Cross-layer QoE Optimization for D2D Communication in CR-enabled Heterogeneous Cellular Networks

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***Abstract*—Device-to-Device (D2D) communication based on cognitive radio (CR) technology can significantly improve the coverage and spectral efficiency. Existing research on D2D communications mainly focus on optimizing the network Quality of Service (QoS) in single-tier networks. However, the exponential growth in data traffic has inspired the move from traditional single-tier cellular networks toward heterogeneous cellular networks (HetNets). Hence, in this paper, we consider a CR-based HetNet coexisting with cognitive D2D pairs and cellular users, where the cellular users are primary users (PUs) and D2D pairs are secondary users (SUs). Considering Quality of Experience (QoE) is an important metric to quantify and measure quality of experience from the user perspective, we focus on the QoE optimization of the D2D pairs via the BS association, the discrete power control, and the resource block (RB) assignment. To do so, we first formulate the cross-layer optimization problem to maximize the average QoE of the D2D pairs while satisfying the QoE requirements of cellular users. We then propose the centralized resource allocation, namely the genetic algorithm (GA), and semi-distributed resource allocation method, namely Stackelberg game based algorithm, to solve the non-convex optimization problem. The GA is proposed to ensure the maximum achievable QoE with known channel state information (CSI), whereas the Stackelberg game based algorithm is proposed to cope with the strong needs for distributed D2D solutions with only local CSI of each D2D link. Our proposed algorithms can achieve substantial improvement of QoE performance for D2D pairs via increasing the number of RBs.**

***Index Terms*—QoE, cross-layer optimization, user association, resource allocation, Genetic Algorithm, Stackelberg game.**

I. Introduction

The dramatic increasing usage of smart devices and applications has largely accelerated the growth of mobile data traffic. The Cisco VNI report predicts that the global mobile users will increase from 4.8 billion to 5.5 billion during 2015 and 2020 [1], and the monthly global mobile data traffic will reach 30.6 exabytes by 2020. It is also estimated that the sum of all mobile videos traffic (Video-On-Demand (VOD), Internet, and P2P) will be over 75% mobile traffic by the end of 2020. Action is being taken to deploy more inexpensive, low-power, small-scale BSs, such as pico, femto BSs, underlaying the conventional cellular networks to improve the spectral efficiency. This is the so called heterogeneous cellular networks (HetNets).

Another way to cope with these increasing traffic is to enable the device-to-device (D2D) communication operating in the licensed bands belong to the cellular user equipments (CUEs). With this technology, D2D users in close proximity can exchange rich content via direct connections while bypassing the cellular base stations (BSs). D2D communication can have dedicated spectrum (overlay) or shared spectrum (underlay) with cellular users. In the overlay mode, however, still the dedicated spectrum for D2D users may not be efficiently utilized. On the other hand, in the underlay mode, the most critical part is the interference mitigation between the D2D users and cellular users due to the shared spectrum [2]. Therefore, cognitive radio (CR) technology is applied in D2D communication. By sensing the spectrum conditions and seek to send their signals by reusing the spectrum of primary users (PUs), CR-enabled D2D communication can improve the spectrum resource utilization more effectively, and be viewed as a cost-efficient way to increase the transmission rate and lower the end-to-end latency [3]. Considering these benefits, the D2D assisted video streaming transmission has been widely applied in social networking applications or media sharing applications [4].

In order to support the CUEs and D2D pairs with customized and personalized services in accordance with their preference in a CR-enabled HetNets, it is crucial for the network operators to guarantee a high Quality of Experience (QoE) for each service user, especially for those using the video streaming services [5]. The negative effects due to the interference caused by the frequency reuse in D2D-enabled HetNets may affect the quality and fluency of streaming videos, and thus affect the user experience. More importantly, from the commercial aspect, the user perception and satisfaction are the dominators for the success of a application and service in the marketplace.

According to International Telecommunication Union Telecommunication Standardization Sector Study Group 12 (ITU-T, SG 12), QoE is the overall perception and satisfaction of an application or service subjectively by the end-user [6]. Different from network-oriented Quality of Service (QoS), which is only determined by the technology-centric metrics, such as the packet loss rate, the delay, and the available

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bandwidth, user-oriented QoE is basically an assessment of the service from the user's point of view. Although a better network QoS in many cases will result in better QoE, fulfilling all traffic QoS parameters alone may not guarantee satisfied service users. For example, throughput maximization can not lead to optimal user perceived quality for multimedia applications, such as video and voice, due to that they are highly sensitive to fluctuations in data rate, packet loss, and delay [7]. This is mainly due to the fact that QoE is also affected by other factors, such as the service type, the viewer demography, the video length and the CUE. Such non-network-related factors may not have a direct impact on the QoS but do influence the QoE. The relationship between QoS and QoE becomes an important research topic for the purpose of QoE assessment.

There is mainly two types of QoE assessment methods, either subjectively or objectively . The subjective assessment method measures the human's subjective satisfaction and interest via questionnaires and rating scales [8]. Although this subjective method may be the only method to assess the actual QoE closest to the "ground truth", it is extremely expensive and time-consuming [9]. The objective assessment method measures QoE using different models of human perceptions, and approximate the QoE automatically without the need of human's participation. In this way, the QoE can be mapped from the the QoS parameters and other media-related parameters using a certain function. Specially, the QoE is characterized by the application-oriented mean opinion score (MOS), which reflects the degree of user satisfaction from a scale of 1 (bad) to 4.5 for audio and video applications (excellent) [10], or 5 for other applications (excellent) [11]. Of course, this objective assessment method is more efficient and feasible for the service provider. Hence, some well-known objective models that allow the mathematical evaluation of the MOS have been proposed, such as the Weber-Fechner law based QoE assessment [12], and these application-oriented QoE models for web browsing [13], voice application [14], [15], video streaming [16], and file download application [7].

The new generation of CR-enabled cellular networks (HetNets) have to support the CUEs and D2D pairs using heterogeneous applications with diverse QoE models and requirements, which suffer from the interference due to the resource reuse between D2D pairs and CUEs in each tier. Meanwhile, the MOS-based QoE models for different applications [7], [13]–[16] are usually determined by various factors in different network layers. To make sure the key parameters of different layers are exchangeable, the cross-layer QoE optimization is the key to realize the efficient resource allocation between different layers in CR-enabled HetNets with diverse QoE requirements.

A. Related works

The cross-layer optimization for video streaming video application have been proposed in MIMO systems [17], single cell cellular networks [18], heterogeneous wireless networks [19], single cell LTE networks [20], multiuser OFDMA system [21] and wireless sensor networks [22]. In [21], the centralized QoE-aware resource allocation of multiuser OFDM systems with users operating in audio, video and best-effort applications was studied. In [23], QoE-aware resource allocation was studied for D2D video streaming, where the scheduling algorithm was proposed for multiple D2D users sharing a single channel.

In the underlay D2D-enabled cellular networks, the D2D pairs and CUEs suffer from the mutual interference between each other, thus, the centralized resource allocation can coordinate between the performance of D2D pairs and that of CUEs to achieve the optimal for the objective. The centralized resource allocation has been studied in D2D-enabled single cell cellular networks via the power allocation [24], and the joint RB assignment and power allocation [25]. The centralized resource allocation can provide the maximum achievable performance of the proposed problem, but large signalling overhead can be induced via collecting the global channel state information (CSI), which may be difficult to obtain in some practical scenarios [26]. As such, in [26], a distributed resource allocation based on stackelberg game was proposed. Furthermore, in [27], an hybrid centralized-distributed resource allocation for single cell D2D-enabled cellular networks was proposed, where the channel allocation was realized via the centralized graph-theoretical approach, and the power control was realized via the distributed game theory approach. However, existing resource allocation for D2D-enabled systems considered continuous transmit power allocation, which can not be directly applied to in systems supporting discrete transmit power allocation. For instance, only discrete power allocation is supported in the 3GPP LTE cellular networks with a use-specific data-to-pilot-power offset parameters [28]. Compared with the continuous power control, the discrete power control offers two main benefits [29]: (i) the transmitter is simplified, and more importantly, (ii) the overhead of information exchange among networks is significantly reduced. Nevertheless, using simple discretization on the solution obtained by existed continuous power control is not an effective approach. Discrete power allocation for cellular networks has been proposed in [29], [30]. In [29], two discrete power control algorithms were proposed to maximize the weighted system capacity. In [30], a discrete power control was proposed for multi-cell networks aiming at improving its energy efficiency. In [31], the joint discrete power control and RB assignment was proposed to improve the availability of HetNets based on spectrum aggregation. However, to the best of our knowledge, there is no work dealing with the discrete power control for D2D-enabled systems.

With the increasing interests in HetNets, research has been extended to the resource allocation of D2D-enabled HetNets from the aspect of QoS [32]–[35], [35], [36]. In [35], the social interactions among UEs in a HetNet was designed, and a UE association algorithm based on recommendation system was proposed.In [36], a UE association scheme aiming at load balancing was proposed, and a low-complexity distributed algorithm was proposed to converge to a near-optimal solution. In [32], an intelligent RB selection and power adaption algorithm in D2D-enabled HetNets was proposed by first determining the maximum and minimum transmission powers, and then selecting the RB. In [33], the centralized resource allocation was proposed to solve the quasi-convex optimization problem in D2D-enabled small cell networks, with an objective to achieve the maximum overall throughput of the D2D pairs and CUEs. In [34], an auction-based distributed resource allocation was proposed to achieve the maximum overall data rate of D2D pairs and small cell UEs in D2D-enabled multi-tier cellular networks with single macrocell BS. They assumed that the UE association was determined and known prior to the resource allocation, thus the UE association was not taken into account in the process of resource allocation, and the resource allocation for the single macrocell BS was also ignored. Observing from the existing literature, we notice that the joint QoE cross-layer optimization taking into account the UE association, the power allocation at both BSs and D2D transmitters, and the RB assignment in a CR-enabled HetNets has never been well treated.

