Resource Allocation for 5G Heterogeneous Cloud Radio Access Networks With D2D Communication: A Matching and Coalition Approach

Biling Zhang, *Member, IEEE*, Xingwang Mao, Jung-Lang Yu, *Member, IEEE*, and Zhu Han, *Fellow, IEEE*

***Abstract*—Device-to-Device (D2D) communication is a promising technology toward the fifth generation mobile communication. However, when D2D communication is incorporated into heterogeneous cloud radio access network (H-CRAN), the interference management between the D2D users and current users is a challenge. In this paper, we study how to assign the sub-channels of different bandwidth to multiple D2D pairs and the remote radio head users. In such a way, the sub-channels that have been pre-allocated to macro-cell users can be reused, the system performance can be maximized while the quality of service of all users can be guaranteed. Such a resource allocation problem is formulated as a mixed integer nonlinear programming (MINLP) problem which is NP-hard. To obtain the solution, the proposed problem is reformulated into a many-to-one matching sub-game with externality followed by a coalition sub-game. Then, a constrained deferred acceptance algorithm and a coalition formation algorithm are proposed to find solutions to these two sequential sub-games, respectively. Finally, we prove theoretically that both the proposed algorithms can convergent with a low computational complexity. Numerical results demonstrate that compared with existing resource allocation schemes, our proposed scheme can significantly improve the system performance in terms of overall throughput, the total number of admitted users and fairness.**

***Index Terms*—H-CRAN, D2D communication, matching theory, coalition game, resource allocation.**

Manuscript received July 6, 2017; revised October 23, 2017 and December 18, 2017; accepted January 21, 2018. Date of publication February 6, 2018; date of current version July 16, 2018. This work was supported in part by the National Natural Science Foundation of China under Grant 61501041, in part by the Open Foundation of State Key Laboratory under Grant ISN19-19, in part by the U.S. National Natural Science Foundation under Grants CNS-1717454, CNS-1731424, CNS-1702850, CNS-1646607, ECCS-1547201, CMMI-1434789, CNS-1443917, and ECCS-1405121, and in part by the Ministry of Science and Technology, Taiwan, under Grant MOST-104-2221-E-030-004-MY2. *(Corresponding author: Biling Zhang.)*

B. Zhang and X. Mao are with the School of Network Education, Beijing University of Posts and Telecommunications, Beijing 100876, China, and the State Key Laboratory of Integrated Services Networks, Xidian University, Xi'an 710071, P. R. China (e-mail: bilingzhang@bupt.edu.cn; xingwangmao@bupt.edu.cn).

J.-L. Yu is with the Department of Electrical Engineering, Fu Jen Catholic University, New Taipei City 24205, Taiwan (e-mail: yujl@ee.fju.edu.tw).

Z. Han is with the Department of Electrical and Computer Engineering, University of Houston, Houston, TX 77004, USA, and the Department of Computer Science and Engineering, Kyung Hee University, Seoul, South Korea (e-mail: zhan2@uh.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TVT.2018.2802900

I. Introduction

Heterogeneous cloud radio access network (H-CRAN) and device-to-device (D2D) communication have attracted significant attentions in recent research and become two important techniques for the next generation wireless communication system [1]. H-CRAN is proposed as one of the promising radio access network architecture which incorporates cloud computing into heterogeneous networks (HetNets). As illustrated in Fig. 1, in an H-CRAN, the evolved Node B (eNB) is interfaced with the baseband unit (BBU) pool through a backhaul link, mitigating the cross-tier interference between the remote radio heads (RRHs) and eNB through centralized cloud-computing based cooperative processing techniques, while the RRHs operate as soft relays by compressing and forwarding the received signals from RRH users (RUEs) to the centralized BBU pool through the wireless fronthaul links. In such a way, the cloud computing based cooperation processing and networking gains are fully exploited, the operating costs are lowered, and the energy consumption of the wireless infrastructure is decreased [2], [3]. With D2D communication, proximity users in a cellular network can communicate directly with each other without going through the base station (BS). Thus, D2D communication holds great promise in improving energy efficiency, throughput, delay and spectrum efficiency [4], [5].

In order to exploit the gains offered by D2D communication, D2D technology has been introduced into the cellular networks, where the resource allocation and interference management problem has attracted significant attentions [6]–[12]. In [6], a three-step admission and power control scheme is proposed to maximize the overall network throughput, guaranteeing the quality of service (QoS) requirements of both macrocell users (MUEs) and device-to-device users (DUEs). In [7], the authors investigate the energy efficient (EE) resource allocation problem in a cellular network with D2D communication, and propose a game theory and matching theory based algorithm to optimize the EE problem. In [9], the authors study mobile D2D video distribution that leverages the storage and communication capacities of smartphones in the cellular networks, taking into account the impact of video size. In [10], when the Base-station-to-Device (B2D), D2D, and Multi-D2D (MD2D) sharing modes coexist, a social-aware rate based content sharing mode selection scheme is proposed for D2D content sharing in the single-cell cellular time division duplex networks.

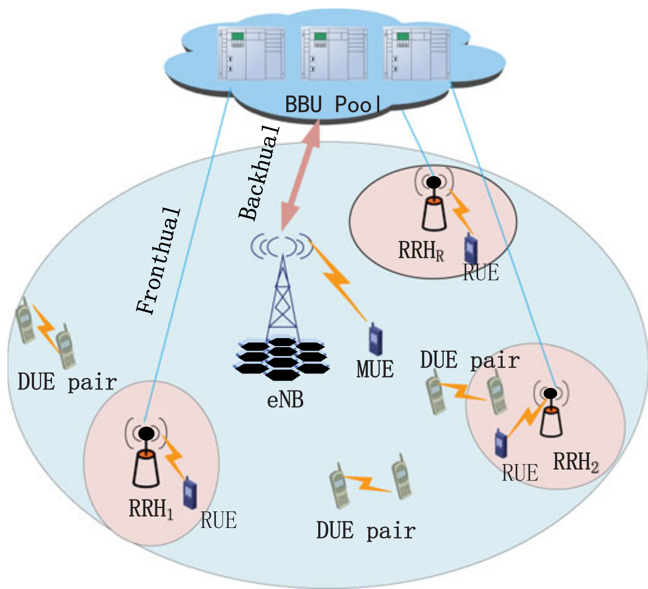


Fig. 1. The architecture of H-CRAN.

While the aforementioned work only focuses on the resource allocation problem in cellular networks, some other work studies the resource allocation problem in HetNets, where the interference scenario is more complicated when D2D communication is incorporated [13]–[17]. In [13], the authors consider a three-tier hierarchical HetNet by exploiting D2D communication in the traditional HetNet, where the spectral efficiency of these two kinds of HetNets is also analyzed and compared. In [14], the resource management issue in the macro/femto/D2D HetNets is investigated, and a network-assisted device-decided (NADD) channel selection and power control scheme is proposed. In [15], to solve the joint power control and sub-channel allocation problem for D2D and small cell uplink communication underlaying cellular networks, the authors first derive the closed-form expressions of optimal power under any given sub-channel allocation profile, and then propose a distributed learning algorithm to find the optimal sub-channel allocation profile.

When D2D communication is introduced into H-CRANs, the resource allocation problem has not gained sufficient investigated. In the H-CRAN, a new emerging radio access network architecture which is different from the cellular networks and HetNets, the dense deployment of RRHs leads to severe interference, making the interference management much more challenging. On the other hand, due to the distinct centralized processing characteristics of BBU pool, information exchange in the H-CRAN can be reduced, and so do the power consumption and latency. In addition, most of the resource allocation schemes largely depend on the channel quality indicator (CQI) [16], neglecting the bandwidth of channels, which leaves room for the spectrum efficiency improvement.

Therefore, in this paper, we present a framework of downlink resource allocation for D2D communication underlaying H-CRANs, where multiple D2D pairs and multiple RUEs are allowed to reuse one sub-channel. Our major contributions are summarized as follows.

- Different from previous works which focus on cellular networks and HetNets, we study the resource allocation scenario of H-CRANs. Since the network architecture of an H-CRAN is different from those of cellular networks and HetNets, the interference management in it is more complicated, especially when multiple D2D pairs and multiple RUEs are allowed to reuse the same sub-channel. In the considered scenario, not only the interference between DUE and DUE/MUE, but also the interference between DUE and RUE as well as the interference between RUE and RUE/MUE need to be managed when the channels are reused. Moreover, we assume different MUEs are equipped with sub-channels of different bandwidths. In such a case, besides the interference and the CQI which are normally considered in the existing works, DUEs and RUEs in our proposed model need to consider the bandwidth when they apply for the sub-channels according to their actual rate requirements.
- The resource allocation problem is formulated as a mixed integer nonlinear programming (MINLP) problem, the objective of which is to maximize the system capacity as well as the number of accommodated underlay users. The formulated problem is NP-hard. Due to the interference, the user's channel association is interdependent, which makes the problem more challenge. We manage to reformulate the problem into a many-to-one matching sub-game followed by a coalition formation sub-game. Then a constrained deferred acceptance (DA) algorithm and a coalition formation algorithm are, respectively, proposed to find the solutions to these two sequential sub-games, which are finally mapped into the solutions to the proposed resource allocation problem. We prove that our proposed algorithms are convergent and have low computational complexity. The characteristics of BBU pool also make our proposed scheme easier to implement.
- Simulation results show that compared with existing schemes, our proposed resource allocation scheme can significantly improve the system performance in terms of overall throughput, the total number of admitted users and fairness.

