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Self-Organized Energy-Efficient Cross-Layer Optimization for Device to Device Communication in Heterogeneous Cellular Networks

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ABSTRACT Device to device (D2D) communication brings numerous benefits for future heterogeneous cellular networks. However, an energy-efficient design of such D2D communications is a critical challenge due to the cochannel deployment and limited power of users. In this paper, we present an energy-efficient self-organized cross-layer optimization scheme, which aims to maximize the D2D communication energy-efficiency without jeopardizing the quality of service (QoS) requirements of other tiers. Specifically, we model the cross-layer optimization, which includes resource block (RB) and power allocation using a noncooperative game. In the proposed scheme, each D2D transmitter user, which is a player in the game, operates in a self-organizing manner and selects the RBs and the power levels for enhancing its energy efficiency while maintaining the QoS requirements of other heterogeneous parties. Concerning the computationally intense nature of the global optimization problem, we decompose the problem into two subproblems: the RB allocation and the power allocation, and solve them iteratively in a game-theoretic manner. Simulation results demonstrate superior energy efficiency performance of the proposed scheme over conventional schemes. In addition, it is also shown via simulation that the performance of the proposed scheme degrades if the channel state information is not precisely available.

INDEX TERMS D2D communication, noncooperative game, Nash equilibrium, cross-layer optimization, self-organization.

I. INTRODUCTION

Due to the advent of real-time bandwidth hungry applications such as video streaming, online gaming, and mobile computing, there is a sharp increase in the bandwidth demand. In addition, it is predicted that by 2020 there are more than seven trillion devices serving people [1]. This avalanche in the traffic demand is a serious threat to the energy consumption for a future cellular network, especially handheld user equipments (UEs). On the other hand, the energy consumption also has a significant impact on the operating cost (OPEX) of service providers [2] due to the continuous increase in the network users. Thereby, the energy-efficient design of a wireless network is a worth investigating area to cope with the future wireless demands.

Device to device (D2D) communication is a novel technology that provides range of benefits including proximity gain, reuse gain, efficient spectrum utilization and increased throughput [3]. The predominant difference with wireless local area networks (WLAN) is that the D2D communication shares and reuses the licensed band, i.e., in-band underlaid D2D under the direct control of a cellular network, whereas WLAN operates in an unlicensed band and possesses high degree of uncertainty in the overall performance [4]. Thus, this study considers an energy-efficient in-band underlaid D2D communication comprised of macrocells, femtocells and D2D networks, which is indeed of vital importance owing to the expected heterogeneous nature of a future cellular network [5].

Despite the numerous benefits of the in-band underlaid D2D communications, critical challenges come along with it due to the co-channel deployment nature of the three-tier heterogeneous macro/femto/D2D networks. One of the major challenges is how to deal with the complicated three-tier interference components, which can be regarded as a real bottleneck in the overall performance of the D2D communications. These three-tier interference components cause a serious threat to the throughput satisfaction of not only D2D communication users but also of those in other tiers. In this study, we consider the downlink case for D2D communication in a three-tier heterogeneous cellular network. Within this context, the three-tier interference components are: macro-to-device, femto-to-device and device-to-device. The first two interference components are termed as cross-tier while the last one is co-tier. A centralized cross-layer optimization comprised of joint resource block (RB) and power allocation can play a vital role in escalating the performance by managing the interference [6]. However, such a centralized control of the D2D communication poses formidable computational complexity and information exchange overhead, which makes it hard to be implemented in practice [7]. Thus, self-organized resource management approaches have drawn attentions because they can help in providing range of benefits including reduced information exchange, low complexity, scalability, and etc [8].

Most of the existing literature on D2D communications focus on the spectrum efficiency (defined as bits/sec/Hz) while the energy efficiency (defined as bits/J) has been mostly ignored. In a real deployment scenario, the energy consumption of UEs is among of prime importance due to the limited battery life. Thus, the energy-efficient design of a wireless network recently attracts much attention from industry, academia and standardization bodies, which motivates us to explore the energy efficiency aspect of the self-organized cross-layer optimization for the D2D communication in a three-tier heterogeneous cellular network. Accordingly, this study focuses on the maximization of the energy efficiency of the D2D communication without creating harmful impact on other tiers.

A. CONTRIBUTIONS

In this study, a self-organized cross-layer optimization for the downlink of the in-band underlaid D2D communication in a three-tier heterogeneous cellular network is modeled as a non-cooperative game. Such a game-theoretic approach provides a mathematical tool for modeling an optimization problem with various conflicting objectives and has been often utilized for solving various resource allocations problem for D2D communications [9]–[11]. The main contributions of our work are categorically defined as under:

1) Self-organized energy-efficient cross-layer optimization in terms of the joint RB and power allocation is modeled as a non-cooperative game, in which D2D transmitter users (D2DTUs) are the players of the game while RBs and power levels are the actions associated with each player.
2) In the proposed game, each player interacts with the environment and determines its own action (RBs and power levels) with the concern of enhancing its own energy efficiency without jeopardizing the performance of macrocell users, femtocell users and other D2D pairs. In order to achieve this, the utility function for each D2DTU is designed in a manner that it is aligned not only with the energy efficiency of the D2D communication but also to the cross-tier and co-tier interference components so as to avoid harmful impacts on other tiers.
3) Concerning the complexity of the joint RB and power allocation, the problem is decomposed into two subproblems: the RB allocation and the power allocation. In the RB allocation step, the allocation of RBs by each player is carried out by assuming the similar signal-to-interference-noise-ratio (SINR) under the power levels of others obtained in the previous iteration of the game. In the power allocation step, a non-cooperative power optimization game is utilized for selecting the power levels on the selected RBs in the first step. According to the designed algorithm, both the RB and power allocation is carried out independently. Under the availability of the precise channel state information (CSI), it is shown that the proposed game converges to the pure and unique Nash Equilibrium. In addition, it is also shown how the performance of the proposed scheme variates if the CSI is not precisely available.
4) Simulations are carried out by comparing the proposed scheme with a round robin non-cooperative power optimization game (RR-NPOG) and a spectrum-efficient scheme which illustrate the efficacy of the proposed scheme.

B. RELATED WORK

The related work is divided into three categories: self-organized resource management [12]–[14], spectrum-efficient resource management in D2D communications [15]–[18] and energy-efficient resource management in D2D communications [19]–[21].

Self-organized resource management has been explored for different networks in various ways including heuristic approaches, learning mechanisms, game theoretic approaches, and etc [12]–[14]. The authors in [12] propose a utility based SINR that reduces the cross-tier interference in a femtocell network. However, they do not cater the co-tier interference component, which is also termed as the bottleneck in performance enhancement in the co-channel environment. The authors in [13] propose a heuristic approach for resource allocation and power control in a femtocell network. However, the assumption of their study is that the information needs to be thoroughly exchanged among a femtocell which is not practical in a real environment. The benefit of incorporating a non-cooperative game for the problem under the consideration is that it requires less information exchange. The authors in [14] employ a novel docitive Q-learning for self-organized resource allocation in a femtocell network. However, it takes time to learn the mechanism for the optimal strategies, which makes it unsuitable for real environments.