B. Contribution

Unlike existing works, the aim of this work is to design a QoE-oriented resource allocation optimization framework in CR-enabled HetNets with discrete power control. At the application layer, the network can accommodate heterogeneous services with different QoE models and requirements. Different from their QoE model applied for web-browsing application in [21], we employ a more practical web-browsing application QoE model, in which the Web page size, the service response time, and the transmission rate are the three main factors in determining the MOS value ranged from 1 to 5. At the bottom layers, the user association for CUEs, RB assignment and power allocation at both BS and D2D transmitters are joint optimized. To the best of our knowledge, this is the first study on the QoE optimization for D2D communication in CR-enabled HetNets. Besides that, this is also the first work taking into account the cell association, the discrete power control and the RB assignment for both D2D pairs and CUEs. The main contributions of this paper are summarized as follows:

- We present a novel cross-layer optimization model to maximize the MOS of D2D pairs in HetNets, which is regarded as an user-oriented QoE metric, rather than typical network oriented QoS metric.
- We propose a GA-based discrete power allocation jointly with the RB assignment and the UE association to optimize the QoE of the D2D pairs while still satisfying the QoE requirement of each CUE. We design an efficient individual encoding scheme and effective constraints handling mechanisms to achieve quick convergence. This algorithm is executed in a centralized manner and serves as a benchmark for the system performance, and can be achieved with polynomial time complexity.
- We then propose the semi-distributed algorithm based on Stackelberg game with low overhead, where the BS is the leader to decide the price of each RB, and the D2D pairs is the followers that compete selfishly in a non-cooperative Nash game to maximize their own QoE values based on the prices set by BS. We also prove the existence of Nash equilibrium and designed the algorithm to converge to the NE.
- Our simulation results shown that our proposed centralized algorithm and semi-centralized algorithm achieve substantial improvement compared with random allocation. With heavy loaded CUEs, increasing the number of RBs can substantially improve the average MOS of D2D pairs while satisfying the minimum MOS requirement at each CUEs.

The remainder of this paper is organized as follows. In Section II, we present the system model and problem formulation. Section III proposes GA-based algorithm and analyzes their computational complexities. Section IV proposes the semi-distributed algorithm based on Stackelberg Game. Section V presents numerical results and Section VI highlights our conclusions.

II. System Model and Problem Formulation

A. System Model

We consider the downlink transmission in a CR-enabled K-tier HetNets with $\mathcal{K} = \{1, ..., K\}$ consists of macro BSs, picocell BSs, femtocell BSs, and further radiating elements. The set of BSs are denoted as $\mathcal{B} = \mathcal{B}_1 \cup \mathcal{B}_2 \cup ... \cup \mathcal{B}_K = \{1, 2, ..., S\}$, where $\mathcal{B}_k$ represents the set of BSs in tier k. We also denote the set of active CUEs as $\mathcal{N} = \{1, 2, ..., N\}$ and the set of active D2D pairs as $\mathcal{D} = \{1, 2, ..., D\}$. Similar as that in [2], [3], we consider CUEs as PUs and D2D pairs as SUs. We consider the open access strategy where a CUE is allowed to connect to any tier without any restriction. The d_{th} D2D pair ($d \in \mathcal{D}$) consists of the D2D transmitter $d_T \in \mathcal{D}_T$ and D2D receiver $d_R \in \mathcal{D}_R$, where $\mathcal{D}_T = \{1_T, 2_T, ..., D_T\}$ and $\mathcal{D}_R = \{1_R, 2_R, ..., D_R\}$. The set of all UEs of the network is denoted as $\mathcal{U} = \mathcal{N} \cup \mathcal{D}_T \cup \mathcal{D}_R$. We denote the set of UEs associated with the sth BS as $\mathcal{N}_s$, and assume each CUE can associate at most one BS, thus $\mathcal{N} = \mathcal{N}_1 \cup \mathcal{N}_2 \cup ... \cup \mathcal{N}_S$ and $\mathcal{N}_i \cap \mathcal{N}_j = \Phi$ for $i \neq j$. For simplicity, we ignore shadowing and consider Rayleigh fading only. The frequency band available for CR transmission is divided into $\mathcal{M} = \{1, 2, ..., M\}$ RBs and each RB occupies a bandwidth of ΔB Hz.

The resource allocation in the proposed CR-enabled HetNets includes the RB assignment, the UE association, and the transmit power allocation as follows:

1) RB Assignment and UE Association: :We assume each BS has the same $\mathcal{M}$ orthogonal RBs.

- **CUE**: Each RB can be allocated to at most one CUE to avoid co-tier interference from other CUEs, and each CUE can associated with a single BS. Similar as the in [31], [36], we assume a CUE can be associated to an arbitrary BS despite its tier. To specify the RB assignment and the UE association of CUE, we define $v_{s,n}^m$ as its RB assignment and UE association indicator, which is a binary variable. If $v_{s,n}^m = 1$, it indicates that nth CUE ($n \in \mathcal{N}$) is associated with the mth RB of sth BS ($s \in \mathcal{B}$), and $v_{s,n}^m = 0$ ($m \in \mathcal{M}$) if otherwise. This is different from [34] where the UE association with the BS in each tier has already been fixed.
- **D2D Pair**: Multiple different D2D pairs can reuse the same RB with CUE during a transmission interval in underlay mode to improve the spectrum utilization. To

specify the RB assignment for D2D pairs, we define the binary variable v_d^m as its RB assignment indicator. If $v_d^m = 1$, it indicates that the mth RB is allocated to dth D2D pair $(d \in \mathcal{D})$, and $v_d^m = 0$ $(m \in \mathcal{M})$ if otherwise.

2) Transmit Power Allocation: We consider the discrete power allocation, where the transmitters can select the transmit power from the power level sets $\mathcal{L} = \{0, 1, 2, \cdots, L\}$, and L is the maximum integral level.

- **CUE**: The CUE occupied at the $m$the RB of the sth BS can select a random power level $l_{s,m}$, where
$$l_{s,m} \begin{cases} \in [1, L], \text{If } m\text{th RB of } s\text{th BS serves one UE}, \\ = 0, \text{If } m\text{th RB of } s\text{th BS serves no UE}, \end{cases} \tag{1}$$
To be more specific, the transmit power allocated to the CUE at the mth RB of the sth BS belongs to the set $[0, \frac{1}{L} P_{s_{RB}}^{\max}, \frac{2}{L} P_{s_{RB}}^{\max}, \cdots, \frac{l_{s,m}}{L} P_{s_{RB}}^{\max}, \cdots, P_{s_{RB}}^{\max}]$, where $P_{s_{RB}}^{\max}$ is the maximum transmit power at each RB of sth BS.
- **D2D Pair**: The dth D2D pair can select a power level η_d, with $\eta_d \in \mathcal{L}$ and $\mathcal{L} = \{0, 1, 2, \cdots, L\}$ while satisfying the minimum transmit power requirement η_d^{min}. To ensure that the D2D receiver is located within the D2D proximity of D2D transmitter $r_{d_T,d_R} < R_d^{max}$, we use the channel inversion power control to compensate the large scale fading, and enable that the average received power at the D2D receiver is larger than the minimum sensitivity ρ_{min} [37]. Hence, we have the D2D proximity as
$$R_d = \left(\frac{\eta_d P_d^{max}}{L \rho_{min}} \right)^{\alpha}, \tag{2}$$
and the minimum transmit power level of the dth D2D transmitter as
$$\eta_d^{min} = \frac{L \rho_{min}}{P_d^{max}} R_{d_T,d_R}^{\alpha}. \tag{3}$$

B. Downlink Data Rate of CUE

It is noted that each CUE is assigned with single RB of a single BS, thus the downlink data rate of the nth CUE is defined as
$$r_n = \sum_{s \in \mathcal{B}} \sum_{m \in \mathcal{M}} v_{s,n}^m r_{s,n}^m, \tag{4}$$
where
$$r_n^{s,m} = W \log(1 + SINR_{s,n}^m), \tag{5}$$
is the downlink data rate of the nth CUE associating sth BS over the mth RB, W is the RB bandwidth (i.e. W=180 kHz), $SINR_{s,n}^m$ is the signal-to-interference-plus-noise ratio (SINR) of the nth CUE at the mth RB of the sth BS, and $\sum\limits_{s \in \mathcal{B}} \sum\limits_{m \in \mathcal{M}} v_{s,n}^m = 1$.

Let us define $H_{i,j}$ as the channel power gain between node i and j and $R_{i,j}$ as the distance between i and j, where $i, j \in \{n, s, d^T, d^R\}$, we then formulate the SINR of the nth CUE at the mth RB of the sth BS as
$$SINR_{s,n}^m = \frac{\frac{l_{s,m}}{L} P_{s_{RB}}^{max} R_{s,n}^{-\alpha} H_{s,n}}{I_{\mathcal{D},n}^m + I_{\mathcal{B},n}^m + N_0}, \tag{6}$$
where $I_{\mathcal{D},n}^m$ is the aggregate interference at the nth CUE from all D2D transmitters over the RB m, and $I_{\mathcal{B},n}^m$ is the aggregate interference at the nth CUE from all the BSs over the mth RB, and N_0 is the noise power. In (6), $I_{\mathcal{D},n}^m$ and $I_{\mathcal{B},n}^m$ are given by
$$I_{\mathcal{D},n}^m = \sum_{d_T \in \mathcal{D}_T} \frac{\eta_d}{L} P_d^{\max} R_{d_T,n}^{-\alpha} H_{d_T,n} v_d^m, \tag{7}$$
and
$$I_{\mathcal{B},n}^m = \sum_{j \in \mathcal{B} \setminus s} \frac{l_{j,m} P_{j,m}^{\max}}{L} R_{j,n}^{-\alpha} H_{j,n}, \tag{8}$$
respectively.

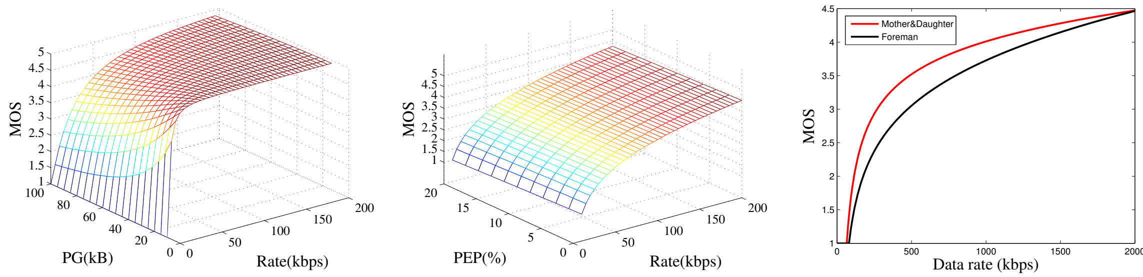
C. Data Rate of D2D Pairs

Each D2D pair can only be allocated with single RB with a certain transmit power level, thus the data rate of the dth D2D pairs is represented as
$$r_d = \sum_{m \in M} \sum_{\eta_d \in L} v_d^m r_d^{m,\eta_d}, \tag{9}$$
where
$$r_d^{m,\eta_d} = W \log(1 + SINR_d^{m,\eta_d}), \tag{10}$$
is the data rate of the dth D2D pair, which is allocated at the mth R with the power level η_d, $SINR_d^{m,\eta_d}$ is the SINR of the dth D2D pair at the mth RB with the power level η_d, and $\sum\limits_{s \in \mathcal{B}} \sum\limits_{m \in \mathcal{M}} v_d^m = 1$.