One work that seems to similar to our work is [18]. However, that work considers the spectrum sharing problem in a cellular network with multiple operators, where only one D2D pair is allowed to reuse the channel of MUE, while our work considers the spectrum sharing problem in an H-CRAN, where multiple D2D pairs and multiple RUEs are allowed to access the same sub-channel. Therefore, the interference management in our problem is more challenging. Moreover, [18] develops a Bayesian non-transferable utility overlapping coalition formation (BOCF) game framework to analyze the problem, the target of which is to maximize the system performance measured by the received signal-to-interference-and-noise ratio (SINR). This is also different from our work. In our paper, the problem is first formulated as an optimization problem with constrains, the objective of which is to maximize the system capacity as well as the number of accommodated underlay users. Our problem is then reformulated into a many-to-one

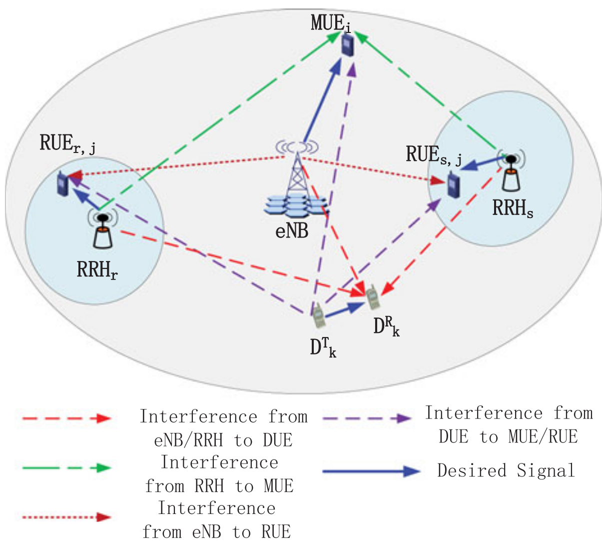


Fig. 2. The system model.

matching sub-game and a coalition formation sub-game for the solutions.

The rest of this paper is organized as follows. Section II describes the system model of D2D communication in H-CRANs. In Section III, we formulate the resource allocation problem as a MINLP problem. Later, in Section IV, the resource problem is transformed into two sub-games and the corresponding algorithms for solutions of the sub-games are proposed. The performance evaluation is shown by extensive simulations in Section V. Finally, we conclude this work in Section VI.

II. System Model

A. Scenario Description

As illustrated in Fig. 2, we consider a downlink transmission scenario in a typical H-CRAN, in which there exists one eNB and R RRHs, i.e., RRH$_r$, $r \in \mathcal{R} = \{1, ..., R\}$. Within the coverage of the macro cell, there are M MUEs, i.e., MUE$_i$, $i \in \mathcal{M} = \{1, ..., M\}$. There are also K D2D pairs, i.e., D$_k$, $k \in \mathcal{K} = \{1, ..., K\}$, randomly distributed in the same macro cell. The transmitter and receiver of D$_k$ are, respectively, denoted by D$_k^T$ and D$_k^R$. Moreover, let RUE$_{r,j}$, $j \in \mathcal{N}_r = \{1, ..., N_r\}$, be the jth RUE in RRH$_r$. Here N_r is the number of RUEs randomly distributed within the coverage of RRH$_r$. Then, the total number of RUEs in the network is $N = \sum_{r=1}^{R} N_r$. In this paper, the set of all the RUEs is denoted as $\mathcal{N}$, and the set of all the RUEs and D2D pairs which are also known as underlay users, is denoted as $\mathcal{V}$.

Assume that the total resource blocks (RBs) of the system in the downlink period is divided into M sub-channels, and each sub-channel is allocated to a MUE according to its location and actual bandwidth requirement. Let the set of sub-channels be $\mathcal{C}$. Without loss of generality, sub-channel i, $i \in \mathcal{M}$, is assumed to be occupied by MUE$_i$. To reuse these sub-channels, we assume that each RUE and DUE are only allowed to access one sub-channel, while each sub-channel can accommodate multiple RUEs and DUEs as long as the interference on the MUE does not exceed its interference threshold. To avoid the serious interference between the RUEs in the same RRH, different RUEs in the same RRH can only access different sub-channels. Additionally, in the H-CRAN, the interference between different RRHs is assumed to be eliminated by the BBU pool using the advanced interference cancelation technology [2].

B. Interference Analysis

Let P_B, P_r, P_k denote the transmission powers of the eNB, RRH$_r$ and D$_k^T$, respectively. The channel gains of the communication link in sub-channel i from eNB to MUE$_i$, from RRH$_r$ to RUE$_{r,j}$ and from D$_k^T$ to D$_k^R$ are represented by h_B^i, $h_{r,j}^i$ and h_k^i, respectively. The channel gains of interference link in sub-channel i from eNB to RUE$_{r,j}$, from eNB to D$_k^R$, from RRH$_r$ to MUE$_i$, from RRH$_r$ to D$_k^R$, from D$_k^T$ to MUE$_i$, from D$_k^T$ to RUE$_{r,j}$ and from D$_k^T$ to D$_{k'}^R$ are represented by $h_{B,r,j}^i$, $h_{B,k}^i$, h_r^i, $h_{r,k}^i$, h_k^i, $h_{k,r,j}^i$ and $h_{k,k'}^i$, respectively. Within a very short scheduling period such as one slot, the channel gains are assumed to be unchanged. The thermal noise at the receivers satisfies the independent Gaussian distribution with zero mean and the same variance σ^2.

To characterize the sub-channel reusing relationship, we further let $\alpha_{r,j}^i = 1$ if sub-channel i is allocated to RUE$_{r,j}$ and $\alpha_{r,j}^i = 0$ otherwise, and let $\beta_k^i = 1$ if sub-channel i is allocated to D$_k$, and $\beta_k^i = 0$ otherwise. Based on $\alpha_{r,j}^i$, we also define $\alpha_r^i = \sum_{j=1}^{N_r} \alpha_{r,j}^i$ to indicate if sub-channel i is assigned to RRH$_r$.

Then, when the RUEs and D2D pairs access sub-channel i, the achievable date rate of MUE$_i$ will be

$$d_M^i = W_i \log_2 (1 + \gamma_M^i), \tag{1}$$

where W_i is the bandwidth of sub-channel i, $\gamma_M^i = \frac{P_B h_B^i}{I_M^i + \sigma^2}$ is the signal to interference plus noise ratio (SINR) of MUE$_i$, and $I_M^i = \sum_{r=1}^{R} \alpha_r^i P_r h_r^i + \sum_{k=1}^{K} \beta_k^i P_k h_k^i$ is the total interference MUE$_i$ suffers from the RRHs and D2D transmitters. Similarly, The achievable date rate of RUE$_{r,j}$ in sub-channel i will be

$$d_{r,j}^i = W_i \log_2 (1 + \gamma_{r,j}^i), \tag{2}$$

where $\gamma_{r,j}^i = \frac{P_r h_{r,j}^i}{I_{r,j}^i + \sigma^2}$ is the SINR of RUE$_{r,j}$, and $I_{r,j}^i = P_B h_{B,r,j}^i + \sum_{k=1}^{K} \beta_k^i P_k h_{k,r,j}^i$ is the total interference suffered by RUE$_{r,j}$ from the eNB and D2D transmitters. The achievable date rate of D$_k$ in sub-channel i will be

$$d_{D,k}^i = W_i \log_2 (1 + \gamma_{D,k}^i), \tag{3}$$

where $\gamma_{D,k}^i = \frac{P_k h_k^i}{I_{D,k}^i + \sigma^2}$ is the SINR of D$_k$, and $I_{D,k}^i = P_B h_{B,k}^i + \sum_{r=1}^{N_R} \alpha_r^i P_r h_{r,k}^i + \sum_{k'=1,k' \neq k}^{K} \beta_{k'}^i P_{k'} h_{k',k}^i$ is the total interference suffered by D$_k$ from the eNB, RRHs and the D2D pairs which use the same sub-channel.

III. Problem Formulation

The key issue of the resource sharing problem is to provide a sub-channel reusing scheme for the RUEs and D2D pairs, satisfying their QoS requirement and keeping the interference of the MUEs in an acceptable range.