The authors in [15] propose a distributed resource and power allocation for the in-band underlaid D2D communication in a cellular network by utilizing a Stackelberg game framework. The goal of the optimization problem is to enhance the capacity of the D2D communication without compromising the quality of service (QoS) of the D2D users. The authors in [16] propose both centralized and distributed two-stage resource allocation schemes for D2D communications. Specifically, different policies are taken into consideration while exploiting the spectrum reuse. The throughput performance of the D2D communications using various resource sharing modes are analyzed in [17]. The authors in [18] propose an optimal power allocation scheme for enhancing the spectrum efficiency of a D2D communication, in which a base station is powered by a sustainable energy. However, the prime focus of the above schemes is on the spectrum efficiency of the D2D communication while the energy efficiency is not considered. Also, a straightforward change in the objective from the spectrum efficiency to the energy efficiency maximization in [15]–[18] would not lead to a stabilized energy-efficient solution with satisfying the QoS requirement due to the lack of interference management for the QoS satisfaction.

The authors in [19] propose an energy-efficient resource allocation by exploiting a reverse iterative combinatorial auction game for D2D communications. They present a joint resource and power allocation for enhancing the uplink energy efficiency of a system. However, the QoS requirement of the cellular and D2D users are not constrained, which is an important issue for a successful deployment of a heterogeneous cellular system. The authors in [20] propose a centralized energy-efficient power allocation in a clustered D2D scenario, which is again not practical due to the formidable computational complexity and information exchange. The authors in [21] propose a distributed optimal power allocation for a D2D communication by utilizing a game-theoretic framework. However, a power only optimization for a given RB creates room for possible improvement by utilizing a joint RB and power allocation, which will be shown as significant from the simulation results.

According to the best of the authors knowledge, a self-organized energy-efficient cross-layer optimization for the in-band underlaid D2D communication in a three-tier heterogeneous cellular network while keeping the QoS requirements of macrocell and femtocell users has not been investigated yet and a straightforward extension of the results in [19]–[21] would not lead to a reduced complexity self-organized cross-layer optimization solution. The following points makes our proposition unique and worth investigating. First, most of the previous energy-efficient resource management in literature consider an in-band D2D on a single tier cellular network while a heterogeneous cellular network is considered as typical in future cellular network. In this study, an inband underlaid D2D on a heterogeneous cellular network comprised of macrocells and femtocells is considered. Second, the proposed scheme is designed in a pure self-organizing manner without any involvement of a centralized entity, which gives various performance benefits including low-cost, scalability and reduced complexity. Third, a low-complexity cross-layer optimization algorithm comprised of the iterative RB and power allocation is proposed and is shown to provide a guaranteed convergence to a unique and pure Nash Equilibrium.

The rest of this paper is structured as follows: the system model and the problem formulation are presented in Section II. The proposed self-organized cross-layer optimization scheme is presented in Section III. Simulation results are presented in Section IV. Finally, Section V concludes this paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. NETWORK MODEL

The network model for a three-tier heterogeneous cellular network employing an in-band underlaid D2D communication is shown in Fig. 1. Concerning the co-channel deployment, the three-tier interference components are also shown in the figure. In the proposed self-organization scheme for D2D communications in a three-tier heterogeneous cellular network, each D2DTU carries out the following steps iteratively: *sensing*, *learning* and *tuning*. In the *sensing* step, each D2DTU senses the environment and acquires channel gain information. In the *learning* step, a non-cooperative game is employed at each D2DTU for the evaluation of RB allocation and power allocation. In the *tuning* part, the best action evaluated in the learning step is updated by each D2DTU. The objective of the proposed self-organized scheme for D2D communications is to enhance its energy efficiency without creating harmful impact on other tiers by exploiting the joint RB and power allocation. In order to achieve this, a non-cooperative game is adopted in which each D2DTU is a player while the joint RB and power levels as the action. A near optimal solution for the game is provided as a low complex iterative algorithm which is suitable for the distributed self-organization protocol. The performance of the proposed scheme is evaluated under two conditions: perfect CSI availability and imperfect CSI availability. Although each D2DTU has the capacity to precisely acquire the CSIs from macrocells, femtocells and other D2D pairs, the performance of the proposed scheme is also analyzed under the imperfect CSI. Although the channels from far apart base stations or other D2D pairs are hardly obtained in practice, the impact from such interferers is small so that the simulation results can provide an upper bound on the performance of a practical system. The systems assumptions are:

1) *Control channels for QoS satisfaction*: It is assumed that if any of the QoS requirements of macrocell users, femtocell users, and D2D pairs is violated,

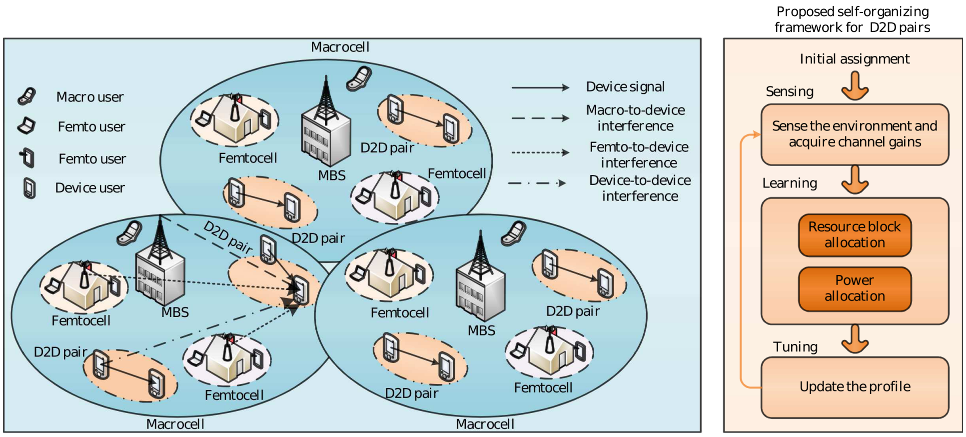


FIGURE 1. **Proposed framework for the in-band underlaid D2D communication in a heterogeneous cellular network.**

the corresponding D2DTU get an alert from the network via the control channel.

2) *Synchronization in RBs*: A tight synchronization is assumed among transmitters in the network so that interference occurs only whenever there is a transmission on the same RB.