We then formulate the SINR of the dth D2D pair over mth RB with power level η_d as
$$SINR_d^{m,\eta_d} = \frac{\frac{\eta_d}{L} P_{d_T}^{\max} R_d^{-\alpha} H_{d_T,d_R}}{I_{\mathcal{D},d}^m + I_{\mathcal{B},d}^m + N_0}, \tag{11}$$
where $I_{\mathcal{D},d}^m$ is the aggregate interference at dth D2D pair from other D2D transmitters over RB m, and $I_{\mathcal{B},d}^m$ is the aggregate interference at dth D2D pair from all BSs over RB m. In (11), $I_{\mathcal{D},d}^m$ and $I_{\mathcal{B},d}^m$ are given as
$$I_{\mathcal{D},d}^m = \sum\nolimits_{i \in D^T \setminus d^T} \frac{\eta_i}{L} P_i^{\max} R_{i,d^R}^{-\alpha} H_{i,d_R} v_i^m, \tag{12}$$
and
$$I_{\mathcal{B},d}^m = \sum_{s \in B} \frac{l_{j,m} P_{j,m}^{\max}}{L} H_{s,d_R} R_{s,d^R}^{-\alpha}, \tag{13}$$
respectively.

D. Application-driven Cross-Layer Optimization

To focus on optimizing the user's perceived quality for interactive and real-time services, and increases the customs' satisfaction from the service provider perspective, the QoE model is required to measure the human perception of quality. The QoE models vary depends on different types of application, in this work, we limit our study to three most typical applications, which are the web browsing, the audio and the video applications. Different from existing QoE model mainly focus on data rate [12], application parameters such as daly,



(a) (b) (c)

Fig. 1: (a) MOS model of web browsing application, (b) MOS model of audio application, (c) MOS model of video application

page size, packet error probability (PEP) is also employed in the design of the QoE models.

The traditional network metrics, such as throughput or delay, are not sufficiently reliable for the QoE evaluation [38]. Alternatively, the application-oriented mean option score (MOS) methodology is a widely used QoE evaluation metric capable of transferring the technical objective parameters to the subjective user perceived quality. The UE's QoE is classified into five levels with corresponding MOS values (ITU-T P.800): "Excellent" $=5$, "Good" $=4$, "Fair" $=3$, "Poor" $=2$, "Bad" $=1$, and the acceptable QoE quality is above the MOS value of 3.5 [11].

Considering that the video application is more bandwidth intensive than the web browsing and audio application, we assume that the D2D pairs are limited to video application, and the CUEs are limited to the web browsing and the audio applications in this work. However, the cross-layer optimization method proposed in the next section of this work can be applied to more general scenario, where the CUEs and the D2D pairs delivers any type of applications. In the following, to evaluate the QoE of the CUEs and D2D pairs in HetNets, we present the QoE models of the web browsing, the audio and the video applications, respectively.

1) Web Browsing Application: The MOS value of the web browsing application is mainly determined by the Web page size, the service response time, and the transmission rate. The QoE model of the web browing application proposed in [13] has been tested and verified using a web page download scenario in a 3G LTE network. This QoE model is given as

$$\mathrm{MOS}_1 = \max\left\{5 - \frac{578}{1+\left(11.77+\frac{22.61}{t}\right)^2}, 1\right\}, \qquad (14)$$

where t is the service response time measured in seconds. This service response time is defined as the delay between the time a request for a web page was sent and the time of reception of the entire web page contents. Note that the QoE value of a web user ranges from 1 to 5 (i.e., the score 1 denotes "extremely low quality" whereas score 5 denotes "excellent quality"). The constants 578, 1, 11.77 and 22.61 are obtained from by analyzing the experimental results for the web browsing application.

We assume TCP and HTTP protocols are applied to set the HTTP request message. If the transmission rate of CUE $n \in N$ is r_n, t can be given by,

$$t \approx 3\mathrm{RTT} + \frac{\mathrm{PS}}{r_n} + \mathbf{L}\left(\frac{\mathrm{MSS}}{r_n} + \mathrm{RTT}\right) - \frac{2\mathrm{MSS}(2^L-1)}{r_n} \qquad (15)$$

where RTT is the round trip time, PS is the web page size, MSS is the maximum segment size, and L is the number of slow start cycles with idle periods. Define L_1 as the number of cycles the congestion window takes to reach the bandwidth-delay product and L_2 as the number of slow start cycles before the web page size is completely transferred. Since L_1 and L_2 should be larger than L, it therefore can be defined as

$$\mathrm{L} = min(\mathrm{L}_1, \mathrm{L}_2) \qquad (16)$$

where $\mathrm{L}_1 = \lceil log_2(\frac{r_n\mathrm{RTT}}{\mathrm{MSS}}+1)\rceil - 1$, and $\mathrm{L}_2 = \lceil log_2(\frac{\mathrm{PS}}{2\mathrm{MSS}}+1)\rceil - 1$. To give an example, Fig .1 (a) plots the MOS value versus various actual transmission rate and web page size with $\mathrm{RTT} \approx 0$.

2) Audio Application: In the audio application, the perceived voice quality mainly depends on the data rate r_n, and the packet error probability (PEP). According to the QoE model in [14], [15], the MOS of the the audio application at the nth CUE is definde as

$$\mathrm{MOS}_2 = a\log\left(br_n(1-\mathrm{PEP})\right) \qquad (17)$$

where constants a and b are calculated by fixing the MOS at a given rate r_n and PEP$=0$. For example, if the BS provides a specific service with rate r_n, and the CUE experiences the service with rate r_n, then the MOS value of the user satisfaction achieves the maximum (i.e., 4.5) when there is no packet loss.

To obtain the constants a and b, we define a minimum transmission rate and the maximum PEP (e.g., 20%), which corresponds to the minimum MOS value 1, and define a maximum transmission rate and the minimum PEP (e.g., 0%), which corresponds to the maximum MOS value 4.5. By fitting a logarithmic curve for the estimated MOS under the predetermined PEP with obtained a and b, we plot Fig. 1(b) to showcase the relationship between the MOS value and various actual transmission rate.

3) Video Application: We apply the QoE model of the video application given in [16], which has been tested and verified using H.264/AVC encoded video test sequences ("Foreman" and "Mother & Daughter"). In this model, the MOS value is mainly determined by the peak signal to noise ratio (PSNR). The PSNR of the dth D2D pair is calculated using

$$\text{PSNR}_d = a + b\sqrt{\frac{r_d}{c}}\left(1 - \frac{c}{r_d}\right), \tag{18}$$

where the parameters a, b, and c is determined by the rate-distortion characteristics of a specific video stream or sequence. In this paper, we apply three MOS-Rate pairs to obtain the parameters a, b and c of a video. Fig. 1(c) plots the QoE curves for different video sequences that correspond to the discrete MOS values of the actual dynamic adaptive streaming over HTTP protocol for mobile LTE users.

The MOS of the video application is defined as

$$\text{MOS}_3 = \begin{cases} 4.5 & \text{PSNR}_i \geq \text{PSNR}_{4.5} \\ d\log(\text{PSNR}_k) + \xi & \text{PSNR}_{1.0} < \text{PSNR}_i < \text{PSNR}_{4.5} \\ 1 & \text{PSNR}_i \leq \text{PSNR}_{1.0}, \end{cases} \tag{19}$$

where PSNR_d is the peak signal-to-noise ratio achieved at the D2D receiver. For the known rate-distortion characteristics of a specific video stream or sequence, we define a minimum transmission rate, which corresponds to the minimum MOS value 1, and define a maximum transmission rate, which corresponds to the maximum MOS value 4.5, in order to derive the parameters $\text{PSNR}_{1.0}$ and $\text{PSNR}_{4.5}$. With the threshold values of $\text{PSNR}_{1.0}$ and $\text{PSNR}_{4.5}$, the constants d and ξ can be derived using

$$\begin{cases} d = \frac{3.5}{\log(\text{PSNR}_{4.5}) - \log(\text{PSNR}_{1.0})} \\ \xi = \frac{\log(\text{PSNR}_{4.5}) - 4.5\log(\text{PSNR}_{1.0})}{\log(\text{PSNR}_{4.5}) - \log(\text{PSNR}_{1.0})}. \end{cases} \tag{20}$$

To give an example, Fig .1 (c) plots the MOS value versus various actual date rate. Here for the video titled "Mother & Daughter", the $\text{PSNR}_{4.5}$ and $\text{PSNR}_{1.0}$ are set as 45 db and 35 db. For the video titled "Foreman", the $\text{PSNR}_{4.5}$ and $\text{PSNR}_{1.0}$ are set as 42 db and 30 db respectively.

E. Cross-layer QoE Optimization

In this section, we formulate the optimization problem with the objective to achieve the maximum average QoE over all D2D pairs while satisfying the minimum QoE requirement of each CUEs in HetNets. This can be achieved by searching the optimal RB assignment, UE association and power allocation for each CUE $n \in \mathcal{N}$ and finding the optimal RB assignment, and power allocation for each D2D pair $d \in \mathcal{D}$.

