device-to-device communications underlaying cellular networks," *IEEE Trans. Comm.*, vol. 61, no. 8, pp. 3541–3551, Aug. 2013.

[10] Y. Chia, K. Doppler, C. B. Ribeiro, and O. Tirkkonen, "Resource sharing optimization for device-to-device communication underlaying cellular networks," *IEEE Trans. Wirel. Comm.*, vol. 10, no. 8, pp. 2752–2763, Aug. 2011.

[11] L. Lei, Y. Kuang, N. Cheng, and X. Shen, "Delay-optimal dynamic mode selection and resource allocation in device-to-device communications - part I: optimal policy," *IEEE Trans. Veh. Tech.*, vol. PP, no. 99, pp. 1–13, Jun. 2015.

[12] C. Xu, L. Song, Z. Han, and Q. Zhao, "Efficiency resource allocation for device-to-device underlay communication systems: a reverse iterative combinatorial auction based approach," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 9, pp. 348–358, Sep. 2013.

[13] J. Liu, N. Kato, J. Ma, and N. Kadowaki, "Device-to-device communication in lte-advanced networks: a survey," *IEEE Commun. Surv. uTutor.*, vol. 17, no. 4, pp. 1923–1940, Nov. 2015.

[14] B. Zhou, H. Hu, S. Huang, and H. Chen, "Intracluster device-to-device relay algorithm with optimal resource utilization," *IEEE Trans. Veh. Tech.*, vol. 62, no. 5, pp. 2315–2326, Jun. 2013.

[15] Y. Cheng, Y. Gu, and X. Lin, "Combined power control and link selection in device-to-device enabled cellular systems," *IET Commun.*, vol. 7, no. 12, pp. 1221–1230, Aug. 2013.

[16] N. Golrezaei, P. Mansourifard, A. F. Molisch, and A. G. Dimakis, "Base-station assisted device-to-device communications for high-throughput wireless video networks," *IEEE Trans. Wirel. Comm.*, vol. 13, no. 7, pp. 3665–3676, Jul. 2014.

[17] J. Liu, H. Nishiyama, N. Kato, , and J. Guo, "On the outage probability of device-to-device communication enabled multi-channel cellular networks: an RSS-threshold-based perspective," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 1, pp. 163–175, Jan. 2016.

[18] J. Liu, S. Zhang, N. Kato, H. Ujikawa, and K. Suzuki, "Device-to-device communications for enhancing quality of experience in software defined multi-tier LTE-A networks," *IEEE Net. Mag.*, vol. 29, no. 4, pp. 46–52, Jul. 2015.

[19] X. Zhang, Z. Zheng, Q. Shen, J. Liu, X. S. Shen, and L. L. Xie, "Optimizing network sustainability and efficiency in green cellular networks," *IEEE Trans. Wirel. Comm.*, vol. 13, no. 2, pp. 1129–1139, Feb. 2014.

[20] C. Xu, L. Song, and Z. Han, *Resource Management for Device-to-Device Underlay Communication*. Springer Briefs in Computer Science, 2014, pp. 1–79.

[21] A. Mukherjee and A. Hottinen, "Energy-efficient device-to-device MIMO underlay network with interference constraints," in *Proc. IEEE WSA'12*, Dresden, Germany, Mar. 2012, pp. 105–109.

[22] S. Wen, X. Zhu, Z. Lin, X. Zhang, and D. Yang, "Energy efficient power allocation schemes for device-to-device (D2D) communication," in *Proc. IEEE VTC Fall'13*, Las Vegas, USA, Sep. 2013, pp. 1–5.

[23] F. Wang, C. Xu, L. Song, Q. Zhao *et al.*, "Energy-aware resource allocation for device-to-device underlay communication," in *Proc. IEEE ICC'13*, Budapest, Hungary, Jun. 2013, pp. 6076–6080.