Let $d_{r,j}^{\min}$ and $d_k^{\min}$ be the minimum rate requirement of $\text{RUE}_{r,j}$ and D_k, respectively. The interference threshold of MUE is represented by I_M^{th}. Let $P = \{\alpha_{r,j}^i \mid r \in \mathcal{R}, j \in \mathcal{N}_r, i \in \mathcal{M}\}$, and $Q = \{\beta_k^i \mid k \in \mathcal{K}, i \in \mathcal{M}\}$ be the sub-channel assignment for RUEs and DUEs, respectively. Then the sub-channel assignment problem can be formulated as

$$\max_{(P,Q)} \left[\sum_{i=1}^{M} d_M^i + \sum_{r=1}^{R} \sum_{j=1}^{N_r} \sum_{i=1}^{M} \alpha_{r,j}^i d_{r,j}^i + \sum_{k=1}^{K} \sum_{i=1}^{M} \beta_k^i d_{D,k}^i \right] \times \frac{\sum_{i=1}^{M} \sum_{r=1}^{R} \sum_{j=1}^{N_r} \alpha_{r,j}^i}{N} \times \frac{\sum_{k=1}^{K} \beta_k^i}{K}, \tag{4}$$

$$\text{s.t.} \quad I_M^i \leq I_M^{\text{th}}, \forall i \in \mathcal{M}, \tag{5}$$

$$\sum_{i=1}^{M} \alpha_{r,j}^i d_{r,j}^i \geq d_{r,j}^{\min}, \forall r \in \mathcal{R}, j \in \mathcal{N}_r, \tag{6}$$

$$\sum_{i=1}^{M} \beta_k^i d_{D,k}^i \geq d_k^{\min}, \forall k \in \mathcal{K}, \tag{7}$$

$$\sum_{i=1}^{M} \alpha_{r,j}^i \leq 1, \forall r \in \mathcal{R}, j \in \mathcal{N}_r, \tag{8}$$

$$\sum_{j=1}^{N_r} \alpha_{r,j}^i \leq 1, \forall r \in \mathcal{R}, i \in \mathcal{M}, \tag{9}$$

$$\sum_{i=1}^{M} \beta_k^i \leq 1, \forall k \in \mathcal{K}. \tag{10}$$

From (4) we can see, our problem formulation takes two factors into consideration: the sum capacity of all the communication links including the eNB-MUE links, RRH-RUE links and D2D links in the network, and the total number of the RUEs and DUEs which can be allocated sub-channels. In such a way, a trade-off between these two factors should be achieved. In constraint (5), for each MUE, i.e., $\text{MUE}_i, i \in \mathcal{M}$, the total interference it suffers should lower it's interference threshold, such that its transmission can be protected from the underlay users when they reuse the same sub-channel. With constraints (6) and (7), the achieved data rate of each RUE, i.e., $\text{RUE}_{r,j}, r \in \mathcal{R}, J \in \mathcal{N}_r$, and each D2D pair, i.e., $\text{D}_k, k \in \mathcal{K}$, in sub-channel i should not lower their minimum data rate requirements, respectively, such that their QoS is guaranteed. Constraint (8) ensures that each RUE should be assigned with at most one sub-channel, and constraint (9) ensures that the RUEs in the same RRH should be assigned with different sub-channels. While (10) gives a constraint that each D2D pair should be associated with at most one sub-channel.

Notice that the above formulated problem is a non-convex and MINLP problem. When the numbers of the MUEs, RUEs and D2D pairs are large, such a problem will be very difficult to solve. Inspired by [19] and [20], in the next section, we will propose the effective algorithms based on matching theory [19]−[23] and coalition formation game [24]−[26] for the solution of the proposed problem.

IV. Resource Allocation Using Matching Theory and Coalition Game Theory

In this section, we solve the NP-hard problem proposed in Section III based on matching theory and coalition game theory. That is, we reformulate the problem into two sequential sub-games: a many-to-one matching game with externality and a coalition formation game with user transfer.[1] In the first sub-game in Sections IV-A and IV-B, we obtain a stable matching between the underlay users and the sub-channels. Then, in the second sub-game in Sections IV-C and IV-D, based on the outcome of the first sub-game, the final partition of underlay users is achieved. In Section IV-E, the final partition of underlay users is mapped into the solution of the proposed problem.

A. Many-To-One Matching Game With Externality

In the proposed resource allocation scheme, the assignment of channels to the underlay users is in fact a kind of matching.

Definition 1 (Matching): A matching μ is defined as a bidirectional mapping between the set of the underlay users $\mathcal{V}$ and the set of the sub-channels $\mathcal{C}$ such that:

a) $\forall v \in \mathcal{V}$, we have $\mu(v) \in \mathcal{C} \cup \{\emptyset\}$ and $|\mu(v)| \in \{0, 1\}$, and

b) $\forall i \in \mathcal{C}$, we have $\mu(i) \in \mathcal{V} \cup \{\emptyset\}$ and $|\mu(i)| \in \{0, ..., R + K\}$,

where $|\mu(\cdot)|$ denotes the cardinality of matching outcome $\mu(\cdot)$.

According to Definition 1, μ becomes a one-to-one or many-to-one matching if the input of the mapping is the user, and μ becomes a one-to-many matching if the input of the mapping is the sub-channel. When a user is not allowed to use a sub-channel, or a sub-channel is not assigned to users, we have $\mu(v) = \emptyset$ or $\mu(i) = \emptyset$.

If we suppose both the sub-channels and underlay users are selfish and rational, then the process of matching, i.e., the process of their decision making, can be formulated as a game.

For any underlay user $v \in \mathcal{V}$, it would choose a sub-channel that can maximize its data rate requirement. Therefore, the utility function of user v on sub-channel i can be defined as

$$U_v^i = W_i \log_2 (1 + \gamma_v^i), \tag{11}$$

where γ_v^i can be $\gamma_{r,j}^i$ or $\gamma_{D,k}^i$ defined in (2) and (3), respectively.

While for any sub-channel i which concerns about the throughput and the total number of the accommodated underlay users, its utility function of accepting user $v \in \mathcal{V}$ is given as

$$U_i^v = W_i \log_2 (1 + \gamma_M^i) + W_i \log_2 (1 + \gamma_v^i) + \tau(I_M^{\text{th}} - I_M^i). \tag{12}$$

In (12), the first and second terms represent the total throughput when user v reuses sub-channel i. The third term is used to describe the user's impact on the number of underlay users that could be accommodated, that is, the less aggregated interference

[1]Comparing to only reformulating into a coalition game, reformulating into the two-stage game is superior in both system performance and computational complexity, as verified in the simulations.

on the MUE, the more underlay users could be accommodated later. The weight on these two factors can be adjusted by τ, a constant whose unit is bit/s/Joule.

To rank the sub-channels or users, a preference relation is used.

Definition 2 (Preference relation $\succ$): A preference relation $\succ$ is a complete, reflexive, and transitive binary relation between the players in $\mathcal{V}$ and $\mathcal{C}$. That is, a strict preference relation $\succ_v$ is defined over the set of sub-channels $\mathcal{C}$ such that for any two sub-channels $c_1, c_2 \in \mathcal{C}, c_1 \neq c_2$, we have

$$c_1 \succ_v c_2 \Longleftrightarrow U_v^{c_1} > U_v^{c_2}. \tag{13}$$

And a strict preference relation $\succ_c$ is defined over the set of underlay users $\mathcal{V}$ such that for any two users $v_1, v_2 \in \mathcal{V}, v_1 \neq v_2$, we have

$$v_1 \succ_c v_2 \Longleftrightarrow U_c^{v_1} > U_c^{v_2}. \tag{14}$$

With the preference relation and the necessary information broadcasted by the eNB, the users and the sub-channels are able to build their preference profiles. The resource allocation problem described in (4)–(10) thus can be formulated as a many-to-one matching game [21].

Definition 3 (Matching game): A matching game $\mathcal{G}(\mu, \mathcal{V} \times \mathcal{C})$ is defined by two sets of players $\mathcal{V}$ and $\mathcal{C}$, and two preference relations $\succ_v$ and $\succ_c$ which allow each player to build preference over one another, resulting in a final matching μ [21].

As we can see, the solution of this game is a matching μ defined on the set $\mathcal{V} \times \mathcal{C}$, which assigns for every sub-channel a subset of users and assigns for every user a sub-channel. In the next subsection, an algorithm is proposed to find the stable solution of this matching game.

B. Algorithm for the Matching Game and Properties

For the underlay users in $\mathcal{V}$, their selections of sub-channel will have influence on each other, which is commonly known as externality [27]. Moreover, the constraints in (5) to (10) must be satisfied when the matching is performed. Therefore, the DA algorithm [28], which is often used to tackle the matching problem, cannot be well applied to such a many-to-one matching. To address this challenge, we propose a constrained DA algorithm as shown in Algorithm 1.

The basic idea of the constrained DA algorithm is as follows. First, the underlay users build their preference profiles based on (13) and (15). When some users send application to sub-channel i, sub-channel i will rank the applicants according to the preference profile based on (14) and (16), and then for the most preferred user, sub-channel i will decide whether or not to add it to the waiting list based on the constraints of (5)–(7). If a user v has been added to the waiting list, the sub-channel should consider its effect when selecting the subsequent applicants. Note that when more than one RUEs in the same RRH apply for the same sub-channel, the sub-channel will accept the most preferred one to satisfy the constraints in (8)–(9) and reject the rest. Then, the rejected applicants should re-apply to their next best choices. Accordingly, the related sub-channels update their waiting lists.

Algorithm 1: Constrained DA Algorithm.

1. Initiate the set of underlay users that are not allocated sub-channels $\mathcal{V}' = \mathcal{V}$.
2. Matching:
   - For $v \in \mathcal{V}'$
     - Build a preference list based on (13) and (15).
   - End

   While $\mathcal{V}' \neq \emptyset$
   - For $v \in \mathcal{V}'$
     - Apply for its most preferred sub-channel.
   - End
   - For sub-channel $i \in \mathcal{C}$
     - Build its preference list based on (14) and (16).
     - Rank its applicants according to preference list.
     - Check from the most preferred applicant. If constraints (5)–(7) are satisfied, then the sub-channel adds the applicant to the waiting list, otherwise rejects it. When more than one RUEs in the same RRH satisfy the constraints, the sub-channel just retains the most preferred one that satisfies the constraints (8)–(9).
   - End
   - Update $\mathcal{V}'$ as the rejected $v \rightarrow \mathcal{V}'$.