We define the binary variable x_n^q as the application service indicator, where $x_n^q = 1$ represents that the application service of the nth CUE is the qth application, and otherwise $x_n^q = 0$. Note that $q = 1$ corresponds to the web browsing application, and $q = 2$ corresponds to the voice application. We also define the minimum QoE requirement of the qth application as τ_q. Similar as that in [21], we assume this QoE requirement is defined according to the application type and is given in priori. For instance, for CUEs with audio application, its minimum QoE should be at least 3.5 [11]. We formulate this optimization problem as

$$\max \frac{\sum_{d\in\mathcal{D}} \text{MOS}_3(r_d)}{D} \tag{21}$$

$$\text{s.t.} \sum\nolimits_{q\in\{1,2\}} x_n^q \text{MOS}_q(r_n) \geq \tau_q,\ \forall n \in \mathcal{N}, \tag{21a}$$

$$\sum\nolimits_{q\in\{1,2\}} x_n^q = 1,\ \forall n \in \mathcal{N}, \tag{21b}$$

$$\sum\nolimits_{m\in M} v_d^m = 1,\ \forall d \in \mathcal{D}, \tag{21c}$$

$$\eta_d \geq \eta_d^{min},\ \forall d \in \mathcal{D}, \tag{21d}$$

$$\sum\nolimits_{s\in S}\sum\nolimits_{m\in M} v_{s,n}^m = 1,\ \forall n \in \mathcal{N} \tag{21e}$$

$$\sum\nolimits_{n\in N_s} v_{s,n}^m = 1,\ \forall s \in \mathcal{B}, m \in \mathcal{M}, \tag{21f}$$

$$\sum\nolimits_{n\in N}\sum\nolimits_{m\in M} v_{s,n}^m \leq M,\ \forall s \in S, \tag{21g}$$

$$l_{s,m} \in [0, \cdots, L],\ \forall s \in \mathcal{B}, m \in \mathcal{M}, \tag{21h}$$

The constraints in (21a)-(21g) are named as the CUE QoE requirement in (21a), the application service constraint in (21b), the D2D per-RB assignment constraint in (21c), the D2D pair power allocation constraint in (21d), the per-CUE association constraint in (21e), the CUE per-RB assignment constraint in (21f), and per-BS association constraint in (21g). The *CUE QoE requirement* in (21a) implies that the minimum QoE requirement τ_q for the qth application of the CUE should be satisfied, which is different from previous work only concerning QoS threshold. The *application service constraint* in (21b) implies that each CUE should select one type of application. The *D2D per-RB assignment constraint* in (21c) represents that each RB can be allocated to at most one D2D pair. The *D2D pair power allocation constraint* in (21d) represents that the minimum discrete transmit power level of ith D2D pair should be larger than η_d^{min}. The *per-CUE association constraint* in (21e) represents each RB of each BS can allocated to at most one CUE. The *CUE per-RB assignment constraint* in (21f) represents that different UEs associated with the same BS should be allocated different RBs. The *per-BS association constraint* in (21g) represents that each BS can serve at most M CUEs.

III. Genetic Algorithm Approach

In this section, we assume the macro BS has global CSI, and propose a centralized algorithm based on genetic algorithm (GA). GA is one of the most popular bio-inspired algorithms and is widely used to tackle real world NP-hard problems, such as BS placement optimization for LTE heterogeneous networks [39] or D2D communication for video streaming [4] and clustering for wireless sensor networks [40]. In general, bio-inspired algorithms imitate the natural evolution of biological organisms to provide a robust, near optimal solution for various problems [41]. GA is inherently an evolutionary process that involves individual encoding, selection, crossover, mutation, and replacement operations [42].

A. Individual encoding

GA cannot deal with the solutions of the optimization problem directly. The solutions needs to be represented as chromosomes in terms of data structure. In our optimization problems, an integer-based encoding scheme containing the joint UE association RB allocation and power allocation for the CUEs, as well as the RB allocation and power allocation for the D2D pairs, is proposed to represent the potential solution.

We generate the initial population $\mathcal{R} = \{1, ..., R\}$ consisting of R different individuals, and each individual consists of four integer-based vectors, which are the potential solutions of the considered optimization problem. These vectors are generated according to **Algorithm 1** in order to satisfy the *D2D per-RB assignment constraint*, the *D2D pair power allocation constraint*, the *per-CUE association constraint*, the *CUE per-RB assignment constraint*, and the *per-BS association constraint* during initialization to accelerate the convergence process. Also note that all the individuals in the initial population are randomly generated, thus to preserve the diversity of the population and avoid converging to a local optima [42]. We represent four integer-based vectors in the rth individual as the following.

1) Joint UE association and RB allocation vector Γ_N^r is

$$\Gamma_N^r = \left[\gamma_1^r, \cdots, \gamma_n^r, \cdots, \gamma_N^r\right], \tag{22}$$

where the matrix elements γ_n^r $(1 \leq n \leq N, 1 \leq \gamma_n^r \leq SM)$ indicates the nth UE associated with the $\gamma_n^r - M(\lceil \gamma_n^r/M \rceil - 1)$th RB of the $\lceil \gamma_n^r/M \rceil$th BS. For instance, if $S = 4$, $M = 10$, and $\gamma_n^r = 36$, it corresponds to $v_{4,n}^6 = 1$, which means nth CUE is occupying the 6th RB of 4th BS.

To initialize the joint UE association and RB allocation vector Γ_N^r of population $\mathcal{R}$, we first generate P_N^{SM} permutation vectors $\mathcal{K}_{1\times N}^i$ $(1 \leq i \leq P_N^{SM})$ based on the vector $[1, 2, 3, ..., SM]$. Note that $P_N^{SM} = \frac{(SM)!}{(SM-N)!}$. Then Γ_N^r at each individual of $\mathcal{R}$ are given from first R vectors in $\mathcal{K}$. Thus, we have to limit the total number of inidividuals $R \leq P_N^{SM}$, the number of active CUEs $N \leq SM$ in this algorithm, which is enough and possible to obtain the optimal after evolution.

2) Power allocation vector at the BS for its associated CUE L_N^r is

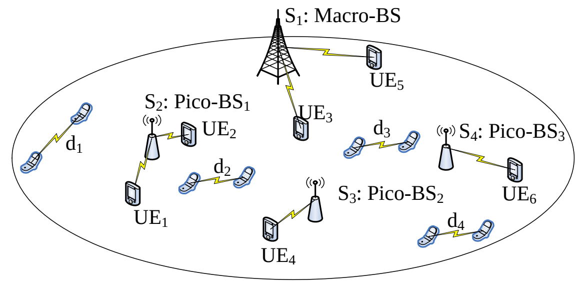
$$L_N^r = \left[l_1^r, \cdots, l_n^r, \cdots, l_N^r\right], \tag{23}$$

where the matrix elements l_n^r $(1 \leq n \leq N, 1 \leq l_n^r \leq L)$ indicates allocated power at the BS to CUE n. The matrix element l_n^r is initialized in correspondence to the initialization of γ_n^r, and its transmit level is randomly selected from $[1, 2, ..., L]$. According to (22), UE n is associated with the $\gamma_n^r - M(\lceil \gamma_n^r/M \rceil - 1)$th RB of the $\lceil \gamma_n^r/M \rceil$th BS, therefore, the actual allocated power of nth UE is $\frac{l_n^r}{L} P_{\lceil \gamma_n^r/M \rceil, RB}^{max}$.

3) D2D pair RB allocation vector Γ_D^r is

$$\Gamma_D^r = \left[\beta_1^r, \cdots, \beta_d^r, \cdots, \beta_D^r\right], \tag{24}$$

where the matrix elements β_d^r $(1 \leq d \leq D, 1 \leq \beta_d^r \leq M)$ indicates the dth D2D pair is allocated with the β_d^rth RB. For instance, if $M = 10$, and $\beta_d^r = 3$, the dth D2D pair is allocated the 3th RB, i.e. $v_d^3 = 1$.



Γ_N^r	γ_1^r	γ_2^r	γ_3^r	γ_4^r	γ_5^r	γ_6^r
	4	5	1	7	2	10

Γ_D^N	β_1^r	β_2^r	β_3^r	β_4^r
	1	2	3	3

L_N^r	l_1^r	l_2^r	l_3^r	l_4^r	l_5^r	l_6^r
	7	8	9	1	10	5

L_D^N	η_1^r	η_2^r	η_3^r	η_4^r
	12	14	4	7

Fig. 2: Individual encoding scheme

4) D2D pair power allocation vector L_D^r

$$L_D^r = \left[\eta_1^r, \cdots, \eta_d^r, \cdots, \eta_D^r\right] \tag{25}$$

where the matrix elements η_d^r $(1 \leq d \leq D, \eta_d^{min} \leq \eta_d^r \leq L)$ indicates the dth D2D pair is allocated with the η_d^rth power level. For instance, if $L = 16$, $\eta_d^{min} = 3$ and $\eta_d^r = 5$, it indicates that the dth D2D pair is allocated with power $\frac{5}{16} P_d^{max}$.

Algorithm 1: Population initialization

set $r = 1$
while $r \leq R$ **do**
  randomly generate a permutation vector $\mathcal{K}_{1\times N}^r = P_N^{SM}$
  for CUE n $= 1$ **to** N **do**
    initialize l_n^r as a random integer from $[1, 2, ..., L]$
  end
  for $D2D$ $pair$ d $= 1$ **to** D **do**
    initialize v_d^r as a random integer from $[1, 2, ..., M]$
    initialize l_d^r as a random integer from $[\eta_d^{min}, \eta_d^{min} + 1, ..., L]$
  end
  $r = r + 1$
end

One example of this encoding scheme is illustrated in Fig. 2 with 4 BSs, 6 CUEs and 4 D2D pairs deployed in HetNets, where each BS has 3 RBs, and the maximum integral power levels as 16. Assume one obtained joint UE association and RB allocation vector Γ_N^r as $[4, 5, 1, 7, 2, 10]$ and the corresponding allocation vector L_N^r as $[7, 8, 9, 1, 10, 5]$, from which we observe that the 2nd BS communicates 1th CUE over the 1st RB and the 7th power level, and the 2nd BS communicates 2nd CUE over the 2nd RB and the 8th power level. Similarly, with RB allocation vector Γ_D^r as $[1, 2, 3, 3]$ and power allocation vector L_D^r as $[12, 14, 4, 7]$, we can observe that the 1th D2D pair occupy the 1st RB with the 12th power level, and the 2nd D2D pair occupy the 2nd RB with the 14th power level. These encoding vectors can be mapped as a feasible resource allocation to all CUEs and D2D pairs. It also can be observed that this encoding scheme meet all the constraints except CUE QoE requirement, which will be satisfied in the following selection process.

B. Fitness functions and natural selection

In GA, selection operation is applied to choose individuals to participate in reproduction, which has a significant impact on driving the search towards a promising trend and finding optimal solutions in a short time. We adopt the famous roulette wheel selection method to select the individual based on its selection probability, which is proportional to its fitness function. The selection probability of the rth individual is defined as

$$q_r = \frac{f(r)}{\sum_{r \in \mathcal{R}} f(r)}, \tag{26}$$

where $f(r)$ is the fitness function of individual r. The quality of the individual is judged by this fitness function.

For the design of fitness function, in order to further satisfy the CUE QoE requirement, we define the fitness function as the objective value of (21). It should be noted that, with the given RB assignment and power allocation for each CUE or D2D pair, the data rate r_n ($\forall n \in \mathcal{N}$) or r_d ($\forall d \in \mathcal{D}$) can be obtained with (4) or (9). Therefore, combined with the priori given application parameters, their MOS value can be obtained according to the MOS model (14), (18) or (20). However, due to the fact the obtained MOS value may violate the the application service constraint in (21b), the penalty method [43] is adopted. Thus to provide an efficient search and ensure that the final best solution is feasible. The fitness function is expressed as

$$\begin{aligned} f(r) = & \frac{\sum_{d \in D} \mathrm{MOS}_3(r_d)}{D} + \\ & \frac{\sum_{n \in N} \mu_n \min\left(\sum_{q \in \{1,2\}} x_n^q (\mathrm{MOS}_q(r_n) - \tau_q), 0\right)}{N_v}, \end{aligned} \tag{27}$$

where μ_n represents the penalty coefficient determined by the CUE QoE requirement, and N_v is the total number of CUEs can not satisfy their QoE requirements.