B. SYSTEM MODEL

In this study, we consider the downlink of a frequency reuse-1 OFDMA-based multi-cellular system comprised of J macrocells, where each macrocell is served by a macro base station (MBS) at its center and is underlaid with femtocells and D2D pairs. Furthermore, there are total K femtocells and L D2D pairs in the system. Each D2D pair is composed of a D2DTU and a D2D receiver user (D2DRU). Note that, although the proposed scheme is shown for the downlink case, it can be directly applied for the uplink case. Also, the frequency reuse-1 means that each D2DTU can have a complete access to the pool of RBs. The total number of X macrocell users (UEs) and Y femtocell users (FUEs) are assumed to be randomly distributed within the coverage areas of the macrocells and the femtocells. The total pool of G RBs is assumed in the system and the numbers of RBs acquired by each MBS, FBS and D2DTU are denoted as S, T and Q respectively, such that $S \leq G$, $T \leq G$ and $Q \leq G$. For each D2DTU, the total number of R power levels are available for each selected Q RBs, while the RBs and power levels of the MBSs and FBSs are assumed to be fixed. Furthermore, let G_s and R_s denote the set of RBs and power levels such that $G_s = \{1, 2, \ldots, G\}$ and $R_s = \{P_1, P_2, \ldots, P_R\}$.

The transmission power of the jth MBS, the kth FBS and the lth D2DTU are denoted by $P_j^M = \left[P_{j,1}^M, P_{j,2}^M, \ldots, P_{j,G}^M\right]$, $P_k^F = \left[P_{k,1}^F, P_{k,2}^F, \ldots, P_{k,G}^F\right]$ and $P_l^D = \left[P_{l,1}^D, P_{l,2}^D, \ldots, P_{l,G}^D\right]$, respectively, where $P_{j,g}^M = 0$ if the gth RB is not acquired by the jth MBS, otherwise $P_{j,g}^M \neq 0$, and similarly for $P_{k,g}^F$ and $P_{l,g}^D$. The maximum power constraint on the acquired S, T and Q RBs by the corresponding MBS, FBS and D2DTU are represented as P_{MAX}^M,P_{MAX}^F and P_{MAX}^D such that $\sum_{g=1}^G P_{j,g}^M \leq P_{MAX}^M$, $\sum_{g=1}^G P_{k,g}^F \leq P_{MAX}^F$ and $\sum_{g=1}^G P_{l,g}^D \leq P_{MAX}^D$, respectively.

The performance of the proposed scheme is represented in terms of the energy efficiency of the D2D communication. The SINR at the lth D2DRU operating on the gth RB can be given as in (2) at the top of the next page, where $H_{ll,g}^{D\to D}$, $H_{jl,g}^{M\to D}$, $H_{kl,g}^{F\to D}$ and $H_{al,g}^{D\to D}$ are the channel gains on the same RBs between the lth D2DTU and D2DRU, between the jth MBS and the lth D2DRU, between the kth FBS and the lth D2DRU and between the ath D2DTU and lth D2DRU, respectively, and δ_{gj}^M, δ_{gk}^F and δ_{gl}^D are the indicator variables whether the gth RB is used by the jth MBS, the kth FBS and the lth D2DTU, respectively, and finally, σ^2 is the noise power. Similarly, the SINRs on the gth RB of the jth MBS and the kth FBS at their corresponding users are represented in (3) and (4) at the top of the next page.

The imperfect CSI is modeled as the deviation of channel estimate from the actual value of the channel and is written as:

$$H_{ll,g}^{D\to D} = \hat{H}_{ll,g}^{D\to D} + \kappa_{ll,g}^{D\to D} \tag{1}$$

where $\kappa_{ll,g}^{D\to D}$ is the channel estimation error and is modeled by a zero-mean Gaussian random variable with variance $\xi_{ll,g}^{D\to D}$. Moreover, the random variables $\kappa_{ll,g}^{D\to D}$ are independent and identically distributed (i.i.d.) on different RBs and on different tiers. Here we are assuming a minimum mean square error (MMSE) estimator where the CSI estimation error and the actual CSI are mutually uncorrelated [22], [23]. Similarly, the imperfect CSI for all the channel gains in (2) - (4), as shown at the top of the next page, can be modeled by (1), respectively.

The throughput of the lth D2D pair and the average throughput of the jth MBS and the kth FBS with respected to their associated users, respectively, can be represented

$$SINR_{l,g}^{D} = \frac{P_{l,g}^{D} H_{ll,g}^{D \to D}}{\sigma^2 + \underbrace{\sum_{j=1}^{J} P_{j,g}^{M} H_{jl,g}^{M \to D} \delta_{gj}^{M}}_{Macro-components} + \underbrace{\sum_{k=1}^{K} P_{k,g}^{F} H_{kl,g}^{F \to D} \delta_{gk}^{F}}_{Femto-components} + \underbrace{\sum_{a=1, a \neq l}^{L} P_{a,g}^{D} H_{al,g}^{D \to D} \delta_{ga}^{D}}_{D2D-components}}, \quad \forall l = \{1, 2, \ldots, L\}, \ g \in G_s. \tag{2}$$

$$SINR_{j,g}^{M} = \frac{P_{j,g}^{M} H_{jj,g}^{M \to M}}{\sigma^2 + \underbrace{\sum_{a=1, a \neq j}^{J} P_{a,g}^{M} H_{aj,g}^{M \to M} \delta_{ga}^{M}}_{Macro-components} + \underbrace{\sum_{k=1}^{K} P_{k,g}^{F} H_{kj,g}^{F \to M} \delta_{gk}^{F}}_{Femto-components} + \underbrace{\sum_{l=1}^{L} P_{l,g}^{D} H_{lj,g}^{D \to M} \delta_{gl}^{D}}_{D2D-components}}, \quad \forall j = \{1, 2, \ldots, J\}, \ g \in G_s. \tag{3}$$

$$SINR_{k,g}^{F} = \frac{P_{k,g}^{F} H_{kk,g}^{F \to F}}{\sigma^2 + \underbrace{\sum_{j=1}^{J} P_{j,g}^{M} H_{jk,g}^{M \to F} \delta_{gj}^{M}}_{Macro-components} + \underbrace{\sum_{a=1, a \neq k}^{K} P_{a,g}^{F} H_{ak,g}^{F \to F} \delta_{ga}^{F}}_{Femto-components} + \underbrace{\sum_{l=1}^{L} P_{l,g}^{D} H_{lk,g}^{D \to F} \delta_{gl}^{D}}_{D2D-components}}, \quad \forall k = \{1, 2, \ldots, K\}, \ g \in G_s. \tag{4}$$

as:

$$\Psi_j^M = \frac{W}{G} \sum_{g=1}^{G} \delta_{gj}^{M} log_2 \left(1 + SINR_{j,g}^{M}\right), \quad \forall j = \{1, 2, \ldots, J\}, \tag{5}$$

