Spectral and Energy Efficient D2D Communication Underlay 5G Networks: A Mixed Strategy Approach

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***Abstract*—4G is now deployed all over the world, but requirements are about to change rapidly face to the exponential growth on devices number, local service applications and spectrum scarce. To deal with that, 5G networks integrated Device To Device (D2D) communication as a key technology in its evolving architecture. From 3GPP Rel-12 to Rel-16, D2D succeeded to improve network capacity by enhancing spectrum reuse, data rates and reducing end-to-end latency. However, despite all these advantages, it implies new challenges in 5G system design as interference, spectrum and energy consumption. As a contribution, in this paper we propose a joint spectrum and energy efficient resource allocation algorithm for D2D communications. This approach maximizes the total spectrum efficiency and reduces UEs power consumption. Contrarily to most of previous studies on resource allocation problems considering only centralized and pure strategies approaches, we propose a distributed algorithm based on new mathematical game theory model as an interpretation of mixed strategy non cooperative game. We extend our previous research, by focusing on power consumption issue. Our proposed solution enhances joint SE/EE tradeoff by minimizing interferences and power consumption via a smart RB allocation. This new approach allows users to adopt more accurate strategies and maximize their utilities according to the random network behavior.**

***Keywords*—5G, Device-to-device communication (D2D), Energy efficiency, Spectral efficiency, game theory, mixed strategy.**

I. Introduction

The expansion of mobiles number and content sharing between user's results a huge increase in wireless data traffic and local services demands. It is expected that there will be more than 20 billion of smart connected devices by the end of 2020; as long as various applications each requires a huge throughput and capacity, in accordance with its priority and QoS requirements.

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Face to this situation, 5G networks via D2D tried to benefit from short range Ad-hoc communications as Wi-fi, Bluetooth and ZigBee in order to provide efficient and scalable connections for proximity devices. Specified by 3GPP in LTE Rel-12, Device-to-device (D2D) communications enable user equipments (UEs) to directly communicate with each other without relying on network infrastructure to route their data.

Therefore, it succeeded to fix many issues related to network capacity, data rates, latency and energy consumption. It offloads traffic from eNodeB and achieved high data rates between communicating pairs. However, it implies other new challenges in cellular networks as resource allocation, interference management and power control.

Underlay 5G networks, any UE can select between D2D and conventional cellular communication. This choice is taken according to different criteria as received signal strength, channel condition, interference situation and distance between transmitter and receiver. If D2D mode is selected, communicating pairs tries to choose the best cellular link to route their data. However, the problem is how to perform this choice, synchronize and fairly meet all UEs demands on spectrum and QoS without relying to eNodeB. To deal with that, a joint interference and power management approach seems urgent to efficiently share spectrum resources between competing UEs without interfering others and preserve battery lifetime as long as possible.

As a contribution, we investigate and present results of a D2D resource allocation algorithm in order to jointly enhance spectral and energy efficiency and reduce interferences in the cell. Focusing on interference management issue, existing works on distributed resource allocation principally rely on pure strategy game theory. Therefore, the convergence of the algorithm is not guaranteed especially with a high UEs number, and these solutions are suitable only for a D2D pair sharing only one resource Block (RB) with a cellular UE. A good solution to deal with that is to apply mixed strategy game. Mixed strategy adds a probability distribution over all possible pure strategies and enables users to adopt a set of better behaviours at each situation. This can efficiently improve their SE/EE tradeoff since the existence of MSNE is always guaranteed by Nash Theorem. By randomly choosing between a set of strategies in a non cooperative game, a player can confuse their behaviours, as opponents won't know how he will act. Therefore, mixed strategy is an ideal framework to model resource blocks sharing between more than one D2D pair and cellular UE. In our previous work [1], we have analyzed and presented solutions to optimize the spectral efficiency (SE) through resource allocation in cellular environment via mixed strategy. However, we studied only interference minimization without analyzing power control.

In this paper, we extend this research, by focusing more on power consumption concern since UEs are little handled equipments with limited battery life. Our proposed solution consists on a simultaneous increase of SE/EE tradeoff in order to minimize interference as well as power consumption via a smart RB allocation. These two metrics are not usually achievable simultaneously and may even conflict with each other.