   End
3. Obtain the sub-channels and users matching result μ^*.

In Algorithm 1, estimated utilities, i.e., (15) and (16), are used instead of accurate utilities, i.e., (11) and (12). This is because in practice, before all the users and sub-channels make their selections, the exact interference that an underlay user or a MUE suffers in a sub-channel is unavailable. To avoid the impact of externality, an underlay user constructs its preference profile based on the estimated utility as

$$\widetilde{U}_v^i = W_i \log_2 (1 + \widetilde{\gamma}_v^i), \tag{15}$$

where $\widetilde{\gamma}_v^i = \frac{P_r h_{r,j}^i}{P_B h_{B,r,j}^i + \sigma^2}$ only depends on the interference from the MUE. Similarly, a sub-channel constructs its preference profile based on the estimated utility as

$$\widetilde{U}_i^v = W_i \log_2 (1 + \widetilde{\gamma}_M^i) + W_i \log_2 (1 + \widetilde{\gamma}_v^i) + \tau (I_M^{\text{th}} - \widetilde{I}_{M,i}), \tag{16}$$

where $\widetilde{\gamma}_M^i$, $\widetilde{\gamma}_v^i$, and $\widetilde{I}_{M,i}$ are all depend on the interference from current RRHs and D2D transmitters. There is a gap between the outcome of matching based on estimated utilities and that of matching based on accurate utilities. However, the gap will be narrowed in the following coalition sub-game.

Remark 1: According to Algorithm 1, since an underlay user constructs its preference profile based on the estimated utility, it only needs to know the channel gains of its own communication links in all sub-channels and the channel gains of interference links between all the MUEs and itself. Therefore, information of $2M(K+N)$ links is needed as per (15). On the other hand, when the sub-channels construct their preference profiles in each iteration, the channel gains of $(K+N)$ underlay users' communication links in their applied sub-channels, as well as the channel gains of M MUEs' communication links are needed as per (16). In such a case, information of $K+N+M$ links is needed. In the worst case, at most $K+N$ iterations are needed for all these underlay users are allocated. In total, the information exchange of Algorithm 1 should be $2M(K+N)+(K+N)(K+N+M)=3M(K+N)+(K+N)^2$, resulting in an overhead of $\mathcal{O}((K+N)^2)$.

Using the constrained DA algorithm, the matching game $\mathcal{G}(\mu, \mathcal{V}\times\mathcal{C})$ can reach a stable matching μ^* [22] defined as following with low computational complexity, which will be proved in Property 1 and Property 2, respectively.

Definition 4 (Stable Matching): A matching μ is said to be stable, if there does not exist any pair of users $v_1, v_2 \in \mathcal{V}$ that are assigned to sub-channels $c_1, c_2 \in \mathcal{C}$ simultaneously satisfy the following conditions:

1) v_2 prefers c_1 to c_2, i.e., $c_1 \succ_{v_2} c_2$, and c_1 prefers v_2 to v_1, i.e., $v_2 \succ_{c_1} v_1$.
2) Equations (5)–(10) are satisfied for all the users in sub-channel c_1, if v_1 is replaced by v_2.

Property 1: The matching μ^* resulting from the constrained DA algorithm is stable.

Proof: It's obvious that Algorithm 1 is convergent as the preference lists of the applicants are finite. Assume there exists a case where $v_1, v_2 \in \mathcal{V}$ are, respectively, assigned to sub-channel $c_1, c_2 \in \mathcal{C}$. If v_1 is replaced by v_2, we have that v_2 prefers c_1 to c_2 and c_1 prefers v_2 to v_1, and (5)–(6) are satisfied for all the users in sub-channel c_1. Then according to step 2 in Algorithm 1, v_2 should be assigned to sub-channel c_1. However, this contradicts with the fact that v_2 is assigned to sub-channel c_2. Therefore, the matching μ^* resulting from the constrained deferred acceptance algorithm is guaranteed to be stable. ∎

Property 2: Algorithm 1 has a complexity of $\mathcal{O}(M(N+K)^3)$ in the worst case.

Proof: The computational complexity of Algorithm 1 is dominated by step 2. Note that the first for-loop in step 2 is related to the underlay users' preference function calculation and the sorting of each sub-channel, its complexity is $(N+K)(M+M^2)$. Moreover, in each iteration of the while-loop, the second for-loop, which is related to the sub-channels' preference function calculation, the sorting of each underlay user and the checking of the constraints for each applicant, has a complexity of $M(N+K)+M(N+K)^2+4M(N+K)=5M(N+K)+M(N+K)^2$. Since at most $K+N$ iterations are needed for all these underlay users are allocated, the computational complexity of the while-loop should be $(K+N)(5M(N+K)+M(N+K)^2)$. Thus, Algorithm 1 has a complexity of $\mathcal{O}(M(N+K)^3)$ in the worst case. ∎

C. Coalition Formation Game With User Transfer

After the matching sub-game, we open a window for the transfers of underlay users. On one hand, the underlay users might have incentive for potential transfers, depending on their actual perceived utility as per (11). For example, if some sub-channels have only accommodated a small number of RUEs and D2D pairs, and the MUEs in these sub-channels suffer little interference, it would be beneficial for some users to transfer from heavy-loaded sub-channels to the light-loaded sub-channels. On the other hand, such transfers enable the system, i.e., sub-channels, to improve the overall performance and reach the optimization target of the originally formulated problem in (4)–(10). To study the users' transfers and the sub-channels' acceptance, we first model such a process as a coalition game [23], [24], and then propose an algorithm to find the solution of the game. Finally, some properties of the proposed algorithm are analyzed.

Here, a coalition $S_i \subseteq \mathcal{V}$ is the set of underlay users and MUE that are allocated to sub-channel i. Then we have $\cup_{i=1}^{M}(S_i \setminus \mathrm{MUE}_i) = \mathcal{V}$. Since each underlay user is allowed to access only one sub-channel, $\forall i, j \in \mathcal{M}$ and $i \neq j$, there is $S_i \cap S_j = \emptyset$.

Let $\mathcal{R}_i = \{r|\mathrm{RUE}_{r,j} \in S_i, \forall j\}$ be the set of subscript of RRH which has RUEs in S_i, $\mathcal{J}_{r,i} = \{j|\mathrm{RUE}_{r,j} \in S_i\}$ be the set of subscript of RUEs of RRH_r in S_i, and $\mathcal{K}_i = \{k|\mathrm{D}_k \in S_i\}$ be the set of subscript of D2D pairs in S_i. Then the utility of MUE in coalition S_i can be defined by its achievable rate as

$$U_M(S_i) = d_M(S_i) = W_i \log_2\left(1 + \frac{P_B h_B^i}{I_M(S_i) + \sigma^2}\right), \quad (17)$$

where $I_M(S_i) = \sum_{r\in\mathcal{R}_i} P_r h_r^i + \sum_{k\in\mathcal{K}_i} P_k h_k^i$ is the interference the MUE suffers. Similarly, within S_i the utility of the RUE, say $\mathrm{RUE}_{r,j}$, will be

$$U_{r,j}(S_i) = d_{r,j}(S_i) = W_i \log_2\left(1 + \frac{P_r h_{r,j}^i}{I_{r,j}(S_i) + \sigma^2}\right), \quad (18)$$

where $I_{r,j}(S_i) = P_B h_{B,r,j}^i + \sum_{k\in\mathcal{K}_i} P_k h_{k,r,j}^i$ is the total interference suffered by $\mathrm{RUE}_{r,j}$ from the eNB and D2D transmitters. The utility of the DUE, say D_k, is

$$U_k(S_i) = d_k(S_i) = W_i \log_2\left(1 + \frac{P_k h_k^i}{I_k(S_i) + \sigma^2}\right), \quad (19)$$

where $I_k(S_i) = P_B h_{B,k}^i + \sum_{r\in\mathcal{R}_i} P_r h_{r,k}^i + \sum_{k'\in\mathcal{K}_i, k'\neq k} P_{k'} h_{k',k}^i$ is the total interference suffered by D_k from the eNB, RRHs and the D2D pairs which access the same sub-channel.

The utility of coalition S_i thus can be given as

$$\Gamma(S_i) = U_M(S_i) + \sum_{r\in\mathcal{R}_i}\sum_{j\in\mathcal{J}_{r,i}} U_{r,j}(S_i) + \sum_{k\in\mathcal{K}_i} U_k(S_i). \quad (20)$$

From (18) and (19), we can see the utility of an underlay user is determined by the bandwidth of the sub-channel as well as the interference from other users in the same sub-channel. Hence, supposing the users are selfish and rational, it is impossible for all of them to access the same single sub-channel, because the more users in a sub-channel, the higher interference that they will suffer, and the lower utility they will obtain. Instead, a user tends to select the sub-channel where there is larger bandwidth and/or less interference. The underlay user keeps changing its selection, until its utility is maximized. In such a case, the process of the underlay users' choosing the sub-channels can be formulated as a coalition game, where the objective is to enable the users to change from one coalition to another, depending on their utilities and the acceptance of the coalition.