$$\Psi_k^F = \frac{W}{G} \sum_{g=1}^{G} \delta_{gk}^{F} log_2 \left(1 + SINR_{k,g}^{F}\right), \quad \forall k = \{1, 2, \ldots, K\}, \tag{6}$$

$$\Psi_l^D = \frac{W}{G} \sum_{g=1}^{G} \delta_{gl}^{D} log_2 \left(1 + SINR_{l,g}^{D}\right), \quad \forall l = \{1, 2, \ldots, L\}, \tag{7}$$

where W denotes the system bandwidth. Also, the energy efficiency (bits/J) of the lth D2D pair can be represented as:

$$EE_l^D = \frac{\frac{W}{G} \sum_{g=1}^{G} \delta_{gl}^{D} log_2 \left(1 + SINR_{l,g}^{D}\right)}{\sum_{g=1}^{G} \delta_{gl}^{D} P_{l,g}^{D} + p_c}, \quad \forall l = \{1, 2, \ldots, L\} \tag{8}$$

where p_c is the circuit power which corresponds to the accumulated power consumption of all the electronic devices involved in signaling and backhauling, and is assumed to be constant in this study.

C. PROBLEM FORMULATIONS

In contemplation of enhancing the energy efficiency of the D2D communications by exploiting a joint RB and power allocation, the optimization problem can be formulated as:

$$\left(B_l^{*D}, C_l^{*D}\right) = \arg \max_{B_l^D \in [1,0]^{G_s}, C_l^D \in R_s^{G_s}} \frac{\frac{W}{G} \sum_{g=1}^{G} \delta_{gl}^{D} log_2 \left(1 + SINR_{l,g}^{D}\right)}{\sum_{g=1}^{G} \delta_{gl}^{D} P_{l,g}^{D} + p_c}, \quad \forall l = \{1, 2, \ldots, L\}, \tag{9}$$

$$\text{subject to:} \quad C1: \Psi_l^D \geq R_{MIN}^D, \quad \forall l, \tag{10a}$$

$$C2: \Psi_j^M \geq R_{MIN}^M, \quad \forall j, \tag{10b}$$

$$C3: \Psi_k^F \geq R_{MIN}^F, \quad \forall k, \tag{10c}$$

$$C4: P_{l,g}^D \in \left[0, \frac{P_{MAX}^D}{Q}\right], \quad \forall l, g, \tag{10d}$$

$$C5: \sum_{g=1}^{G} \delta_{gl}^{D} \leq Q, \quad \forall l \tag{10e}$$

where $B_l^D = \left[\delta_{1l}^D, \delta_{2l}^D, \ldots, \delta_{Gl}^D\right]$ and $C_l^D = [P_{l,1}^D, P_{l,2}^D, \ldots, P_{l,G}^D]$ corresponds to the allocation of Q RBs and their corresponding power levels by each lth D2DTU. The constraints C1 - C3 represent the satisfaction of the minimum throughput requirements of the considered three-tier users, respectively, the constraint C4 represents the minimum power allocation bound on each RB and the constraint C5 represents that maximum number of RBs acquired by each D2DTU.

D. NOTATIONS

The notations and assumptions presented in Table 1 will be used throughout the rest of the paper.

III. SELF-ORGANIZED CROSS-LAYER OPTIMIZATION USING A NON-COOPERATIVE GAME

A. NON-COOPERATIVE GAME

A non-cooperative game is a powerful mathematical tool which has been utilized in various resource allocation problems in wireless networks [24]. In the problem formulation in Section II.C, we consider each D2DTU is selfish and an irrational player which tends to increase its utility function. Therefore, the problem presented in (9) and (10) can be modeled as a non-cooperative game. In this study, we model the cross-layer optimization task in the form of a joint RB and power allocation as a non-cooperative game. Generally,

TABLE 1. Notation and assumptions.

Parameters	Meaning
MBS	Micro base station;
FBS	Femto base station;
D2DTU	D2D transmitter user;
D2DRU	D2D receiver user;
UE	Macrocell user;
FUE	Femtocell user;
RB	Resource block;
J	Number of macrocells;
K	Number of femtocells;
L	Number of D2D pairs;
j	Index for MBSs;
k	Index for FBSs;
l	Index for D2D pairs;
X	Number of UEs;
Y	Number of FUEs;
G	Total pool of RBs;
Q	Maximum number of RBs acquired by each D2DTU;
W	System bandwidth;
R	Number of power levels at each D2DTU;
$P_{j,g}^{M}$	TX power of the jth MBS on the gth RB;
$P_{k,g}^{F}$	TX power of the kth FBS on the gth RB;
$P_{l,g}^{D}$	TX power of the lth D2DTU on the gth RB;
P_{MAX}^{M}	Maximum TX power constraint for MBS;
P_{MAX}^{F}	Maximum TX power constraint for FBS;
P_{MAX}^{D}	Maximum TX power constraint for D2DTU;
Ψ_{j}^{M}	Throughput of the jth MBS;
Ψ_{k}^{F}	Throughput of the kth FBS;
Ψ_{k}^{D}	Throughput of the lth D2DTU;
B_{l}^{D}	RB allocation vector of the lth D2DTU;
C_{l}^{D}	Power allocation vector of the lth D2DTU;
A_l	Action profile associated with the lth player;
U_l	Utility function associated with the lth player;
A^{*}	Optimal action profile;
B_{l}^{*D}	Optimal RB allocation by the lth D2DTU;
C_{l}^{*D}	Optimal power allocation by the lth D2DTU;

a game γ is represented by a tuple $\gamma = \left\{L, \{A_l\}, \{U_l(.)\}_{l\in L}\right\}$, where L is the finite set of players, A_l denotes the action associated with the lth player and U_l is the reward or the utility function belongs to the lth player. In other words, the utility function imitates the level of satisfaction to each player. Mathematically, the utility function can be thought as a mapping function that maps the action A_l into the real number $\Re$ such that $U_l : A_l \rightarrow \Re$. Also, let the actions of others players can be represented by a vector $A_{-l} = \{A_1, A_2, \ldots, A_{l-1}, A_{l+1}, \ldots, A_L\}$.