C. Crossover and mutation

The crossover operation is used to mix between the individuals to increase their fitness. The conventional two-points crossover [42] is performed to produce new child individuals for power allocation vector of CUEs L_N^r, D2D pair RB allocation vector V_D^r and D2D pair power allocation vector L_D^r. However, the conventional crossover operation can not be directly applied to the joint user association and RB allocation vector Γ_N^r, due to the fact that some genes in Γ_N^r may be the same after operation, and violate the *per-RB assignment constraint*. Thus, we propose an enhanced two-points crossover method to produce new child individuals for Γ_N^r.

1) Conventional two-points crossover: For L_N^r, Γ_D^r and L_D^r, every genes between the two crossover points are switched between two parent individuals to produce two child individuals, where this two crossover points are generated randomly. To give an example for parent A L_D^a and parent B L_D^b in Fig. 3 (a), with the randomly generated two crossover points $c_1 = 1$ and $c_2 = 4$, the 1st and $5 \sim 6$th genes of L_D^{Pa} are swapped with the 1st and $5 \sim 6$th genes of L_D^{Pb}, while the 2nd ~ 4th genes remain as the same as their parents. Here, those elements in L_D^{Pb} are shown in dark to make the results after crossover more obvious. Note that this crossover operation always satisfy the *D2D per-RB assignment constraint*, the *D2D pair power allocation constraint* constraint.

2) Enhanced two-points crossover: The enhanced two-points crossover is performed to satisfy the *per-RB assignment constraint* for arbitrary parent A Γ_N^{Pa} and parent B Γ_N^{Pb}, as shown in Fig. 3 (b). First, the genes between the randomly generated points c_1 and c_2 in parents are inherited to child individuals Γ_N^{Ca} and Γ_N^{Cb}. Second, all the genes in parent B Γ_N^{Pb} are filled into the child individual Γ_N^{Ca}, and all the genes in parent A Γ_N^{Pa} are filled into the child individual Γ_N^{Cb}. Third, the repetitive values in the genes of Γ_N^{Ca} and Γ_N^{Cb} are removed, and the genes out of the original length of Γ_N^{Pa} and Γ_N^{Pb} are also removed, which become the final child individuals Γ_N^{Ca} and Γ_N^{Cb} after the enhanced two-points crossover. By doing so, different feasible individuals can be produced and the population diversity can be maintained.

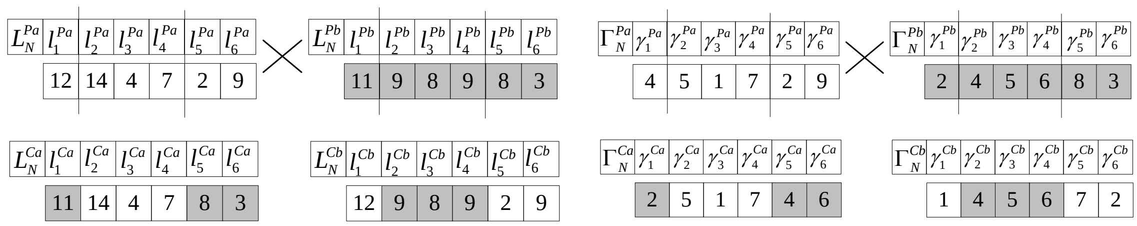
In the mutation operation, the genes in both vectors of each individual are randomly altered to diversify the population after the crossover operation, which will pave the way towards global optima. 1) For the mutation occurring at the arbitrary element γ_n^r, repair operation may be required to satisfy the CUE *per-RB assignment constraint* to speed up the convergence; 2) For the mutation occurring at the arbitrary element l_n^r, v_d^r and η_d^r, mutation operation will be performed using the random integer generated from its valid range, and no repair execution is needed.

D. Replacement

After generating a new population through the crossover and mutation operators, an elitist model based replacement is employed to update a certain number of individuals in the old population with the new generated individuals. The low quality individuals with the low fitness values in the parental population are replaced by their children in the next generation.

E. Joint optimization algorithm

In this section, we present the joint optimization algorithm based on GA, which consists of individual encoding, population initialization, selection, crossover, mutation, and replacement operations. The joint optimization of UE association, RB assignment and power allocation based on GA is depicted in **Algorithm 2**, where G is the given number of generations, R is the population size, q_c is the crossover probability, and q_m is the mutation probability. According to [44], we can derive the time complexity of our algorithm is



(a) (b)

Fig. 3: (a) conventional crossover for vector L_N^r, (b) enhanced crossover for vector Γ_N^r

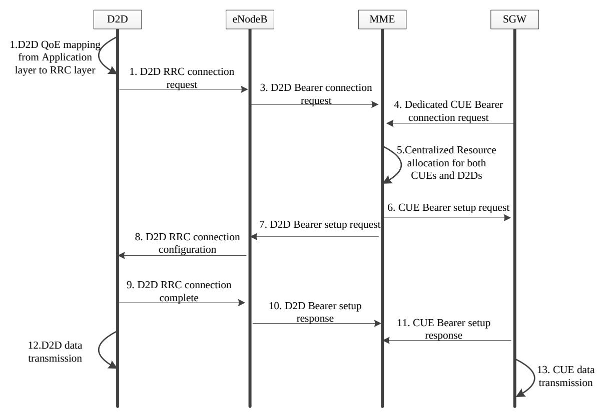


Fig. 4: Signaling procedure of the centralized algorithm

$o(GR((N+D)+R))$. Since this algorithm is executed in a centralized manner, we assume there exists a centralized resource manager (RM) located at the Macro BS, which are responsible for determining the UE association, the RB allocation and power level allocation for each CUE, and to determine the RB allocation and power level allocation for D2D pair.

For clarification, , Fig. 4 plots the signaling procedure of this centralized algorithm. Here, we assume a Long Term Evolution (LTE) system of release 8 is applied, which is comprised of a core network and a access network. In our paper, we assume the core network consists two logical nodes, the Mobility Management Entity (MME) and the Serving Gateway (SGW). Here, MME is responsible for the resource management, and SGW is responsible for transferring all downlink data to CUEs. The access network is made up of the evolved NodeB (eNodeB), where all D2D pairs connecting via LTE-Uu interfaces. Due to the fact the application layer is above the Radio Resource Control (RRC) layer, the D2D QoE mapping is first executed to transform a QoE request as a RRC connection request, as shown in the message 1 and 2. And then, the eNodeB transforms it to a bearer connection request message on the S1 Application Protocol (S1-AP) to the MME node, as shown in message 3. Except from message 3, the MME node also receives the downlink resource request of all CUEs from the SGW node, as shown in message 4. When the MME node successfully receives all these resource requests, the centralized resource allocation algorithm is executed to determine the UE association, RB assignment and power allocation for CUEs, and determine the RB assignment and power allocation for all D2D pairs. If the resource allocation configuration is finished by these CUEs and D2D pairs, a response message is sent back to the RM module. After that, the requested data will be transmitted via this allocated resources.

Algorithm 2: Joint optimization based on GA

set $g=1$
Generate initiation population $\mathcal{R}$ using **Algorithm 1**
Calculate fitness value for each individual in $\mathcal{R}$
while $g \le G$ **do**
  Set $\mathcal{R}' = \Phi$
  for $i = 1$ **to** $R/2$ **do**
    Select two parents A and B from $\mathcal{R}$ using roulette wheel selection method
    Cross the vector Γ_N^A of A with Γ_N^B of B using enhanced two-point crossover with probability q_c, and produce two children vectors Γ_N^A and Γ_N^B
    Cross vectors L_N^A, Γ_D^A, and L_D^A of A with L_N^B, Γ_D^B, and L_D^B of B using conventional two-point crossover with probability q_c, and produce children vectors L_N^A, Γ_D^A, L_D^A and L_N^B, Γ_D^B, and L_D^B
    Combine the vectors Γ_N^A, L_N^A, Γ_D^A, L_D^A to produce child A, and combine the vectors Γ_N^B, L_N^B, Γ_D^B, L_D^B to produce child B
    Mutate A and B using mutation strategy with probability q_m
    Repair elements in Γ_N^A in A and Γ_N^B in B if needed
    $\mathcal{R}' = \mathcal{R}' \cup \{A, B\}$
    Calculate fitness value for each individual in $\mathcal{R}'$
  end
  Replace the individuals with low fitness values in population $\mathcal{R}$ with the children in offspring $\mathcal{R}'$
  $g = g + 1$
end
Return the fittest individual in $\mathcal{R}$

IV. Semi-distributed Algorithm

In this section, we present a semi-distributed algorithm, where the D2D pairs independently determine their power allocation and RB assignment with the minimum assistance of BSs based on the Stackelberg game, considering its large signalling overhead, and the lack of reliable channel state information (CSI). The Stackelberg game is a strategic game, which includes a leader and some followers competing with each other on certain resources. The leader sets the price of the resource first, and then the followers compete with each other for better price.

A. Stackelberg Game Formulation

In our model, the BS plays the role as the leader in this Stackelberg game, it owns all the RB resources and has the right to set the "price" per RB per unit power. The BSs can gain profit according to the set price by allowing the D2D pairs to use RB with certain transmit power, this will encourage the BS to share more resources, which belongs to CUEs, with the D2D pairs. From the perspective of D2D pairs, they are always intend to transmit with optimal power and RB, but it will cost a lot of money, thus, each D2D pair interacts with each other in a non-cooperative manner to maximize its revenue. While from the perspective of BSs, they wants to maximize their revenue, under the condition that the QoE requirements of all CUEs are fulfilled. As such, we maximize the utility function of BS as

$$\max U_{BS}(\mathbf{R}_{\mathcal{D}}, \mathbf{R}_{\mathcal{N}}, \mathbf{F}_{\mathcal{M}}) = \sum\nolimits_{d\in D}\sum\nolimits_{m\in M} f_m v_d^m \eta_d \frac{p_d^{\max}}{L} \tag{28}$$

$$\text{s.t.} \sum\nolimits_{q\in\{1,2\}} x_n^q \text{MOS}_q(r_n) \geq \tau_q,\ \forall n \in \mathcal{N}, \tag{28a}$$
$$\sum\nolimits_{q\in\{1,2\}} x_n^q = 1,\ \forall n \in \mathcal{N}, \tag{28b}$$
$$\sum\nolimits_{s\in S}\sum\nolimits_{m\in M} v_{s,n}^m = 1,\ \forall n \in \mathcal{N} \tag{28c}$$
$$\sum\nolimits_{n\in N_s} v_{s,n}^m = 1,\ \forall s \in \mathcal{B}, m \in \mathcal{M}, \tag{28d}$$
$$\sum\nolimits_{n\in N}\sum\nolimits_{m\in M} v_{s,n}^m \leq M,\ \forall s \in S, \tag{28e}$$
$$l_{s,m} \in [0,\cdots,L],\ \forall s \in \mathcal{B}, m \in \mathcal{M}, \tag{28f}$$

where $\mathbf{F}_{\mathcal{M}} = \{f_1, f_2, \cdots, f_M\}$ is the charging price for all RBs per unit power, $\mathbf{R}_{\mathcal{D}} = \begin{bmatrix} \Gamma_{\mathcal{D}}^1 \\ L_{\mathcal{D}}^1 \end{bmatrix}$ and $\mathbf{R_N} = \begin{bmatrix} \Gamma_{\mathcal{N}}^1 \\ L_{\mathcal{N}}^1 \end{bmatrix}$ are the RB assignment and power allocation of all the D2D pairs and all the CUEs, respectively.