To achieve this goal, we present a formula that takes into consideration these two parameters as a ratio of the spectrum and energy consumed by UE to route its data via a specific RB. Then we try to maximize this ratio; maximize the numerator (SE) and minimize the denominator (consumed power) via mixed strategy game theory approach. By this way, we preserve energy efficiency for DUEs and farther enhance SINR and SE of the entire network.

The paper is structured as follows. In section II; we present an overview of existing works on interference management and power control underlay D2D scenarios. Our system model for direct D2D communications applied to this solution is drawn at the third part. Section IV, models the resource allocation problem as a mixed strategy non cooperative game, and propose a distributed spectrum sharing based on interference and power consumption minimization algorithm. In section V, Interference, spectrum efficiency (SE) and Energy Efficiency (EE) results are analyzed and verified through computer simulations. We interpret our MSNE vector, the final RBs allocation table and compare interference factor and spectral efficiency obtained from our algorithm to state of the art solutions. Finally, Section VI concludes the paper and proposes some perspectives for future work.

II. State of the Art

A. Related Works

Cellular spectrum efficiency describes how the spectrum is accurately shared between UEs. It depends on diverse parameters as the available bandwidth, the number of users simultaneously sharing the service and mainly the resource allocation strategy. In this context, a main concern is how to deal with the interference caused by spectrum resource reuse between cellular and D2D users over the same RB.

A lot of research tried to solve this problem either through network coding, mode selection, resource allocation or signal processing [3, 10]. Authors in [3] studied resource sharing between cellular and D2D devices underlay cellular network for different modes. Whereas the resource allocation problem in [4] is divided into two steps; channel allocation and power management and solved using graph theory. In [5], authors propose a framework based on graph theory to manage D2D resource allocation, while in [6], a power control schema is proposed to minimize interferences and maximize D2D SINR.

Also in [7], a power control based approach is further analysed and proposed to constraint D2D transmissions in order to ensure interference caused to cellular links below a tolerable threshold. Authors in [8], proposed a framework to analyze mode selection and power control of underlaying D2D communications. Whereas in [9], a joint power allocation and mode selection scheme is developed to enhance performances for both D2D and cellular communication.

In [10], the maximum transmission power of a D2D UE was derived from its location compared to eNodeB; consequently a dynamic power based resource allocation scheme was proposed to assign the best cellular link that mitigates interferences. In [11], a joint modulation, resource allocation, and mode selection schema is considered to minimize interferences and guarantee the QoS requirement. In [12], a distributed stochastic approach is proposed to minimize interference among cellular UEs and their co-channel D2D UEs. In [13], a smart resource allocation scheme is analysed where contiguous sub channels are allocated to further mitigate interference from cellular to D2D UEs using the same links.

In [14], a learning based solution was presented to share potential RBs between DUEs. While [15] evaluated Resource allocation in a cognitive radio D2D network and presented an adaptive allocation of a subcarrier schema.

Focusing on resource allocation schemas, centralized and distributed approaches have been investigated even with or without perfect channel state information (CSI). Many papers focused on analytical approximations, such as stochastic geometry [16], game theory [17], and mixed integer programming [18] to propose a centralized scheduling algorithm that manages all D2D and cellular communications. However these approaches require the knowledge of the CSI of all D2D links' at the eNodeB level. D2D pairs must estimate their communication channel and feed it back to the eNodeB in order to allocate the best link. Two main issues are encountered in this case. The first is from a logical point of view: D2D communications are self organized and did not rely on eNodeB except in pair discovery process. The second is that CSI reporting requires a considerable number of resources to feedback this information, while a limited number of resources are available for network control.

To deal with that, many existing research working on centralized approach assume the global CSI knowledge at the eNodeB. However, two other challenges appear in this case, the first is the imperfect knowledge of the channels' states and the second is the large amount of overhead caused by broadcasting CSI to eNodeB. Therefore the scheduling will always depend on the efficiency and the availability of CSI reporting and limited by the UEs number. This weakness will be multiplied by the use of D2D technique where the D2D channels are estimated at the D2D receiver level and then reported to the BS. Therefore, centralized approaches are NP-Hard, not always feasible and pushes for performing distributed approaches for D2D resource allocation.