In the proposed scheme, a set of L D2DTUs are the players of the game which interact with the environment in a self-organizing manner and find out the best actions, in which the action comprised of two parts: the RB allocation and the power allocation. Mathematically, the action of the lth D2DTU is represented as $A_l = \left(B_l^D, C_l^D\right)$, where B_l^D represents the indication vector for the allocation RBs among the total pool of G RBs while C_l^D denotes the power levels on the RBs within the maximum power constraint. For given B_l^D and C_l^D, the RB and the power allocations of other players are represented as $B_l^D = \left\{B_1^D, B_2^D, \ldots, B_{l-1}^D, B_{l+1}^D, \ldots, B_L^D\right\}$ and $C_l^D = \left\{C_1^D, C_2^D, \ldots, C_{l-1}^D, C_{l+1}^D, \ldots, C_L^D\right\}$. Since the goal of the proposed scheme is to enhance the energy efficiency of the D2D communications, the utility function is set as the energy efficiency and is written as:

$$U_l(A_l, A_{-l}) = \frac{\frac{W}{G}\sum_{g=1}^{G}\delta_{gl}^{D}log_2\left(1+SINR_{l,g}^{D}\right)}{\sum_{g=1}^{G}\delta_{gl}^{D}P_{l,g}^{D}+p_c}, \quad \forall l = \{1, 2, \ldots, L\}. \quad (11)$$

Definition 1: For given B_{-l}^D and C_{-l}^D, the best response of the joint RB and power allocation for the lth player is represented as:

$$\left(B_l^{*D}, C_l^{*D}\right) = \arg\max_{B_l^D\in[1,0]^{G_s}, C_l^D\in R_s^{G_s}} U_l\left(B_l^D, C_l^D | B_{-l}^D, C_{-l}^D\right). \quad (12)$$

Primarily, the optimal joint RB and power allocation is mathematically intractable and is an NP-hard problem. In order to reduce the complexity, the joint problem is decomposed into two suboptimal subproblems: the RB allocation and the power allocation.

B. RESOURCE BLOCK ALLOCATION

In the RB allocation subproblem, the following theorem provides an optimal RB allocation at a given power allocation of others in the previous iteration by assuming its own power allocation to make the SINRs on the selected RBs equal. Note that the power allocation of each selected RB will be carried out under the network constraints C1-C5.

Theorem 1: A group of Q RBs among the pool of G RBs is allocated to each lth player (D2DTU), if the following condition is satisfied:

$$B_l^{*D} = \arg\min_{B_l^D\in[0,1]^{G_s}} \sum_{g=1}^{G}\delta_{gl}^{D}\frac{I_{l,g}^{D}}{H_{ll,g}^{D\rightarrow D}}, \quad s.t. \sum_{g=1}^{G}\delta_{gl}^{D} = Q, \quad (13)$$

where $I_{l,g}^D = \sigma^2 + \sum_{j=1}^{J}P_{j,q}^{M}H_{jl,q}^{M\rightarrow D}\delta_{gj}^{M} + \sum_{k=1}^{K}P_{k,q}^{F}H_{kl,q}^{F\rightarrow D}\delta_{gk}^{F} + \sum_{a=1,a\neq l}^{L}P_{a,q}^{D}H_{al,q}^{D\rightarrow D}\delta_{ga}^{D}$ denotes the accumulated interference on the gth RB at the lth D2DRU.

Proof: Given power allocation of the lth player, the best response of the RB allocation can be written as:

$$\left(B_l^{*D}\right) = \arg\max_{B_l^D\in[1,0]^{G_s}} U_l\left(B_l^D | C_{-l}^D\right). \quad (14)$$

Note that information about B_{-l}^D is also available in C_{-l}^D so that B_l^{*D} can be determined at a given C_{-l}^D. Substituting (2) and (11) in (14) we get,

$$\left(B_l^{*D}\right) = \arg\max_{B_l^D\in[1,0]^{G_s}} \frac{\frac{W}{G}\sum_{g=1}^{G}\delta_{gl}^{D}log_2\left(1+\frac{P_{l,g}^{D}H_{ll,g}^{D\rightarrow D}}{I_{l,g}^{D}}\right)}{\sum_{g=1}^{G}\delta_{gl}^{D}P_{l,g}^{D}+p_c}, \quad s.t. \sum_{g=1}^{G}\delta_{gl}^{D} = Q. \quad (15)$$

Assuming ρ to be the target SINR on the selected RB and substituting the power of D2DTUs $P_{l,g}^D = \frac{\rho I_{l,g}^D}{H_{ll,g}^{D\rightarrow D}}$ in (15), we get

$$\left(B_l^{*D}\right) = \arg \max_{B_l^D \in [1,0]^{G_s}} \frac{\frac{W}{G}\sum_{g=1}^{G} \delta_{gl}^D log_2\left(1+\rho\right)}{\rho \sum_{g=1}^{G} \delta_{gl}^D \frac{I_{l,g}^D}{H_{ll,g}^{D\to D}} + p_c},$$

$$s.t. \sum_{g=1}^{G} \delta_{gl}^D = Q, \tag{16}$$

which is equivalent to

$$\left(B_l^{*D}\right) = \arg \min_{B_l^D \in [1,0]^{G_s}} \sum_{g=1}^{G} \delta_{gl}^D \frac{I_{l,g}^D}{H_{ll,g}^{D\to D}}, \quad s.t. \sum_{g=1}^{G} \delta_{gl}^D = Q,$$

which concludes the proof. ■

C. POWER ALLOCATION

Given the RB allocation by each D2DTU, the power allocation problem can be considered as a non-cooperative power optimization game $\gamma_p = \left\{L, C_l^D, U_l\left(.\right)_{l\in L}\right\}$. Since the utility function of the proposed scheme depends upon the behavior (power levels) of two or more players, we model the power optimization problem via a non-cooperative power optimization game [25]. Then for a given RB power allocation of all other players, the best response of the lth player is given by

$$\left(C_l^{*D}\right) = \arg \max_{C_l^D \in R_s^{G_s}} U_l\left(C_l^D | C_{-l}^D\right). \tag{17}$$

The players involved in a non-cooperative power optimization game optimize their power levels independently on each selected Q RBs in the resource block step. Since the goal of the overall game is to enhance the energy efficiency of the D2D communication without jeopardizing the performance of other tiers, the power optimization is carried out within the network constraints C1 - C5. Note that changes in the power allocation of each player impact significantly on the other players. Thus, it is of prime importance whether the proposed scheme can converge to an equilibrium point where all the competing influences are balanced.

1) THE EXISTENCE AND UNIQUENESS OF THE Nash EQUILIBRIUM

In a non-cooperative game, the set of actions $C^{*D} = \left\{C_1^{*D}, C_2^{*D}, \ldots, C_L^{*D}\right\}$ is termed as the Nash Equilibrium if none of the player can change the action by increasing the utility function. The strict definition of Nash Equilibrium is represented as in the following definition.

Definition 2: In the energy-efficient non-cooperative power optimization game, a Nash Equilibrium for the given power allocation of all the players $C^{*D} = \left\{C_1^{*D}, C_2^{*D}, \ldots, C_L^{*D}\right\}$ exists in the game if the following inequality is satisfied,

$$U_l\left(C_l^{*D}, C_l^{*D}\right) \geq U_l\left(C_l^D, C_{-l}^{*D}\right). \tag{18}$$

In other words, a Nash Equilibrium is defined as a stable optimal point in which none of the players can change the actions profitably. The existence of such a Nash Equilibrium is justified with the below-presented theorem.