As a follower, with the predefined price $\mathbf{F}_{\mathcal{M}}$, we maximize the utility function of the dth D2D pair at the mth RB with power level η_d as

$$\max U_d(\mathbf{R}_{\mathcal{D}}, \mathbf{R}_{\mathcal{N}}, \mathbf{F}_{\mathcal{M}}) = \text{MOS}_3(r_d) - f_m \eta_d \frac{p_d^{\max}}{L}, \forall d \in D. \tag{29}$$

$$\text{s.t.} \sum\nolimits_{m\in M} v_d^m = 1,\ \forall d \in \mathcal{D}, \tag{29a}$$
$$\eta_d \geq \eta_d^{min},\ \forall d \in \mathcal{D}. \tag{29b}$$

B. Stackelberg Equilibrium

Equilibrium is a stable state of the Stackelberg game, where the BSs and D2D pairs interact through self-optimization and reach a point where no player wishes to deviate. The Stackelberg equilibrium (SE) of the the proposed game is defined in the following.

Definition 1: Assuming $\mathbf{R}_{\mathcal{N}}, \mathbf{F}_{\mathcal{M}}$ be a solution for (28) and $\mathbf{R}_{\mathcal{D}}$ be the solutions for (29) of all the D2D pairs with $\mathbf{R}_{\mathcal{D}} = \begin{bmatrix} \Gamma_{\mathcal{D}}^1 \\ L_{\mathcal{D}}^1 \end{bmatrix}$. The optimal point $\mathbf{R}_{\mathcal{D}}^*, \mathbf{R}_{\mathcal{N}}^*, \mathbf{F}_{\mathcal{M}}^*$ is the Stackelberg equilibrium of the proposed game if the following conditions are satisfied:

$$\begin{aligned} U_{BS}(\mathbf{R}_{\mathcal{D}}^*, \mathbf{R}_{\mathcal{N}}^*, \mathbf{F}_{\mathcal{M}}^*) &\geq U_{BS}(\mathbf{R}_{\mathcal{D}}, \mathbf{R}_{\mathcal{N}}, \mathbf{F}_{\mathcal{M}}) \\ U_d(\mathbf{R}_{\mathcal{D}}^*, \mathbf{R}_{\mathcal{N}}^*, \mathbf{F}_{\mathcal{M}}^*) &\geq U_d(\mathbf{R}_{\mathcal{D}}, \mathbf{R}_{\mathcal{N}}, \mathbf{F}_{\mathcal{M}}), \forall d \in \mathcal{D}, \end{aligned} \tag{30}$$

To achieve the SE, a two-stage iterative algorithm is executed in a consecutive manner, which includes the optimal resource allocation among all the D2D pairs, the resource allocation among all the CUEs and the update of prices at the BSs to avoid violating *CUE QoE requirement*. More specifically, the BS sets a price for each RB and broadcasts it in the system, then each follower compete in a non-cooperative fashion to select its best RB and power level. The leader will update the price for all RBs and allocate the optimal RBs for all CUEs based on $\mathbf{R}_{\mathcal{D}}$. These steps will be repeated until the two conditions in Definition 1 are satisfied to arrive at SE.

C. Non-cooperative Game for D2D pairs

With the given price $\mathbf{F}_{\mathcal{M}}$ decided by the BS, RB allocation and power level selection can be modeled as a non-cooperative game $\mathcal{G} = [\mathcal{D}, \mathbf{R}_{\mathcal{D}}, \{\mathbf{U_d}\}]$, the existence of Nash equilibrium (NE) at D2D pairs is proved in the following theorem when the RB predetermined.

Theorem 1. *With the predetermined $\mathbf{F}_{\mathcal{M}}$, the non-cooperative game $\mathcal{G} = [\mathcal{D}, \mathbf{R}_{\mathcal{D}}, \{\mathbf{U_d}\}]$ admits at least one NE, only when the utility function $\{U_d\}$ of the dth D2D pair occupying the mth RB is concave on η_d.*

Proof. Let $A_0 = \text{PSNR}_d$, and substituting (19) into (29), we have

$$U_d = \begin{cases} 4.5 - f_m \eta_d \frac{p_d^{\max}}{L} & A_0 \geq \text{PSNR}_{4.5} \\ d\log(A_0) + \xi - f_m \eta_d \frac{p_d^{\max}}{L} & \text{PSNR}_{1.0} < A_0 < \text{PSNR}_{4.5} \\ 1 - f_m \eta_d \frac{p_d^{\max}}{L} & A_0 \leq \text{PSNR}_{1.0}, \end{cases} \tag{31}$$

Taking the first-order derivative of (31), we have

$$\frac{\partial U_d}{\partial \eta_d} = \begin{cases} -f_m \frac{p_d^{\max}}{L} & A_0 \geq \text{PSNR}_{4.5} \text{ or } A_0 \leq \text{PSNR}_{1.0} \\ \frac{d}{\ln 2}\frac{1}{A_0}A_0' - f_m \frac{p_d^{\max}}{L} & \text{PSNR}_{1.0} < A_0 < \text{PSNR}_{4.5}, \end{cases} \tag{32}$$

where $A_0' = \frac{\partial A_0}{\partial \eta_d}$. Further, the second-order derivative is given by

$$\frac{\partial^2 U_d}{\partial {\eta_d}^2} = \begin{cases} 0 & A_0 \geq \mathrm{PSNR}_{4.5} \text{ or } A_0 \leq \mathrm{PSNR}_{1.0} \\ \frac{-d(A_0^{-2})(A_0')^2}{\ln 2} + \frac{dA_0''}{\ln 2 A_0} & \mathrm{PSNR}_{1.0} < A_0 < \mathrm{PSNR}_{4.5}, \end{cases} \tag{33}$$

where $A_0'' = \frac{\partial^2 A_0}{\partial {\eta_d}^2}$. Based on (18), it can be calculated by

$$\begin{aligned} A_0'' &= b\left(\frac{-1}{4\sqrt{c}}{r_d}^{-\frac{3}{2}} + \frac{-3\sqrt{c}}{4}{r_d}^{-\frac{5}{2}}\right)\left(\frac{\partial r_d}{\partial \eta_d}\right)^2 \\ &+ b\left(\frac{1}{2\sqrt{c}}{r_d}^{-\frac{1}{2}} + \frac{\sqrt{c}}{2}{r_d}^{-\frac{3}{2}}\right)\frac{\partial^2 r_d}{\partial {\eta_d}^2} \end{aligned} \tag{34}$$

According to (10), the second-order derivative of $\frac{\partial^2 r_d}{\partial {\eta_d}^2}$ can be calculated by

$$\frac{\partial^2 r_d}{\partial {\eta_d}^2} = \frac{-W}{\ln 2}(\mathrm{SINR}_d^{m,\eta_d})^{-2}\frac{P_{d_T}^{\max} R_d^{-\alpha} H_{d_T,d_R}}{L(I_{\mathcal{D},d}^m + I_{\mathcal{B},d}^m + N_0)} \tag{35}$$

Combining (35) and (34) into (33), we have $\frac{\partial^2 U_d}{\partial {\eta_d}^2} \leq 0$. Therefore, the utility function of utility function U_d of dth D2D pair selecting mth RB is concave with respect to η_d. $\square$

In the non-cooperative game among D2D pairs, there may exists multiple NEs, and each NE varies dramatically. Hence, we apply the smoothed better response (SBR) learning scheme to enable the convergence to the optimal SE with high probability [45]. For the dth D2D pair, the probability that it updates with the randomly generated resource allocation strategy $\mathbf{R_d^{new}}$ is

$$p = \frac{1}{1 + \exp\left((U_d^{old} - U_d^{new})/\chi\right)}, \tag{36}$$

where χ is the smoothing factor ($\chi > 0$), U_d^{old} and U_d^{new} are the utility values before and after $\mathbf{R_d^{new}}$ is adopted. As seen from (36), if $U_d^{new} > U_d^{old}$, the dth D2D pair will change to use the new strategy $\mathbf{R_d^{new}}$ with high probability; otherwise, it will keep the same strategy with high probability. If a small difference occurs, the player will use the same strategy or change to new strategy almost randomly. In this case, the player may select a “worse” strategy or not to select a marginally “better” strategy, this uncertainty allows this player to move from a local optimum state and start the negotiation towards a new SE. In (36), smoothing factor is responsible for controlling the tradeoff between the algorithmic performance and convergence speed. With larger smoothing factor, the more extensive strategy search and slower convergence speed will be needed. In our simulations, we employ the concept of temperature in simulated annealing [45] with χ calculated as $10/t^2$, where t denotes the negotiation iterations. It is advisable that χ keeps deceasing as the negotiation iterates.

We present the distributed algorithm for the non-cooperative game in the following **Algorithm** 3, where each player updates its resource allocation strategy according to SBR.