Definition 5 (Coalition game): A coalition game is identified by the pair (Π, Φ), where $\Pi = \{S_1, S_2, \cdots, S_M\}$ is a partition of the underlay users, and Φ is a mapping with Π that assigns for every coalition $S_i \in \Pi$ a utility $\Gamma(S_i)$.

Note that when some users transfer from one coalition to another, the partition of the underlay users Π changes, and finally reaches a stable partition, if there exists.

Generally, the optimal partition, i.e., the optimal solution, of a coalition game is obtained through exhaustive search. However, the number of all possible partition increases exponentially with the number of underlay users [29], making exhaustive search impractical. In such a case, we will propose a suboptimal algorithm with low computational complexity.

D. Algorithm for the Coalition Formation Game and Properties

Before proposing the algorithm for the coalition game, a transfer rule and an acceptance rule for the underlay users and the sub-channels, respectively, are first introduced to better understand the nature of their selection.

Definition 6 (Transfer rule): Given a partition $\Pi = \{S_1, S_2, \cdots, S_M\}$ of $\mathcal{V}$, for any underlay user $v \in S_i$ to transfer to S_m, $i, m \in \mathcal{M}$ and $i \neq m$, if 1) $U_v(S_i) > U_v(S'_m)$, and 2) v is accepted by S_m. Here, $S'_m = S_m \cup \{v\}$, and $U_v(\cdot)$ is defined in (18) and (19).

Definition 7 (Acceptance rule): Given a partition $\Pi = \{S_1, S_2, \cdots, S_M\}$ of $\mathcal{V}$, for any underlay user $v \in S_i$ to be accepted by coalition S_m, $i, m \in \mathcal{M}$ and $i \neq m$, the following conditions should be satisfied:

1) $I_M(S'_m) \leq I_M^{\text{th}}$,
2) $d_{r,j}(S'_m) \geq d_{r,j}^{\min}, \forall r \in \mathcal{R}_m, \forall j$,
3) $d_k(S'_m) \geq d_k^{\min}, \forall k \in \mathcal{K}_m$,
4) $\Gamma(S'_i) + \Gamma(S'_m) > \Gamma(S_i) + \Gamma(S_m)$,

where $S'_i = S_i \backslash \{v\}$.

The transfer rule ensures that the user's utility will be improved after transfer, and this is why an underlay user has incentive to deviate from the current coalition. While the acceptance rule lists the necessary conditions for a coalition to accept a new comer. Under these conditions, the QoS of existing members in the coalition will be guaranteed by 1), 2) and/or 3), and the collaboration of the original and the target coalitions is stimulated to value the overall social welfare of the network by 4).

Note that when multiple underlay users apply to transfer to the same sub-channel, the transfer order is a significant factor that should be taken into consideration. For example, user $v_1 \in S_{i_1}$ and $v_2 \in S_{i_2}$ both expect to transfer to S_{i_3} and their conditions both satisfy the transfer rule. However, when one of the user is accepted by S_{i_3}, it is possible that the other's condition may not meet the transfer rule. In such a case, the transfer order will have an effect on the utility of coalition and the resource allocation results. To capture the sub-channel's preference to the transfer, we define a transfer factor for any user $v \in S_i$ which attempts to transfer to S_m as follow

$$\phi_v(S_i, S_m) = \Gamma(S_i \backslash \{v\}) + \Gamma(S_m \cup \{v\}) - \Gamma(S_i) - \Gamma(S_m). \tag{21}$$

Then when multiple underlay users apply to transfer, coalition S_m will accept the one with the largest transfer factor. As we can see, the transfer factor provides an efficient way to distinguish the potential user transfers to improve the performance of the system.

Algorithm 2: Coalition Formation Algorithm.

1. Set $t = 0, \Pi^0 = \Pi^{\text{ini}}, \varepsilon = 0.01$ and $\varepsilon_1 = 1$.
2. While $\varepsilon_1 > \varepsilon$
   - For $v \in \mathcal{V}$
     – Indicate its most preferred transfer according to the transfer rule defined in Definition 6.
   - End
   - For $S_i^t \in \Pi^t$
     – Filter the applicants according to the acceptance rule defined in Definition 7.
     – Select the applicant with the largest transfer factor defined in (21) and rejects the rest.
     – Update S_i^{t+1} with S_i^t and the accepted applicant.
   - End
   - $t = t + 1$.
   - Update Π^t as $\Pi^t = \{S_1^t, S_2^t, \cdots, S_M^t\}$.
   - $\varepsilon_1 = ||\Pi^t - \Pi^{t-1}||^2$.

   End
3. Return Π^t as the final partition, i.e., $\Pi^{\text{final}} = \Pi^t$.

With the transfer rule, acceptance rule and the transfer factor, we design the coalition formation algorithm to obtain the final partition of underlay users, as presented in Algorithm 2.

According to the coalition formation algorithm, an initial partition Π^0 is set as $\Pi^0 = \{S_1^0, S_2^0, \cdots, S_M^0\}$ at the beginning of the coalition game. Here $\{S_1^0, S_2^0, \cdots, S_M^0\}$ is the corresponding partition of the underlay users when the stable matching μ^* is given. Then each underlay user has the chance to indicate its most preferred transfer to another coalition, if the transfer satisfies the transfer rule. Based on the users' indication, each coalition filters the applicants according to the acceptance rule, and chooses the applicant with the largest transfer factor according to (21) and rejects the rest. The coalition's acceptance or rejection results in a new partition Π^t. This process repeats until Π^t converges, i.e., $||\Pi^t - \Pi^{t-1}||^2 < \varepsilon$. At last, we have the final partition Π^{final}, which can be mapped into the final solution to the resource allocation problem defined in (4)–(10).

The proposed coalition formation algorithm has some nice properties, as described in Property 3 and Property 4.

Property 3: Starting from any initial partition Π^{ini}, Algorithm 2 is guaranteed to converge to a final partition Π^{final}.

Proof: Given any initial partition Π^{ini} and let $\Pi^0 = \Pi^{\text{ini}}$, the coalition formation process can be seen as a sequence of transfer operations, e.g.,

$$\Pi^0 \rightarrow \Pi^1 \rightarrow \Pi^2 \rightarrow \cdots \rightarrow \Pi^t \rightarrow \Pi^{t'} \cdots, \tag{22}$$

where $\Pi^t = \{S_1^t, S_2^t, \cdots, S_M^t\}$ is a partition formed after t transitions.

Given any partition Π^t, according to the definition of transfer rule and the acceptance rule, after user $v \in \mathcal{V}$ transfers from coalition S_{i_1} to S_{i_2}, we have $\Gamma(S_{i_1} \backslash \{v\}) + \Gamma(S_{i_2} \cup \{v\}) > \Gamma(S_{i_1}) + \Gamma(S_{i_2})$. On the other hand, since there exists no

Algorithm 3: Sub-Channel Allocation Algorithm.

1. Given the set of the RUEs and D2D pairs $\mathcal{V}$, the set of sub-channels $\mathcal{R}$.
2. Get a stable matching μ^* based on Algorithm 1.
3. Map μ^* to Π^{ini} as $\mu^* \to \Pi^{\text{ini}}$, and obtain the final partition Π^{final} of the set $\mathcal{V}$ based on Algorithm 2.
4. Map Π^{final} into $P \times Q$ as $\Pi^{\text{final}} \to P \times Q$, and obtain the resource allocation solution to the problem defined in (4)–(10).

interference between different sub-channels, the user v's transfer between coalition S_{i_1} and S_{i_2} does not affect the utilities of other coalitions in $\Pi^t \backslash \{S_{i_1}, S_{i_2}\}$. Therefore, for any transfer $\Pi^t \to \Pi^{t'}$, the following inequality always holds:

$$\sum_{S_i \in \Pi^{t'}} \Gamma(S_i) > \sum_{S_i \in \Pi^{t}} \Gamma(S_i). \tag{23}$$

Equation (23) suggests that the user's transfer will increase the overall utility of the system. Equation (23) also suggests that for any transfer $\Pi^t \to \Pi^{t'} (t \neq t')$, $\Pi^t \neq \Pi^{t'}$ always holds. Since the number of partitions of a set is finite and equal to the Bell number [19], and the total utility of the system is bounded, the transfer sequence in (22) is guaranteed to converge to a final partition Π^{final}. ■

Property 4: Algorithm 2 has a complexity of $\mathcal{O}(TM(N+K))$, where T is the number of while-loop iterations.

Proof: The computational complexity of Algorithm 2 is dominated by step 2. Within each iteration of the while-loop in step 2, the complexity of the first for-loop is $(N+K)M$ and $(N+K)M$ when the users get the most preferred transfers and check the transfer rule for transfers, respectively. For sub-channels to select the applicant with the largest transfer factor, the second for-loop has a complexity of $(7+M)(N+K)$. In total, the computational complexity of step 2 will be $T[2M(N+K)+(7+M)(N+K)] = T(7+3M)(N+K)$, where T is the number of while-loop iterations. Therefore, Algorithm 2 has a complexity of $\mathcal{O}(TM(N+K))$. ■

E. Algorithm for the Solution to the Proposed Problem

The sub-channel allocation algorithm which aims to solve the proposed problem in (4)–(10) is shown in Algorithm 3. Algorithm 3 includes four steps. In the first step, the sets $\mathcal{V}$ and $\mathcal{R}$ are given. In the second step, a stable matching μ^* is obtained by Algorithm 1. Based on the outcome of the second step, a final partition Π^{final} of the set $\mathcal{V}$ can be obtained through Algorithm 2. Finally, Π^{final} is mapped into $P \times Q$, which is the resource allocation solution to the problem defined in (4)–(10).