Theorem 2 [26]: A Nash Equilibrium exists in a non-cooperative power optimization game $\gamma_p = \{L, \left\{C_l^D\right\}, \{U_l\left(.\right)\}_{l\in L}\}$, if the following two conditions are satisfied:

1) $\left\{C_l^D\right\}$ to a non-empty, convex and compact subset of some Euclidean space.
2) The utility function $U_l\left(C_l^D, C_{-l}^D\right)$ is continuous and quasi-concave.

Definition 3: Let $U_l\left(C^D\right)$ be a function that maps from a convex set θ of n-dimensional vectors to a real number. Then, $U_l\left(.\right)$ is quasi-concave if for any $C_1^D, C_2^D \in \theta$, and $C_1^D \neq C_2^D$,

$$U_l\left(\lambda C_1^D + \left(1-\lambda\right) C_2^D\right) \geq \min\left\{U_l\left(C_l^D\right), U_l\left(C_2^D\right)\right\}. \tag{19}$$

First the existence is proved. Since the power allocation vector C_l^D is confined within the power constraints, condition 1 in Theorem 2 is satisfied. Also, in order to prove that U_l is quasi-concave, define the upper contour set Ψ_μ of $U_l\left(C_l^D, C_{-l}^D\right)$ as

$$\Psi_\mu = \left\{C^D \succ 0 | U_l\left(C_l^D, C_{-l}^D\right) \geq \mu\right\}, \quad \forall \mu \in \Re, \tag{20}$$

where a vector $S \succ 0$ means that each element in S is non-negative. In accordance with the preposition C.9 in [27], the utility function $U_l\left(C_l^D, C_{-l}^D\right)$ is strictly quasi-concave in C^D if and only if the upper contour set Ψ_μ is convex for all $\mu \in \Re$. In addition, if $\mu < 0$, the upper contour set becomes the whole space $\left\{C_l^D\right\}$ so that Ψ_μ is strictly convex for $\mu \leq 0$. For $C^D \in \Psi_\mu$, the utility function satisfies

$$U_l\left(C_l^D, C_{-l}^D\right) = \frac{\frac{W}{G}\sum_{g=1}^{G} \delta_{gl}^D log_2\left(1+SINR_{l,g}^D\right)}{\sum_{g=1}^{G} \delta_{gl}^D P_{l,g}^D + p_c} \geq \mu. \tag{21}$$

Therefore, the upper contour set Ψ_μ is equivalent to:

$$\Psi_\mu = \left\{C_l^D \succ 0 | \frac{W}{G}\sum_{g=1}^{G} \delta_{gl}^D log_2\left(1+SINR_{l,g}^D\right) - \left(\sum_{g=1}^{G} \delta_{gl}^D P_{l,g}^D + p_c\right)\mu \geq 0\right\}. \tag{22}$$

which is convex and it concludes the proof for condition 2.

In the contemplation of the uniqueness of a non-cooperative power optimization game, the following theorem is presented.

Theorem 3 [28]: A non-cooperative power optimization game γ_p posses a unique Nash Equilibrium if the below-listed conditions satisfied:

1) Positivity: $U_l\left(C^D\right) > 0$.
2) Monotonicity: if $C_1^D > C_2^D$, $U_l\left(C_1^D > U_l\left(C_2^D\right)\right)$.
3) Scalability: $\forall \beta > 1, \beta U_l\left(C^D\right) > U_l\left(\beta C^D\right)$.

The utility function U_l (.) used in this paper has a similar form to that in [29] and can be proved to satisfy the above conditions in a similar way.

D. PROPOSED ALGORITHM

In Section III.B, the optimal Q RB allocation of each D2DTU is shown at a given power allocation of others and the same SINR assumption while satisfying the constraints C1-C5. Also, in Section III.C, it was proven that a non-cooperative power allocation game using the utility function of the energy efficiency of each D2DTU within the constraints C1-C5 provides a pure and unique Nash Equilibrium if the CSIs and actions of other players are assumed to be known. Thus, the proposed Algorithm 1 employs two steps iteratively at each D2DTU: the RB allocation and the power allocation step. In the RB allocation step, the allocation of Q RBs among the pool of G RBs is carried out by each D2DTU with the concern of minimizing the impact of interference in the three-tier heterogeneous cellular network. Here, the given power allocation of other users are the results obtained in the power allocation step of the previous iteration. In the power allocation step, a non-cooperative power optimization game with discrete power levels is utilized for selecting the power levels on the selected RBs in the RB allocation step of the current iteration. The detailed procedure is given as follows:

In the proposed game, the best response of the RB and the power allocation in (14) and (17) depends on the power levels of other D2DTUs i.e., C^D_{-l}, which is hardly obtained in practice. However, the power levels of other D2DTUs impacts on total interference $I^D_{l,g}$ so that the proposed algorithm can be operated approximately at the cost of slight performance degradation only with the total interference information at each D2DRU, similarly as in [27].

Algorithm 1: Proposed Self-Organized RB and Power Allocation Using Non-Cooperative Game

Input:
- All link gains that connect macrocells, femtocells and D2D pairs on the pool of G RBs for both perfect CSI availability and imperfect CSI availability.
- Randomly initialize the RBs and power allocation by each D2DTU
- Set the proposed scheme maximum iteration count: **ITER1**
- Set the proposed non-cooperative power optimization game maximum iteration count:**ITER2**

Output:
- Resource block and power allocation, $A^* \leftarrow \{B^{*D}_l, C^{*D}_l\}$

Allocate same power on each RB
while *the maximum iteration **ITER1** has passed or the convergence is achieved* **do**
  Step-1: Resource block allocation
  for *each D2DTU (player)* **do**
    $\{B^{*D}_l\} \leftarrow \arg\max_{B^D_l \in [0,1]^{G_s}} \sum_{g=1}^{G} \delta^D_{gl} \frac{I^D_{l,g}}{H^{D\to D}}$, s.t. C5 $\{B^D_l\} \leftarrow \{B^{*D}_l\}$
  end
  Step-2: Power allocation
  Initialize $C^D_l \leftarrow 0, \forall l$
  while *the maximum iteration **ITER2** has passed or the the Nash Equilibrium point has achieved* **do**
    for *each D2DTU (player)* **do**
      Find $\{C^{*D}_l\} \leftarrow \arg\max_{R^{G_s}_s} U_l\left(C^D_l, C^D_{-l}\right)$, s.t. C1-C5
      (By exploiting the power levels of the best RBs in terms of maximization of the utility function)
      $\{C^D_l\} \leftarrow \{C^{*D}_l\}$
    end
  end
end
return $A^* \leftarrow \{B^{*D}_l, C^{*D}_l\}$

IV. SIMULATION RESULTS AND ANALYSIS

In this section, the performance of the proposed self-organized energy-efficient scheme is evaluated in terms of the energy efficiency as the performance measure including the convergence performance, the energy efficiency distribution, and the impact of varying Q, G and D2D pairs on the average energy efficiency in the three-tier network. In addition, the throughput satisfaction of the D2D pairs while employing the proposed scheme is evaluated and compared by using the Jains fairness index [30]. For the comparison, two distributed self-organizing schemes using a round robin non-cooperative power optimization game (labeled as RR-NPOG) and a spectrum-efficient game (labeled as spectrum-efficient) are utilized which can be considered as the representatives for those enhancing the energy efficiency by a power allocation only (similarly as in [21]) and for those enhancing the energy efficiency by using a joint RB and power allocation (similarly as in [31]).