Algorithm 3: Distributed resource allocation based on non-cooperative game

Given the the price $\mathbf{F}_{\mathcal{M}}$ and resource allocation of all the CUEs $\mathbf{R_N}$
Randomly generate a resource allocation strategy $\mathbf{R_d^{new}}$
Calculate the utility function $\{U_d^{new}\}_{d=1}^D$ with $\mathbf{R_d^{new}}$
repeat
  Randomly select $d \in \mathcal{D}$ with probability of $1/D$
  $U_d^{old} = U_d^{new}$ and $\mathbf{R_d^{old}} = \mathbf{R_d^{new}}$
  Randomly choose a strategy $\mathbf{R_d^{rand}}$
  Calculate U_d^{rand} with (29)
  Calculate the updating probability p with (36)
  if $p \leq$ *rand*$(0,1)$ **then**
    Update its current strategy $\mathbf{R_d^{new}}$ as $\mathbf{R_d^{rand}}$
  else
    reserve its current strategy $\mathbf{R_d^{new}}$ as $\mathbf{R_d^{old}}$
  end
  Broadcast negotiation ending message with $\mathbf{R_d^{new}}$
  for $j \in \mathcal{D} \backslash d$ **do**
    Calculate utility function U_j^{new} with $\mathbf{R_d^{new}}$
  end
until *convergence*;

D. Price mechanism at the BS

In this subsection, we present the price optimization algorithm at the BSs to achieve (28) via the CUE association, the CUE RB assignment, and the power allocation at the CUE. The centralized resource allocation algorithm based on GA is applied to ensure the *CUE QoE requirement* is not violated, which follows from **Algorithm 2** with fixed resource allocation of the D2D pairs obtained from the Nash Equilibrium.

For the case where there still exists the QoE of CUE violating the *CUE QoE requirement* after GA optimization, we adopt the *uni-direction update algorithm* [46] to increase the price $\mathbf{F}_{\mathcal{M}}$. For the mth RB, this algorithm starts at $f_m = 0$ and updates price according to

$$f_m^{new} = \begin{cases} f_m^{old} + \Delta & \text{if } v_{s,n}^m = 1 \text{ and } \mathrm{MOS}_q(r_{s,n}^m) \leq \tau_q, \\ f_m^{old} & \text{otherwise} \end{cases} \tag{37}$$

where Δ is a leader defined parameter using to converge to the optimal price. A larger Δ leads to a faster convergence. However, Δ should not be set excessively high so as to prevent other D2D players from accessing the RB, a proper Δ should be set to balance between CUE protection and maximum profit gained by selling this RB to D2D pairs.

E. Semi-distributed optimization algorithm

At last, we present our proposed semi-distributed optimization algorithm in **Algorithm 4**, which includes the inner loop and the outer loop. In the inner loop, each D2D pair competes for the RB via a non-cooperative game, which is executed in a distributed manner. In the outer loop, the BSs allocate the optimal RBs for CUEs and updates the price

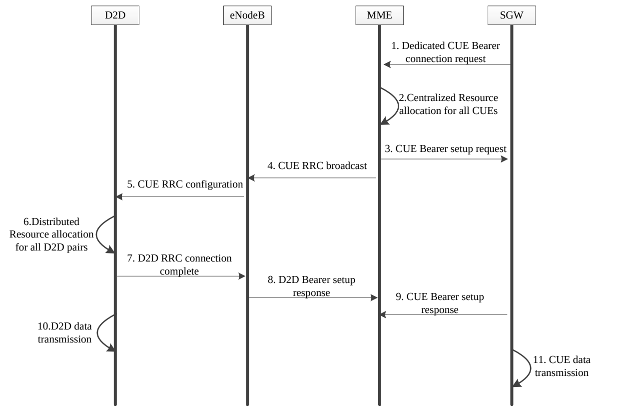


Fig. 5: Signaling procedure of the semi-distributed algorithm

for each RB to maximize its profit, which is executed in a centralized manner. Denote G_o as the number of iterations required for convergence in the outer loop, and G_i as the number of iterations required for convergence of **Algorithm** 3, we can derive the time complexity of this algorithm as $o(G_o((G_iN)+GR(N+R)))$. Fig. 5 plots the signaling procedure of this semi-distributed algorithm. Unlike the centralized algorithm, the MME node module is only responsible for the resource allocation of all CUEs, and only the resource allocation of all CUEs are broadcast to all D2D pairs. With the received price $\mathbf{F}_{\mathrm{M}}$, the resource allocation for all D2D pairs is executed in a distributed manner, thus to save the signaling overhead.

Algorithm 4: Semi-distributed optimization

Initialize $t = 1$ and $\mathbf{F}_{\mathrm{M}} = \mathbf{0}$
Initialize random $\mathbf{R}_{\mathcal{N}}$ for all the CUEs
repeat
  Run **Algorithm 3** to with $\mathbf{R}_{\mathcal{N}}$ and $\mathbf{F}_{\mathrm{M}}$ to generate $\mathbf{R}_{\mathcal{D}}$
  $f_m^{old} = f_m^{new}\ \forall m \in \mathcal{M}$
  Run **GA** with $\mathbf{R}_{\mathcal{D}}$ to generate $\mathbf{R}_{\mathcal{N}}$
  for $\mathrm{n} = 1$ ***to*** N **do**
    if *QoE_q with the allocated RB $m < \tau_q$* **then**
      $f_m^{new} = f_m^{old} + \Delta$
    else
      $f_m^{new} = f_m^{old}$
    end
  end
until *convergence*;

V. Numerical Results

In this section, we provide numerical results to illustrate the performance of our proposed algorithm. We consider HetNets consisting of 2 tiers (Macro and Pioc) with no more than 10 RBs. The set-up is a circle area with size $(\pi 500^2)$ m^2, where the macro BS is located at the center, the pico BSs and UEs are randomly distributed in this circle area. The details of parameters are summarized in Table I unless otherwise specified. All the results are obtained by Monte Carlo simulations.

TABLE I: SIMULATION PARAMETERS

Parameter	Value
The number of macro BS	1
The number of pico BS	$4 \sim 10$
The number of CUEs	$10 \sim 20$
The number of D2D pairs	$10 \sim 20$
Maximum transmit power of macro BS	46dBm (40W)
Maximum transmit power of pico BS	30dBm (1W)
Maximum transmit power at D2D Transmitter	10dBm (0.01W)
D2D link length	$100m$
The number of RBs M	$3 \sim 10$
Bandwidth of each RB W	180KHz
Web Page Size PS	50KB
BER	$\leq 10^{-4}$
RTT	30ms
MSS	1460bytes
$\mathrm{PSNR}_{1.0}$	30dB
$\mathrm{PSNR}_{4.5}$	42dB
path loss exponent α	4
Maximum integer power level	16
Noise PSD	-174dBm/Hz
SINR threshold τ	1
Population size	40
Crossover probability	0.95
Mutation probability	0.005

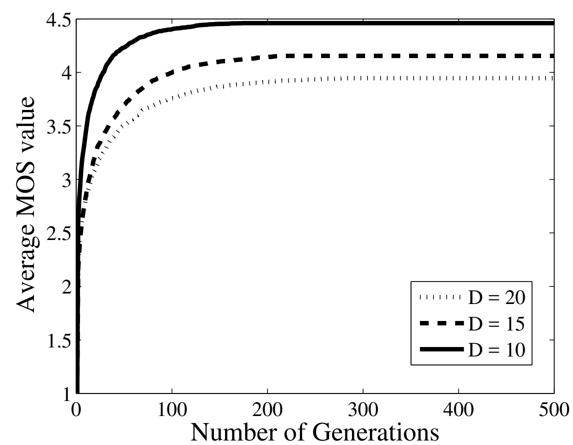


Fig. 6: Convergence behavior with 10 CUEs

A. Convergence behavior

In this subsection, we present the convergence behavior of the GA algorithm, and the Stackelberg game. Fig. 6 $\sim$ 10 are plotted with the number of BSs $S = 7$ (1 Macro BS and 6 Pico BSs), the number of CUEs $N = 10$, and the number of RBs $M = 4$.

Fig. 6 plots the convergence behavior of the average MOS of D2D pairs with increasing the number of generations using GA algorithm. It is shown that the GA algorithm converges after 250 generations for various number of D2D pairs, and decreasing the number of D2D pairs improves the converge speed. Importantly, it is shown that the GA algorithm achieves at least 65% increase of QoE value compared with that of the random resource allocation at the initialization, which testify the effectiveness of algorithm. Fig. 7 plots the CDF of the

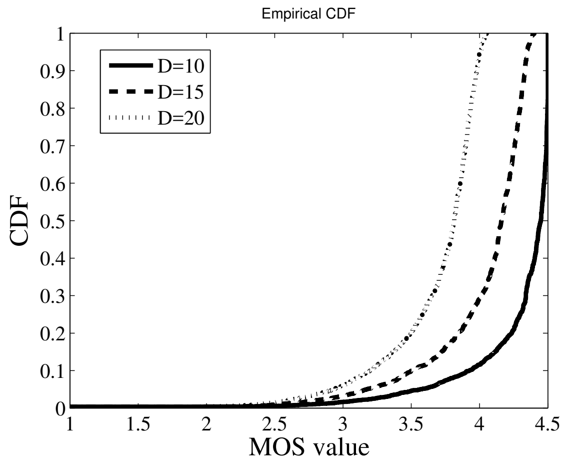


Fig. 7: CDF of the MOS value of D2D pair

MOS value of D2D pair during the evolution of GA algorithm. For $D = 10$, we notice that almost 35% individuals has a MOS value of 4.5, and increasing the number of D2D pairs reduces the maximum MOS value can be achieved at the D2D pair.

Fig. 8 plots the MOS value for each D2D pair versus the number of iterations using Stackelberg game. We observe the interactions between all the D2D pairs before converge, and at last converge to a SE with less than 20 iterations. Fig. 9 plots the price of each RB versus the number of iterations, which also showcase the convergence after 17th iterations. Due to the fact that the 1st RB is occupied by many D2D pairs, the CUE with the 1st RB has a lower QoE value than required. Thus, the price of 1th RB is increasing until the CUE QoE requirement constraint is not violated.

Fig 10 compares the MOS value of each D2D pair using GA algorithm with that using the Stackelberg game after convergence. We also calculate the optimal solutions by brute force approach, and present the obtained MOS value that maximize date rate for each D2D pair. In this simulation, the first 8 D2D pairs are set to be audio application, and the other 12 D2D pairs are set to be video application. We observe that the MOS value of some D2D pairs obtained through Stackelberg game is almost the same as that using centralized GA algorithm, but with less computational complexity and signaling overhead. We also observe that the MOS values obtained by these two algorithms are very close to the optima, which showcase the benefits of our proposed algorithms. Additionally, we observe that for audio applications, the MOS value obtained by MaxDate aglortihm is larger than that achieved by GA and Stackelberg Game. However, for video applications, the MOS value obtained by MaxDate aglortihm is much smaller than that achieved by GA and Stackelberg Game. This can be explained by the fact that small capacity is required for audio applications to achieve a high QoE, whereas a higher capacity is required to achieve the QoE threshold for video applications. As the MaxData algorithm aims at maximizing the date rate for all D2D pairs while not considering users' application type, network resource allocation is not effective.