Remark 2: To evaluate the fairness of underlay users in Algorithm 3, the Jain's fairness index [30] is used to verify whether all the underlay users can have their minimum rate requirement satisfied, i.e.,

$$F = \frac{\left[\sum_{i=1}^{K+N} (T_i - d_i^{\min})\right]^2}{(K+N)\sum_{i=1}^{K+N} (T_i - d_i^{\min})^2}, \tag{24}$$

where T_i is the throughput of underlay user i, and $d_i^{\min}$ is its minimum rate requirement. From Algorithm 3 we can see, the fairness of underlay users can be guaranteed. This is because Algorithm 3 is mainly constructed by Algorithm 1 and Algorithm 2. In Algorithm 1, each underlay user has a chance to select the best sub-channel for its rate requirement. Moreover, in Algorithm 2, an underlay user may transfer to another coalition, where it can further increase its utility. Notice the new comer may degrade the performance of underlay users which have already in the target coalition, in that the new comer introduces more interference to the original coalition members, thus lower their utilities. Nevertheless, such unfairness, i.e., individual utility degradation, can be controlled by the acceptance rule, which not only requires that the achievable rate of original coalition members should not lower than their minimum rate requirements after accepting the new comer, but also requires that the sum utility of the original and target coalitions should be increased after the user's transfer, meaning the social welfare as well as the average utility of each user is improved.

In the following, we will prove in Theorem 1 that Algorithm 3 can converge in a finite number of steps.

Theorem 1: Algorithm 3 converges to a final stable resource allocation outcome in a finite number of steps.

Proof: Notice that Algorithm 3 is mainly constructed by Algorithm 1 and Algorithm 2. According to Property 1 and Property 3, we can conclude that Algorithm 3 converges to a final stable outcome, which is the solution to the proposed resource allocation problem. In the worst case, Algorithm 1 has a complexity of $\mathcal{O}(M(N+K)^3)$ according to Property 2, while Algorithm 2 has a complexity of $\mathcal{O}(TM(N+K))$ according to Property 4. Since $T << (N+K)^2$, the computational complexity of Algorithm 3 is dominated by Algorithm 1, and thus has a complexity of $\mathcal{O}(M(N+K)^3)$. In summary, we can conclude that Algorithm 3 converges to a final stable resource allocation outcome in a finite number of steps. ■

V. Performance Evaluation

In this section, numerical simulations are performed to validate the efficiency and performance of the proposed resource allocation algorithm.

A. Simulation Settings

We consider a 10 MHz LTE-A macro-cell with $R = 3$ small cells. The eNB is located at $(0, 0)$ of the plane with a radius of 500 m, while the positions of RRHs is located at (0, 350), $(-175\sqrt{3}, -175)$, $(175\sqrt{3}, -175)$ with equal radius of 150 m. To avoid the severe co-channel interference from the base stations to the D2D pairs, we require that the distance from the D2D transmitter to the eNB must exceed $d_1 = 40$ m, while the distance from the D2D transmitter to the RRHs exceed $d_2 = 100$ m. The minimum data rates of RUEs and DUEs are chosen randomly in the set of $(0.1, 0.2, ..., 2)$Mbps, and the interference threshold for RUEs and DUEs is set to -75 dBm. Each MUE in system is randomly pre-allocated 1 to 3 RBs. Other simulation

TABLE I
SIMULATION SETTINGS

Parameters	Value
System bandwith	10 MHz (50 RBs)
Number of RRH (R)	3
Number of MUEs	20
Number of RUEs in each RRH	8
eNB/RRH/D2D transmission power	43 dBm /33 dBm /23 dBm
Noise spectral density	-174 dBm/Hz
Path loss model for CUE and DUE	$128.1 + 37.6 \log_{10}(d)$[km]
Path loss model for D2D pair	$148 + 40 \log_{10}(d)$[km]
Antenna Gain for eNB, RRH and UEs	14 dBi, 12 dBi, 0 dBi
Shadow fading for cellular link/D2D link	10 dB/12 dB
Bandwidth per RB	$12 * 15$ kHz $= 180$ kHz
τ	$2 * 10^{-2}$

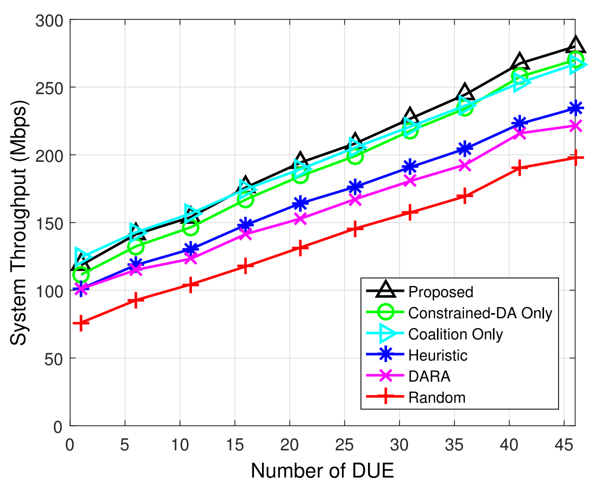


Fig. 3. The system throughput vs. the number of DUEs when the MUE's interference threshold is -90 dBm.

settings are listed in Table I and all the results are averaged over 10000 simulations.

B. Performance Analysis

To evaluate the performance, we compare our scheme with the Heuristic scheme in [31] and the deferred acceptance based resource allocation algorithm (DARA) in [8]. In the Heuristic scheme, the sub-channels are first sorted in descending order based on their CQI, and then, from the sub-channel with the largest CQI, the unsigned D2D pairs are associated with the sub-channels in the ascending order of channel gain. In the DARA scheme, the D2D pairs are matched with the cellular users according to a preference matrix which is calculated based on the location of the D2D pairs and the cellular users. We also evaluate the performance of the constrained deferred acceptance algorithm (Constrained-DA) which is the first phase of our proposed scheme, and the performance of Coalition Only algorithm where the proposed problem is purely reformulated into a coalition game. In addition, a random resource allocation algorithm is given as a benchmark.

We first compare the performance of the six schemes in terms of system throughput, and the results are shown in Figs. 3 and 4. From Figs. 3 and 4, we can see the that given the number of DUEs or the interference threshold of MUE, the random allocation algorithm performs the worst as expected, in that it just randomly allocates the sub-channels to the DUEs and RUEs. The performance of Heuristic and DARA approaches is worse, because they only consider the channel gain or the interference between the MUE and D2D pairs, neglecting the interference between RUEs and MUEs and the interference between RUEs and D2D pairs. The Constrained-DA and Coalition Only outperform all the above three approaches, because they consider the channel gain, bandwidth and the actual data requirement of the underlay users when performs resource allocation. While our proposed scheme, which includes the Constrained-DA and the coalition formation algorithm, performs the best among the six schemes. This is because other than matching, the coalition formation algorithm allows some users to deviate from the more preferred but congested sub-channels to the less preferred but less congested ones.

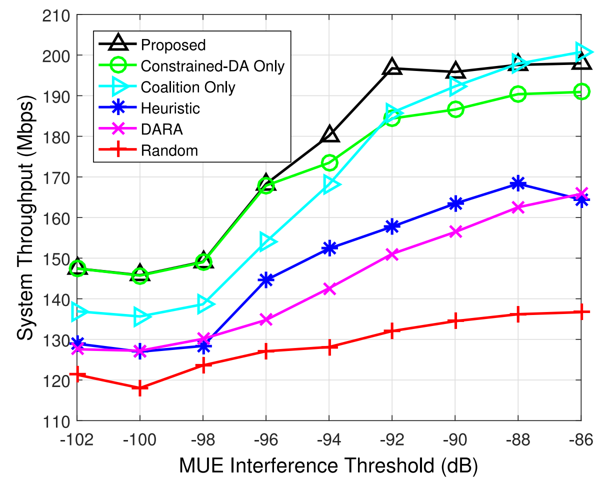


Fig. 4. The system throughput vs. the MUE's interference threshold when the number of DUEs is 22.