A. SIMULATION SETUP

We consider the downlink of an OFDMA-based three-tier heterogeneous cellular network operating at the carrier frequency of around 2GHz that closely follows the 3GPP TR 25.814. For simplicity, a single macrocell (J=1) is assumed with a radius of 1000m. In the macrocell, it is assumed that K femtocells with radius of 40m and L D2D pairs with distance of 25m are randomly located in an underlaid manner. The MBS or each FBS is located at the center of the corresponding cell and X UEs and Y FUEs are randomly deployed within the coverage of the macrocell and femtocells.

Since we consider the three-tier heterogeneous network based on long term evaluation (LTE), the frequency band is divided into RBs, each of bandwidth 180KHz in frequency and 0.5ms in time domain. Each RB is comprised of 12 subcarriers with a spacing of 15KHz and consist of 7 OFDM symbols. Further, we consider the total pool of RBs $G = 25$

and $G = 50$ which represents an LTE implementation with a system bandwidth of $W = 4.5MHz$ and $9MHz$, respectively. With incorporating the guard intervals of 0.5MHz and 1MHz, respectively, the system bandwidth becomes 5MHz and 10MHz, respectively, which is in accordance with the LTE specifications. The number of RBs for each D2DTU is assumed that $Q \in \{2, 3, 4, 5, 6\}$ while those for the MBS and each FBS are fixed at $T = 10$ and $S = 25$. The maximum powers of the MBS and each FBS are set to $P^M_{MAX} = 43$dBm and $P^F_{MAX} = 23$dBm, respectively. The maximum power on each RB of a D2DTU is set to P^D_{MAX}=23-10 $\log_{10}(Q)$dBm. Also, $R = 100$ discrete power levels uniformly distributed in the range from -80 to 23dBm are assumed. Finally, the constant circuit power of $p_c = 100$ mW, similarly as in [32] and the noise spectral efficiency is set to $N_0 = -141$dBW/MHz.

The path loss (PL) model that we have utilized in this study is in accordance to the 3GPP [33], [34], where PL models are given as

1) For macrocell and femtocell (outdoor): $PL(dB) = 127 + 30\log_{10}(d)$;
2) For macrocell and femtocell (indoor): $PL(dB) = 128.1 + 37.6\log_{10}(d)$;
3) For D2D system: $PL(dB) = 148 + 40\log_{10}(d)$.

Also, the log-normal shadowing with the shadowing factor of 8dB and 4dB are utilized for the indoor and the outdoor model, respectively. The variance of channel estimation error is considered to be: $\xi^D_{ll,g} = 0.05$. The performance of the proposed and comparative counterpart schemes are evaluated over 500 different realizations of the location of network entities and the fading channel among them.

B. CONVERGENCE PERFORMANCE EVALUATION

The convergence performance of the proposed scheme for each perfect and imperfect CSI availability is evaluated and compared for the cases: $L = 25$ and $L = 35$ as shown in Fig. 2. The lack of CSI availability degrades the performance of the proposed scheme with perfect CSI and this trend increases from 10% to 15%, respectively, with the increase of D2D pairs. Although all three schemes require similar number of iteration for convergence, the proposed scheme for each condition outperforms the other two schemes. Specifically, the spectrum-efficient scheme performs worst so that it becomes apparent that enhancing the spectrum efficiency without considering the required power results in a non-satisfactory energy efficiency performance. It is shown that, although the energy efficiency is considered, a power-only allocation with a round robin or random RB allocation as in conventional schemes is not sufficient. Furthermore, although the energy efficiency of each D2D pair decreases as the D2D pair density increases, the improvement by using the proposed scheme over two conventional schemes increases from 23% and 52% to 35% and 98%, respectively.

C. ENERGY EFFICIENCY DISTRIBUTION

The energy efficiency distributions according to the various realizations on the locations of the network entities and fading channels among them are illustrated for the proposed and the two conventional schemes in Fig. 3. The results are plotted for two different D2D pair densities $L = 25$ and $L = 35$ for each of the scheme. It is cleared from the distribution also that the performance trend of the proposed scheme under two CSI conditions remains similar as did for the convergence analysis. On the other hand, it is also apparent that the spectrum-efficient scheme performs worst again through the whole distribution, which again confirms the importance of considering the energy efficiency. Also, a round-robin or random RB allocation used in the RR-NPOG scheme is shown to be very inefficient and the joint allocation of RB and power level by considering the interference in the proposed scheme can provide a significant gain through the whole distribution. More precisely, the min-max energy efficiency bounds, defined as the interval of energy efficiency from 5% to 95%, of the proposed scheme with perfect CSI, the proposed scheme with imperfect CSI, the RR-NPOG scheme and the spectrum-efficient scheme are [1.76 - 10.88Mbits/J], [1.73 - 10.69Mbits/J], [1.70 - 10.4Mbits/J] and [1.4 - 8.3 Mbits/J] for $L = 25$ and [1.76 - 5.35Mbits/J], [1.73 - 5.25Mbits/J], [1.70 - 4.32Mbits/J] and [1.4 - 3.6Mbits/J] for $L = 35$, respectively.

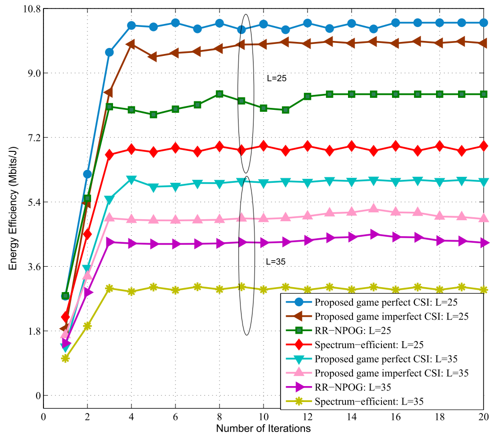


FIGURE 2. Convergence performance.