[24] T. Ta, J. S. Baras, and C. Zhu, "Improving smartphone battery life utilizing device-to-device cooperative relays underlaying LTE networks," in *Proc. IEEE ICC'14*, Sydney, Australia, Jun. 2014, pp. 1–6.

[25] Z. Wang, C. Xu, L. Song, and Z. Han, "Energy-efficient resource allocation for device-to-device underlay communication," *IEEE Trans. Wirel. Commun.*, vol. 14, no. 4, pp. 2082–2892, Aug. 2015.

[26] S. Mumtaz, K. M. S. Huq, A. Radwan, J. Rodriguez, and R. L. Aguiar, "Energy-efficient interference-aware resource allocation in LTE-D2D communication," in *Proc. IEEE ICC'14*, Sydney, Australia, Jun. 2014, pp. 1–6.

[27] D. Wu, J. Wang, R. Q. Hu, Y. Cai *et al.*, "Energy-efficient resource sharing for mobile device-to-device multimedia communications," *IEEE Trans. Veh. Tech.*, vol. 63, no. 5, pp. 2093–2103, Mar. 2014.

[28] Z. Zhou, M. Dong, K. Ota, J. Wu, and T. Sato, "Energy efficiency and spectral efficiency tradeoff in device-to-device D2D communications," *IEEE Wirel. Commun. Lett.*, vol. 3, no. 5, pp. 485–488, Jul. 2014.

[29] D. Wu, L. Zhou, Y. Cai, R. Q. Hu, and Y. Qian, "The role of mobility for D2D communications in LTE-Advanced networks: energy vs. bandwidth efficiency," *IEEE Wirel. Comm. Mag.*, vol. 21, no. 2, pp. 66–71, Apr. 2014.

[30] L. Wei, R. Q. Hu, Y. Cai, and G. Wu, "Energy-efficiency and spectrum-efficiency of multi-hop device-to-device communications underlaying cellular networks," *IEEE Trans. Veh. Tech.*, vol. PP, no. 99, pp. 1–13, Aug. 2015.

[31] M. R. Garey and D. S. Johnson, *Computers and Intractability: A Guide to the Theory of NP-Completeness*. USA: W H Freeman and Company, 1979.

[32] Z. Zhou, M. Dong, K. Ota *et al.*, "A game-theoretic approach to energy-efficient resource allocation in device-to-device underlay communications," *IET Commun.*, vol. 9, no. 3, pp. 375–385, Feb. 2015.

[33] Y. Gu, W. Saad, M. Bennis, M. Debbah, and Z. Han, "Matching theory for future wireless networks: fundamentals and applications," *IEEE Comm. Mag.*, vol. 53, no. 5, pp. 52–59, May. 2015.

[34] D. Gale and L. S. Shapley, "College admissions and the stability of marriage," *The American Mathematical Monthly*, vol. 69, no. 1, pp. 9–15, Jan. 1962.

[35] A. E. Roth and M. Sotomayor, *Two Sided Matching: A Study in Game-Theoretic Modeling and Analysis*, 1st ed. Cambridge, UK: Cambridge University Press, 1991.

[36] G. O'Malley, "Algorithmic aspects of stable matching problems," Ph. D. dissertation, University of Glasgow, 2007.

[37] A. M. EI-Hajj, Z. Dawy, and W. Saad, "A stable matching game for joint uplink/downlink resource allocation in OFDMA wireless networks," in *Proc. IEEE International Conference on Communications 2012 (ICC 2012)*, Ottawa, Canada, Jun. 2012, pp. 5354–5359.

[38] X. Feng, G. Sun, X. Gan *et al.*, "Cooperative spectrum sharing in cognitive radio networks: a distributed matching approach," *IEEE Trans. Comm.*, vol. 62, no. 8, pp. 2651–2664, May. 2014.

[39] D. Niyato, P. Wang, T. H. Pink, W. Saad, and D. I. Kim, "Cooperation in delay tolerant networks with wireless energy transfer: performance analysis and optimization," *IEEE Trans. Veh. Tech.*, vol. 64, no. 8, pp. 3740–3754, Sep. 2014.