Next, the performance of the six schemes in terms of the number of admitted users is investigated, and the results are shown in Figs. 5 and 6. From both Figs. 5 and 6, we can see that the number of admitted users of all the schemes increases as the number of DUEs increases or the interference threshold of MUE decreases. Specifically, in Fig. 6, when the interference threshold of MUE reaches -86 dBm, the number of admitted users can reach $96.7\%, 96.7\%, 95.2\%, 95.6\%, 93.9\%$ of the total number of underlay users in our proposed scheme, the Coalition Only scheme, the Constrained-DA scheme, Heuristic scheme and DARA scheme, respectively. In both figures, our proposed scheme and Coalition Only scheme have the best performance. This is because these two scheme not only allow some users to deviate to the less congested sub-channels, but also gives some unallocated users a chance to access to some less congested sub-channels with the coalition formation algorithm. We notice that the number of admitted users of Constrained-DA is slightly less than that of the Heuristic approach, because more system

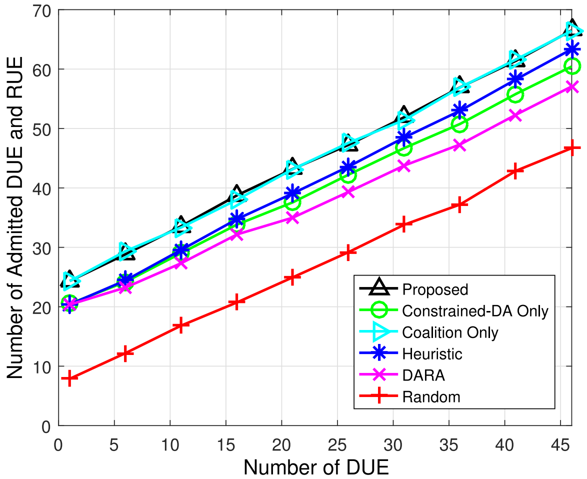


Fig. 5. The number of admitted DUEs and RUEs vs. the number of DUEs when the MUE's interference threshold is −90 dBm.

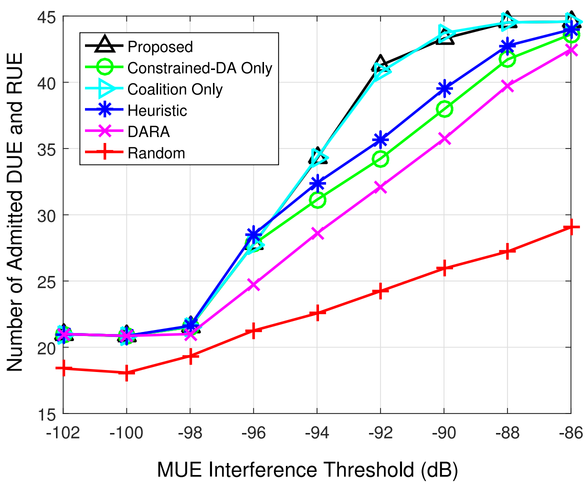


Fig. 6. The number of admitted DUEs and RUEs vs. the MUE's interference threshold when the number of DUE is 22.

throughput is achieved by Constrained-DA as a tradeoff through reasonable channel and user association. The DARA scheme does not performs as well as the Heuristic and Constrained-DA scheme, since the preference function of the DARA is only based on proximity measurements and neither channel condition nor the channel bandwidth is incorporated. The random scheme, which allocates the DUEs and RUEs sub-channels randomly, has the worst performance.

In the third simulation, we evaluate the performance of the six schemes in terms of fairness. Hence, the Jain's fairness index defined in (24) is used. Note that the fairness index varies between 0 and 1, with a larger value meaning more fairness. From Fig. 7 we can see that the Jain's fairness index of our proposed scheme is comparable to that of the Coalition Only scheme, both of which are the highest. Moreover, the Jain's fairness index of our proposed scheme is almost unchanged along with the increase of the number of underlay users, indicating that our scheme can achieve a fairly good performance on fairness.

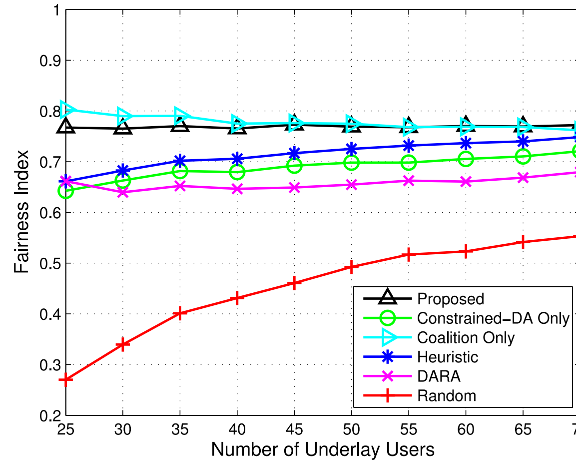


Fig. 7. The fairness index of six schemes.

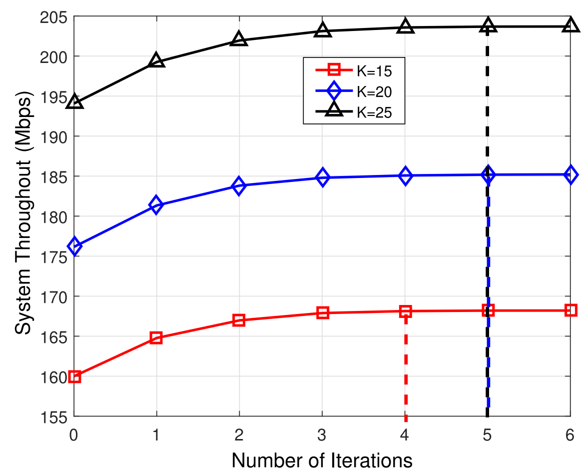


Fig. 8. Convergence of our proposed scheme.

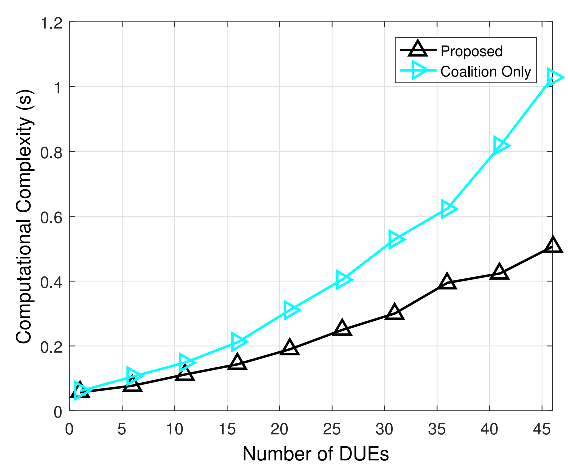


Fig. 9. The computational complexity vs. the number of DUEs.

Finally, we verify the convergence property and computational complexity of our proposed scheme, and the results are shown in Figs. 8 and 9, respectively.

From Fig. 8 we can see that as the iteration times increase, the system throughput increases and finally reaches the maximum value after several iterations. When the number of DUEs K increases from 15 to 25 and then to 35, the final iteration times just increases from 4 to 5, meaning the convergence trend will not be affected too much by the number of DUEs. Such a phenomenon results from the fact that in each round of the matching algorithm, each sub-channel only accepts the user with the largest preference, while in each round of the coalition formation algorithm, each sub-channel only accepts the user with the largest transfer factor.

Fig. 9 verifies that the computational complexity of our two-stage approach is lower than that of Coalition Only. This is because Algorithm 1 (i.e., the matching subgame) has a complexity of $\mathcal{O}(M(N+K)^3)$ in the worst case, and Algorithm 2 (i.e., the coalition subgame) has a complexity of $\mathcal{O}(TM(N+K))$, according to Property 2 and Property 4, respectively. When Algorithm 2 starts from any initial partition, there is $T >> (N+K)^2$, implying a very high computational complexity if the proposed problem is reformulated into the Coalition Only scheme. Nevertheless, if Algorithm 2 follows Algorithm 1, i.e., the coalition sub-game follows the matching subgame and starts from the partition obtained by the matching subgame, it only takes the coalition sub-game a few iterations to converge, resulting a very small T and a low computational complexity of this two-stage approach.

VI. Conclusion

In this paper, we investigate the resource allocation problem in a downlink H-CRAN with D2D communication, where multiple D2D pairs and RUEs are allowed to reuse the sub-channel that has preassigned to a MUE. We formulate the resource allocation problem as a MINLP problem which is NP-Hard. To solve this problem, we reformulate it into a many-to-one matching game with externality followed by a coalition game. Then a constrained DA algorithm and a coalition formation algorithm are proposed to give solutions to these two sequential sub-games, respectively. The stability and complexity of these two algorithm are also theoretically proved. Based on the above two algorithms, the solution of our proposed problem is finally achieved. Through simulations, we demonstrate the effectiveness of the proposed algorithm in terms of system throughput, the number of admitted users, and fairness.

References

[1] M. Agiwal, A. Roy, and N. Saxena, "Next generation 5G wireless networks: A comprehensive survey," *IEEE Commun. Surveys Tut.*, vol. 18, no. 3, pp. 1617–1655, Jul.–Sep. 2016.

[2] M. Peng, Y. Li, J. Jiang, J. Li, and C. Wang, "Heterogeneous cloud radio access networks: A new perspective for enhancing spectral and energy efficiencies," *IEEE Wireless Commun.*, vol. 21, no. 6, pp. 126–135, Dec. 2014.

[3] Y. Zhang, Y. Wang, and W. Zhang, "Energy efficient resource allocation for heterogeneous cloud radio access networks with user cooperation and QoS guarantees," in *Proc.2016 IEEE Wireless Commun. Netw. Conf.*, Doha, Qatar, Apr. 2016, pp. 1–6.

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

[5] A. Sultana, L. Zhao, and X. Fernando, "Efficient resource allocation in device-to-device communication using cognitive radio technology," *IEEE Trans. Veh. Technol.*, vol. 66, no. 11, pp. 10024–10034, Nov. 2017.

[6] D. Feng, L. Lu, Y. Yuan-Wu, G. Y. Li, G. Feng, and S. Li, "Device-to-device communications underlaying cellular networks," *IEEE Trans. Commun.*, vol. 61, no. 8, pp. 3541–3551, Aug. 2013.