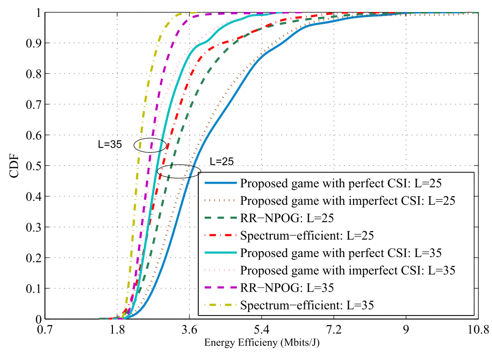
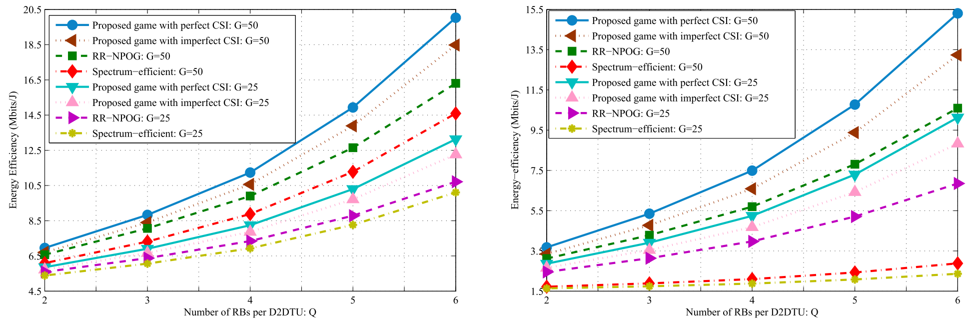


FIGURE 3. Energy efficiency distribution.

D. IMPACT OF VARYING Q, G AND L

The impacts of varying Q and G on the energy efficiency of the D2D communications are illustrated in



(a) (b)

FIGURE 4. Impact of varying G and Q on the energy efficiency (a): $L = 25$ and (b) $L = 35$.

Figs. 4(a) and 4(b), when $L = 25$ and $L = 35$, respectively. As the number of RBs acquired by D2DTU increases at a fixed amount of total RBs, the energy efficiency of each scheme increases. From the results, it is shown that the proposed scheme, with both CSI conditions, improves faster than the two conventional schemes, which comes from the significant advantage of the joint RB and power allocation of the proposed scheme. Also, comparing the results of the $G = 50$, $L = 25$ case, the relative performance improvement of the proposed scheme becomes more significant as G decreases or L increases, i.e., D2D resource utilization over total resource ($\frac{QL}{G}$) increases, which shows the efficiency of the proposed scheme again.

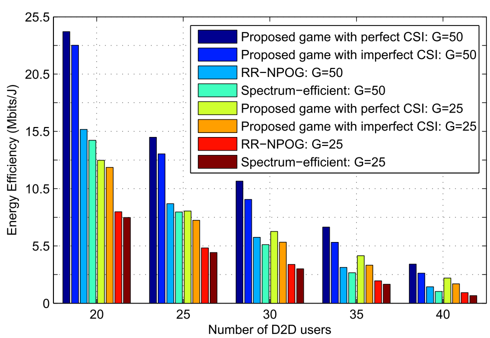


FIGURE 5. Impact of D2D density on the energy efficiency.

In Fig. 5, the impact of varying the D2D pair density on the energy efficiency is shown. Due to the co-channel deployment among the heterogeneous parties, the energy efficiency can be improved by employing a larger pool of RBs because an increase in the number of RBs provides more opportunities to reduce the interference. However, as the D2D resource utilization increases (G decreases or L increases), the proposed scheme shows more graceful degradation in the energy efficiency of each D2D pair than the conventional schemes. On the other hand, the performance degradation of the proposed scheme, while considering perfect and imperfect CSI, increases with the increase of D2D pairs which is due to the increase in competition in the non-cooperative game.

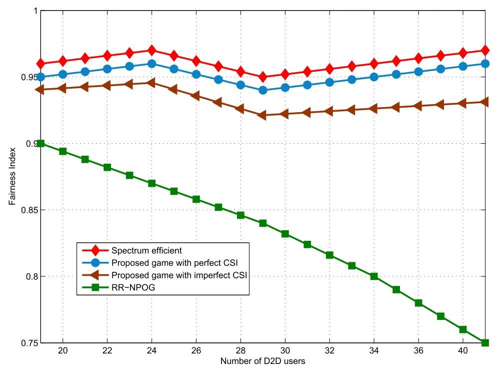


FIGURE 6. Fairness index.

E. FAIRNESS INDEX

Although the energy efficiency is of the prime interest in this study, the throughput performance of the proposed scheme is compared with the conventional schemes in Fig. 6 using the Jains fairness index formula given as

$$f_L = \frac{\left(\sum_{l=1}^{L} I_l\right)^2}{L\sum_{l=1}^{L} I_l^2}, \tag{23}$$

where $I_l = E\left\{\Psi_l^D\right\}$ denotes the average throughput of the lth D2D pair and the fairness index f_L, $0 \le f_L \le 1$, indicates a level of satisfaction among D2D pairs in terms of the fairness in the average throughput. From the result, it is shown that although the proposed scheme focuses on the energy efficiency, the throughput performance of the proposed scheme with perfect CSI remains almost the same to that of the spectrum efficiency scheme while that of RR-NPOG scheme deteriorates. On the other hand, the throughput performance of the proposed scheme with imperfect CSI also slightly variates as compared to its perfect CSI counterpart and spectrum efficient scheme and this is due to the sight degraded performance of it while achieving the Nash Equilibrium. This is due to the efficiency of the joint RB and power allocation by minimizing required power by reducing interference while managing the required QoS.

V. CONCLUSION

In this study, we propose a self-organized cross-layer optimization for enhancing the energy efficiency of the D2D communications without creating harmful impact on other tiers by employing a non-cooperative game in a three-tier heterogenous cellular network. Specifically, each D2D pair iteratively performs the *sensing*, *learning* and *tuning* steps for jointly optimizing the RB and power allocation to enhance its energy efficiency in a distributed manner without jeopardizing the user performance in other tiers. In order to achieve the energy efficiency maximization while maintaining the QoS requirement of other parties, the utility function is designed to consider not only the energy efficiency of its own but also the interference to other tiers. The joint RB and power allocation algorithm for each D2DTU is proposed by iteratively applying an optimal RB selection for given other users' power levels determined in the previous iteration and power allocation on the selected RBs using the proposed non-cooperative game. The performance of the proposed scheme with both CSI conditions is evaluated and compared with conventional RR-NPOG and spectrum-efficient schemes. The results illustrates that superior performance of the proposed scheme is achieved in terms of the energy efficiency over the conventional schemes. Furthermore, the performance gap between the proposed scheme and the conventional schemes increases as D2D pair density increases, which makes it an attractive option for dense environments. This study can be extended by considering the asynchronous OFDMA and it is worth investigating to see the existence of Nash Equilibrium for this case.

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