[40] M. Hasan and E. Hossain, "Distributed resource allocation in 5G cellular networks," no. 4, pp. 1–26, Sep. 2014. [Online]. Available: http://arxiv.org/abs/1409.2475

[41] ——, "Distributed resource allocation for relay-aided device-to-device communication under channel uncertainties: a stable matching approach," *IEEE Wirel. Comm.*, vol. 63, no. 10, pp. 3882–3897, Oct. 2015.

[42] B. Ma, H. S. Mansouri, and V. W. S. Wong, "A matching approach for power efficient relay selection in full duplex D2D networks," in *Proc. IEEE ICC'16*, Kuala Lumpur, Malaysia,, May. 2016, pp. 1–6.

[43] Y. Gu, Y. Zhang, M. Pan, and Z. Han, "Matching and cheating in device to device communications underlying cellular networks," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 10, pp. 2156–2166, Oct. 2015.

[44] W. Dinkelbach, "On nonlinear fractional programming," *Management Science*, vol. 13, no. 7, pp. 492–498, Mar. 1967.

[45] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, UK: Cambridge University Press, 2004.

[46] A. Asadi, Q. Wang, and V. Mancuso, "A survey on device-to-device communication in cellular networks," *IEEE Commun. Surv. uTutor.*, vol. 16, no. 4, pp. 1801–1819, Apr. 2014.

[47] H. Kwon and T. Birdsall, "Channel capacity in bits per joule," *IEEE J. Ocean. Eng.*, vol. OE-11, no. 1, pp. 97–99, Jan. 1986.

[48] M. J. Osborne and A. Rubinstein, *A Course in Game Theory*. Cambridge, MA, USA: MIT Press, 1994.

[49] K. T. K. Cheung, S. Yang, and L. Hanzo, "Achieving maximum energy-efficiency in multi-relay OFDMA cellular networks: a fractional programming approach," *IEEE Trans. Comm.*, vol. 61, no. 8, pp. 2746–2757, Jul. 2013.

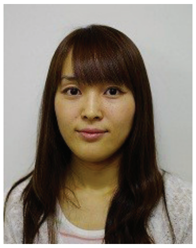
[50] D. Gusfield and R. W. Irving, *The Stable Marriage Problem: Structure and Algorithms*, 1st ed. Cambridge, MA, USA: MIT Press, 1999.

[51] S. Luo, R. Zhang, and T. J. Lim, "Downlink and uplink energy minimization through user association and beamforming in C-RAN," *IEEE Trans. Wirel. Comm.*, vol. 14, no. 1, pp. 494–508, Aug. 2014.

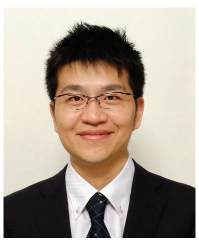
[52] G. Miao, N. Himayat, and G. Y. Li, "Energy-efficient link adaptation in frequency-selective channels," *IEEE Trans. Comm.*, vol. 58, no. 2, pp. 545–554, Feb. 2010.

[53] A. Goldsmith, *Wireless Communications*. Cambridge, UK: Cambridge University Press, 2005.

Zhenyu Zhou (S'06-M'11) received his M.E. and Ph.D degree from Waseda University, Tokyo, Japan in 2008 and 2011 respectively. From April 2012 to March 2013, he was the chief researcher at Department of Technology, KDDI, Tokyo, Japan. From March 2013 to now, he is an Associate Professor at School of Electrical and Electronic Engineering, North China Electric Power University, China. He is also a visiting scholar with Tsinghua-Hitachi Joint Lab on Environment-Harmonious ICT at University of Tsinghua, Beijing from 2014 to now. He served as workshop co-chair for IEEE ISADS 2015, and TPC member for IEEE VTC 2017, IEEE VTC 2016, IEEE ICC 2016, IEEE ICC 2015, Globecom 2015, ACM Mobimedia 2015, IEEE Africon 2015, etc. He received the "Young Researcher Encouragement Award" from IEEE Vehicular Technology Society in 2009. His research interests include green communications and smart grid. He is a member of IEEE, IEICE, and CSEE.