B. Impact of the number of D2D pairs and CUEs

To further compare and showcase the impact of the GA algorithm and the Stackelberg game, we plot the average MOS per D2D pair versus the number of CUEs with $D = 15$, and the number of D2D pairs with $N = 15$ in Fig. 11, and Fig. 12, respectively. We set $S = 7$ and $M = 5$ in both figures.

It is revealed that the GA algorithm outperforms the semi-distributed algorithm, which is mainly because the price in the semi-distributed algorithm updated with a defined parameter Δ, and resulting in a lower performance than the centralized algorithm. We also observe that both algorithms achieve substantial improvement in terms of the average MOS compared with random allocation, which showcases the benefits of our proposed algorithm. We observe that the average MOS value decreases with increasing the number of CUEs and D2D pairs. This can be explained by the fact that the interference from the CUEs and the D2D pairs using the same RB increases with increasing N and D. We also noticed that the decreasing speed with increasing N is faster than that with increasing D, which can be contributed to the higher interference from BSs with more underlay transmission with D2D pair.

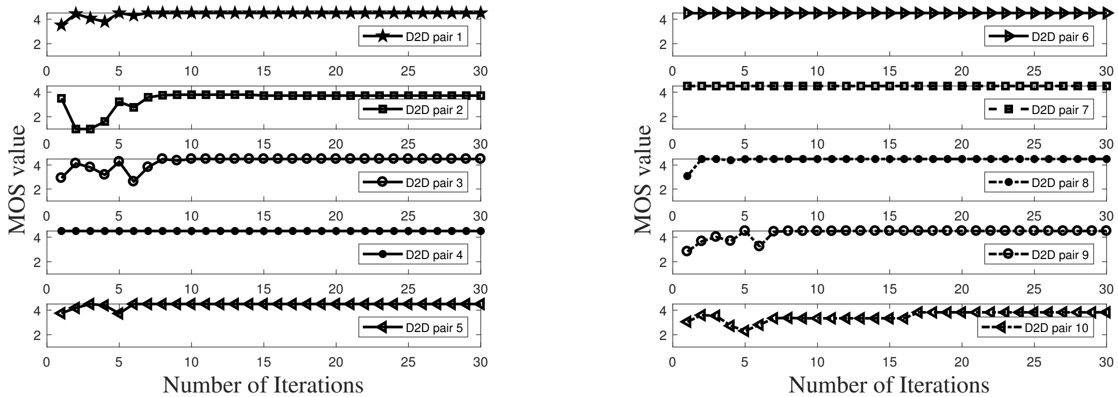
C. Impact of the number of Pico BSs and RBs

Fig. 13 (a) and (b) plot the average MOS versus the number of Pico BSs S with $M = 5$. It is shown that substantial improvement of average MOS can be achieved with increasing the number of Pico BSs, which is due to the reduced interference from less underlay transmissions between CUEs and D2Ds. Fig. 14 (a) and (b) plot the average MOS versus the number of RBs M with $S = 5$. We also see the substantial improvement of average MOS when increasing M.

Another important observations is that the increasing trend of average MOS with increasing the number of RBs is much faster than that with increasing the number of Pico BSs, which can be explained by the fact that increasing the number of Pico BSs can only relieve the pressure of hot spots, but the network interference still exists. However, when the number of RBs are slightly large, network interference can be eliminated by assigning different subcarriers to all active communications. With heavy loaded CUEs in Fig. 13 (b) and Fig. 14 (b), the maximum average MOS for D2D pairs can not be achieved by increasing the number of Pico BSs, which indicates that increasing the number of RBs can be a better option to achieve maximum MOS compared with increasing the number of Pico BSs.

VI. CONCLUSIONS

In this paper, we have formulated the cross-layer QoE optimization problem mathematically to maximize the average QoE value of D2D pairs in CR-enabled HetNets. The joint optimization taking into account the UE association, the power allocation at both BSs and D2D pairs, and the RB assignment in a CR-enabled HetNet were performed via our proposed centralized algorithm based on GA and semi-distributed algorithm based on Stackelberg Game. Our results shown that the centralized algorithm based on GA outperforms the semi-distributed algorithm based on Stackelberg Game,



(a) (b)

Fig. 8: (a) MOS value of $1 \sim 5$ D2D pairs in different iterations, (b) MOS value of $6 \sim 10$ D2D pairs in different iterations

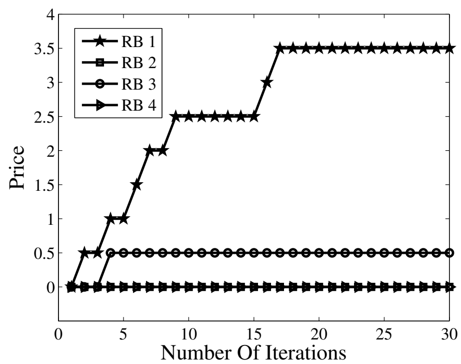


Fig. 9: Convergence behavior of the price of each RB

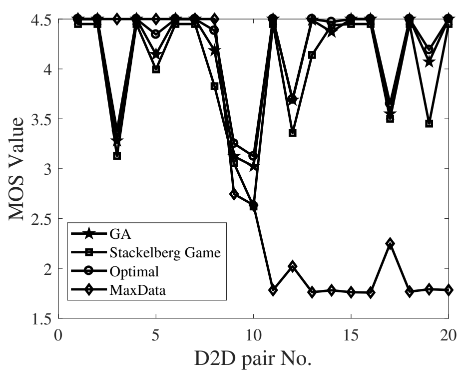


Fig. 10: MOS comparision with 20 D2D pairs

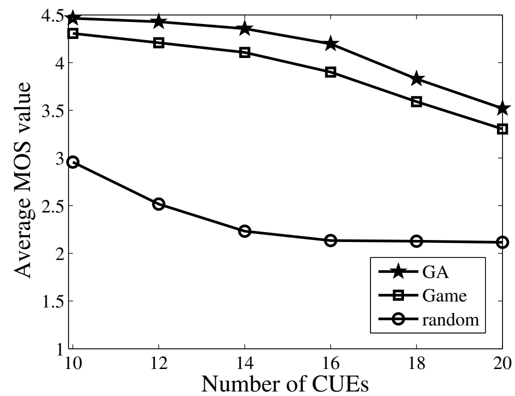


Fig. 11: MOS comparison with different CUEs with 6 Pico BSs

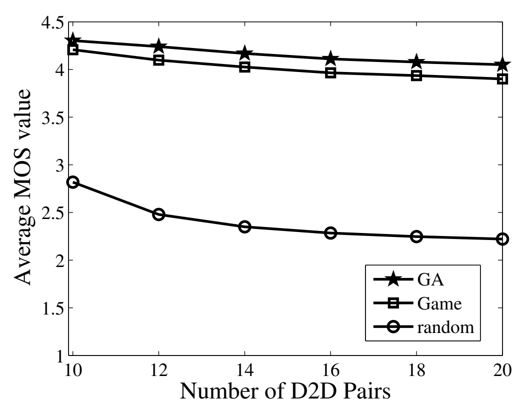


Fig. 12: MOS comparison with different D2D pairs with 6 Pico BSs

and both of them achieves substantial improvement compared with the random allocation and very close to the optima, which showcase the effectiveness of our proposed algorithms in optimizing the QoE of D2D pairs in CR-enabled HetNets.

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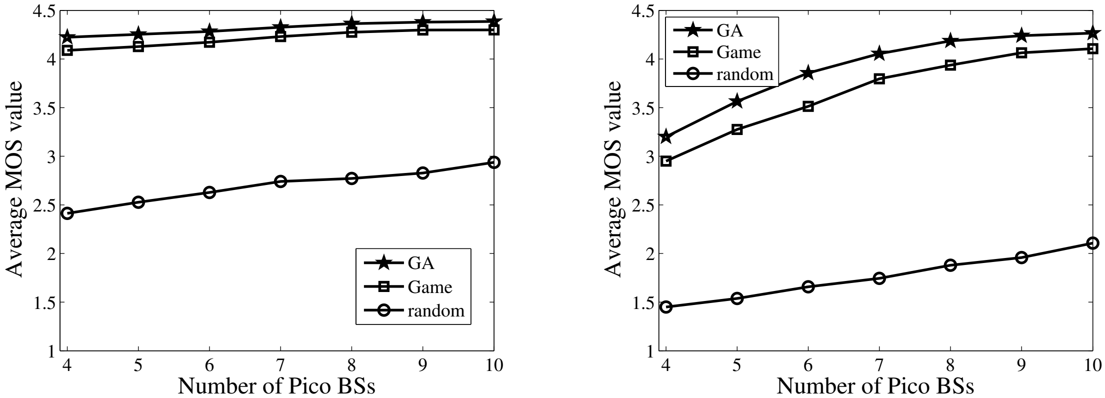
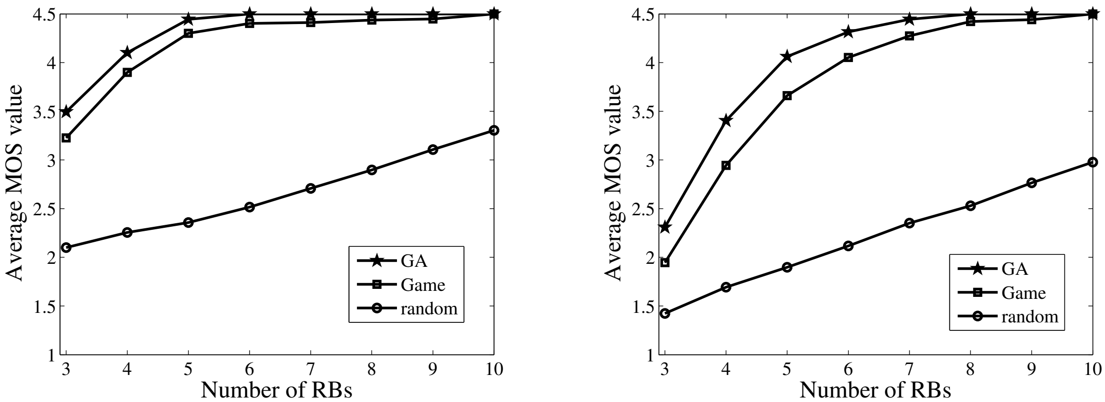


(a) (b)

Fig. 13: MOS comparison with different Pico BSs with (a) N=10 and D=15, (b) N=15 and D=15



(a) (b)

Fig. 14: MOS comparison with different RBs with (a) N=10 and D=20, (b) N=20 and D=20.

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