[7] Z. Zhou, G. Ma, C. Xu, Z. Chang, and T. Ristaniemi, "Energy-efficient resource allocation in cognitive D2D communications: A game-theoretical and matching approach," in *Proc. IEEE Int. Conf. Commun.*, Kuala Lumpur, Malaysia, May 2016, pp. 1–6.

[8] M. T. Islam, A. E. M. Taha, S. Akl, and M. Abu-Elkheir, "A stable matching algorithm for resource allocation for underlaying device-to-device communications," in *Proc. IEEE Int. Conf. Commun.*, Kuala Lumpur, Malaysia, May 2016, pp. 1–6.

[9] L. Zhou, "Mobile device-to-device video distribution: Theory and application," *ACM Trans. Multimedia Comput., Commun. Appl.*, vol. 12, no. 3, pp. 1253–1271, Jun. 2016.

[10] D. Wu, L. Zhou, and Y. Cai, "Social-aware rate based content sharing mode selection for D2D content sharing scenarios," *IEEE Trans. Multimedia*, vol. 19, no. 11, pp. 2571–2582, Nov. 2017.

[11] A. Asheralieva and Y. Miyanaga, "Dynamic buffer status-based control for LTE-A network with underlay D2D communication," *IEEE Trans. Commun.*, vol. 64, no. 3, pp. 1342–1355, Mar. 2016.

[12] A. Asheralieva and Y. Miyanaga, "QoS-oriented mode, spectrum, and power allocation for D2D communication underlaying LTE-A network," *Trans. Veh. Technol.*, vol. 64, no. 12, pp. 9787–9800, Dec. 2016.

[13] H. A. Mustafa, M. Z. Shakir, Y. A. Sambo, K. A. Qaraqe, M. A. Imran, and E. Serpedin, "Spectral efficiency improvements in HetNets by exploiting device-to-device communications," in *Proc. IEEE Globecom Workshops*, Austin, TX, USA, Dec. 2014, pp. 857–862.

[14] S. H. Yang, L. C. Wang, J. H. Huang, and A. H. Tsai, "Network-assisted device-decided channel selection and power control for multi-pair device-to-device (D2D) communications in heterogeneous networks," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Istanbul, Turkey, Apr. 2014, pp. 1356–1361.

[15] H. Dai, Y. Huang, C. Li, K. Song, and L. Yang, "Resource allocation for device-to-device and small cell uplink communication networks," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Doha, Qatar, Apr. 2016, pp. 1–6.

[16] A. Asheralieva, "Bayesian reinforcement learning-based coalition formation for distributed resource sharing by device-to-device users in heterogeneous cellular networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 8, pp. 5016–5032, Aug. 2017.

[17] A. Asheralieva and Y. Miyanaga, "An autonomous learning-based algorithm for joint channel and power level selection by D2D pairs in heterogeneous cellular networks," *IEEE Trans. Commun.*, vol. 64, no. 9, pp. 3996–4012, Sep. 2016.

[18] Y. Xiao, K. Chen, C. Yuen, Z. Han, and L. A. DaSilva, "A Bayesian overlapping coalition formation game for device-to-device spectrum sharing in cellular networks," *IEEE Trans. Wireless Commun.*, vol. 14, no. 7, pp. 4034–4051, Jul. 2015.

[19] W. Saad, Z. Han, R. Zheng, M. Debbah, and H. V. Poor, "A college admissions game for uplink user association in wireless small cell networks," in *Proc. IEEE INFOCOM*, Toronto, Canada, Apr. 2014, pp. 1096–1104.

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

[21] A. E. Roth and M. A. O. Sotomayor, *Two-Sided Matching: A Study In Game-Theoretic Modeling and Analysis*. Cambridge, UK: Cambridge Univ. Press, 1992.

[22] S. Kazmi *et al.*, "Mode selection and resource allocation in device-to-device communications: A matching game approach," *IEEE Trans. Mobile Comput.*, vol. 16, no. 11, pp. 3126–3141, Nov. 2017.

[23] T. Sanguanpuak, S. Guruacharya, N. Rajatheva, M. Bennis, and M. Latva-Aho, "Multi-operator spectrum sharing for small cell networks: A matching game perspective," *IEEE Trans. Wireless Commun.*, vol. 16, no. 6, pp. 3761–3774, Jun. 2017.

[24] R. Zhang *et al.*, "Distributed resource allocation for device-to-device communications underlaying cellular networks," in *Proc. IEEE Int. Conf. Commun.*, Budapest, Hungary, Jun. 2013, pp. 1889–1893.

[25] S. Zhan and D. Niyato, "A coalition formation game for remote radio head cooperation in cloud radio access network," *IEEE Trans. Veh. Technol.*, vol. 66, no. 2, pp. 1723–1738, Feb. 2017.

[26] X. Hao, M. Cheung, V. W. S. Wong, and V. C. M. Leung, “Hedonic coalition formation game for cooperative spectrum sensing and channel access in cognitive radio networks,” *IEEE Trans. Wireless Commun.*, vol. 11, no. 11, pp. 3968–3979, Nov. 2012.

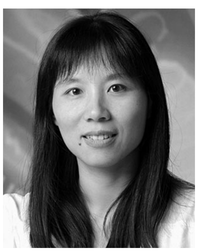
[27] B. Zhang, Y. Chen, C. Wang, and K. J. R. Liu, “A Chinese restaurant game for learning and decision making in cognitive radio networks,” *Comput. Netw.*, vol. 91, pp. 117–134, Nov. 2015.

[28] K. Li, Q. Zhang, S. Kwong, M. Li, and R. Wang, “Stable matching-based selection in evolutionary multiobjective optimization,” *IEEE Trans. Evol. Comput.*, vol. 18, no. 6, pp. 909–923, Dec. 2014.

[29] V. Menon, “On the maximum of Stirling numbers of the second kind,” *J. Combinatorial Theory, Series A*, vol. 15, no. 1, pp. 11–24, Jul. 1973.

[30] R. Jain, A. Durresi, and G. Babic, “Throughput fairness index: An explanation,” ATM Forum/99-0045, Feb. 1999.

[31] M. Zulhasnine, C. Huang, and A. Srinivasan, “Efficient resource allocation for device-to-device communication underlaying LTE network,” in *Proc. IEEE 6th Int. Conf. Wireless Mobile Comput., Netw. Commun.*, Niagara Falls, Canada, Oct. 2010, pp. 368–375.



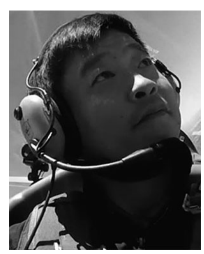
Biling Zhang (M’12) received the B.S., M.S., and Ph.D. degrees from Beijing University of Posts and Telecommunications (BUPT), Beijing, China, in 2000, 2003, and 2013, respectively.

From 2011 to 2012, she was a visiting scholar with the Department of Electrical and Computer Engineering, University of Maryland, College Park, MD, USA. She is currently an Associate Professor with BUPT, Beijing, China. Her research interests include wireless resource allocation, wireless communications and networking, game theory, and smart grid.

Xingwang Mao received the B.S. degree from the Xi’an University of Posts and Telecommunications, Xi’an, China, in 2015, and the M.S. degree from Beijing University of Posts and Telecommunications, Beijing, China, in 2018. He is currently an Engineer with Zhongyuan Bank Company, Ltd., Zhengzhou, China. His research interests include wireless communications and game theory.

Jung-lang Yu (M’04) received the B.S. degree from the National Cheng-Kung University, Tainan, Taiwan, in 1986, and the M.S. and Ph.D. degrees from the National Taiwan University, Taipei, Taiwan, in 1988 and 1997, respectively, all in electrical engineering.

From 1998 to 2000, he was an Associate Professor with the Department of Electronic Engineering, Tungnan University, Taipei, Taiwan. He is currently a Professor with the Department of Electrical Engineering and the Associate Dean with the College of Science and Engineering, Fu Jen Catholic University, New Taipei City, Taiwan. His research interests include massive MIMO, MIMO-OFDM systems, cooperative network communications, and space-time signal processing.



Zhu Han (S’01–M’04–SM’09–F’14) received the B.S. degree in electronic engineering from Tsinghua University, Beijing, China, in 1997, and the M.S. and Ph.D. degrees in electrical and computer engineering from the University of Maryland, College Park, MD, USA, in 1999 and 2003, respectively.

From 2000 to 2002, he was an R&D Engineer with JDSU, Germantown, MD, USA. From 2003 to 2006, he was a Research Associate with the University of Maryland. From 2006 to 2008, he was an Assistant Professor with Boise State University, Boise, ID, USA. He is currently a Professor with the Electrical and Computer Engineering Department and the Computer Science Department, University of Houston, Houston, TX, USA. His research interests include wireless resource allocation and management, wireless communications and networking, game theory, big data analysis, security, and smart grid. He was the recipient of an NSF Career Award in 2010, the Fred W. Ellersick Prize of the IEEE Communication Society in 2011, the EURASIP Best Paper Award for the Journal on Advances in Signal Processing in 2015, IEEE Leonard G. Abraham Prize in the field of Communications Systems (best paper award in IEEE JSAC) in 2016, and several best paper awards in IEEE conferences. He is currently an IEEE Communications Society Distinguished Lecturer.