Kaoru Ota (M'12) was born in Aizu Wakamatsu, Japan. She received M.S. degree in Computer Science from Oklahoma State University, USA in 2008, B.S. and Ph.D. degrees in Computer Science and Engineering from The University of Aizu, Japan in 2006, 2012, respectively. She is currently an Assistant Professor with Department of Information and Electronic Engineering, Muroran Institute of Technology, Japan. From March 2010 to March 2011, she was a visiting scholar at University of Waterloo, Canada. Also she was a Japan Society of the Promotion of Science (JSPS) research fellow with Kato-Nishiyama Lab at Graduate School of Information Sciences at Tohoku University, Japan from April 2012 to April 2013. Her research interests include Wireless Networks, Cloud Computing, and Cyber-physical Systems. She has received best paper awards from ICA3PP 2014, GPC 2015, IEEE DASC 2015 and IEEE VTC 2016. She serves as an editor for Peer-to-Peer Networking and Applications (Springer), Ad Hoc & Sensor Wireless Networks, International Journal of Embedded Systems (Inderscience), as well as a guest editor for IEEE Wireless Communications, IEICE Transactions on Information and Systems. She is currently a research scientist with A3 Foresight Program (2011-2016) funded by Japan Society for the Promotion of Sciences (JSPS), NSFC of China, and NRF of Korea.



Mianxiong Dong (M'13) received B.S., M.S. and Ph.D. in Computer Science and Engineering from The University of Aizu, Japan. He is currently an Associate Professor in the Department of Information and Electronic Engineering at the Muroran Institute of Technology, Japan. Prior to joining Muroran-IT, he was a Researcher at the National Institute of Information and Communications Technology (NICT), Japan. He was a JSPS Research Fellow with School of Computer Science and Engineering, The University of Aizu, Japan and was a visiting scholar with BBCR group at University of Waterloo, Canada supported by JSPS Excellent Young Researcher Overseas Visit Program from April 2010 to August 2011. Dr. Dong was selected as a Foreigner Research Fellow (a total of 3 recipients all over Japan) by NEC C&C Foundation in 2011. His research interests include Wireless Networks, Cloud Computing, and Cyber-physical Systems. He has received best paper awards from IEEE HPCC 2008, IEEE ICESS 2008, ICA3PP 2014, GPC 2015, IEEE DASC 2015 and IEEE VTC 2016. Dr. Dong serves as an Editor for IEEE Communications Surveys and Tutorials, IEEE Network, IEEE Wireless Communications Letters, IEEE Cloud Computing, IEEE Access, and Cyber-Physical Systems (Taylor & Francis), as well as a leading guest editor for ACM Transactions on Multimedia Computing, Communications and Applications (TOMM), IEEE Transactions on Emerging Topics in Computing (TETC), IEEE Transactions on Computational Social Systems (TCSS). He has been serving as Symposium Chair of IEEE GLOBECOM 2016, 2017. Dr. Dong is currently a research scientist with A3 Foresight Program (2011-2016) funded by Japan Society for the Promotion of Sciences (JSPS), NSFC of China, and NRF of Korea.

Chen Xu (S'12-M'15) received the B.S. degree from Beijing University of Posts and Telecommunications, in 2010, and the Ph.D. degree from Peking University, in 2015. She is now a lecturer in School of Electrical and Electronic Engineering, North China Electric Power University, China. Her research interests mainly include wireless resource allocation and management, game theory, optimization theory, heterogeneous networks, and smart grid communication. She received the best paper award in International Conference on Wireless Communications and Signal Processing (WCSP 2012), and she is the winner of IEEE Leonard G. Abraham Prize 2016.