Assuming the rationality of the players and based on the knowledge of utility function of all UEs inside the cell, game theory has been proven as an efficient framework to elaborate distributed resource allocation algorithms by: auction, pricing, coalitions and non cooperative games. Game-theoretical approaches are the most appropriate due to limited amount of information sharing as strategies, bids or prices.

Various non-cooperative and cooperative game models have been extensively applied to analyze interactive decision makings of network agents. However, pure strategic cooperative games suffer from many problems, which make them inadequate to apply for a self organized D2D communications. In particular, using pure strategic cooperative game models can suffer from the huge overhead caused by information sharing, the slow convergence to equilibrium especially when UEs number increases, the inefficiency of equilibrium in some cases and the complexity of characterizing the equilibrium. In contrast to cooperative games, non-cooperative mixed strategic models can fit the characteristics of our system more appropriately.

Little number of works on mixed strategic games is presented in the literature, but only in cellular mode, where D2D communication was not taken into account. Paper [19] presented a game with few players representing channel selection game which is quite far from real cellular environment. And [20] presented a stochastic non-cooperative game where each player is a learning to facilitate the convergence to the equilibrium.

The main contribution that we add compared to the mentioned works where only spectrum efficiency of cellular UEs is guaranteed, is that we provide a joint EE/SE of all cellular and D2D UEs. More importantly, the above works assumed that the problem of mode selection has already been solved, and all cellular links are already been set, but none of D2D links. This is quite far from reality. In real case, at every time slot any D2D pair or cellular UE can reach the cell.

The previous works also consider games with few users' number, each one can adopt only a pure strategy and presented by discrete probability mass functions. Contrarily we investigate mixed strategies (MS) and mixed strategy Nash equilibrium (MSNE) in non cooperative resource allocation games which still always efficient with an important number of UEs (players) and strategies.

B. Motivation and Contribution

In this paper, we consider the SC-FDMA uplink scenario of cellular network to route D2D data. We consider that each user's device has already selected its communication mode: cellular / D2D. For conventional cellular communication cellular UE directly allocates resources; (frequency and time) from the eNodeB and communicate via Uplink/Downlink mode, where preformed D2D pairs reuse opportunistically the same channels allocated by cellular UEs.

We model our cellular environment as a set of UEs scattered randomly inside a circular cell and centred by the eNodeB. Then we propose a novel distributed joint spectral-and energy efficient resource allocation to deal with interferences between co-channel UEs and power consumption. Our resource allocation problem is mathematically modelled by a mixed strategy non cooperative game with N players. Each UE compete to maximize its payoff represented by a joint capacity, bandwidth and energy formula. Every UE behaves selfishly, thus the first player outcome reaches the optimum whereas results decreases exponentially with the increase of players number, therefore the overall network capacity degrades respectively due to competition and conflicts between players. The most optimal outcome is to increase the combined pay-off of the players without reducing any one's. But the problem is not as simple as it appears. It is too much to expect the players to act rationally, especially when the problem is one of distributing their joint profit equitably. The Nash Equilibrium tries to arrive at a "fair division" by evaluating the pay-off for both players. In Nash equilibrium, each player adopts a strategy representing his best choice, given what the other player does.

The combination of the best-chosen strategy for every player is referred to the equilibrium point MSNE. Then SE distribution is analyzed for both cellular and D2D users in the uplink resource links.

We validate our analysis with simulation plots, which demonstrates a considerable gain on network performances and system capacity due to the interference decrease compared to other state of art solutions.

Finally, the conclusion drawn from this paper provides a guideline in the design of D2D communication network considering resource allocation, interference management, and some perspectives for future work are presented.

III. SYSTEM MODEL AND MATHEMATICAL FORMULATION

A. System Model

In this paper, we consider the uplink scenario of a single cell presented by an eNodeB placed in the centre. A number of S UEs are present in the cell. This set is formed by two types of UEs: Cellular and D2D UEs. S = {C, D}. The spatial distribution of cellular UEs and device UEs both follow an independent homogeneous Poisson Point Process PPP model with intensity λ_c and λ_d respectively [9], the distance between a D2D pair is maintained under a maximum threshold to preserve the quality of D2D communication.

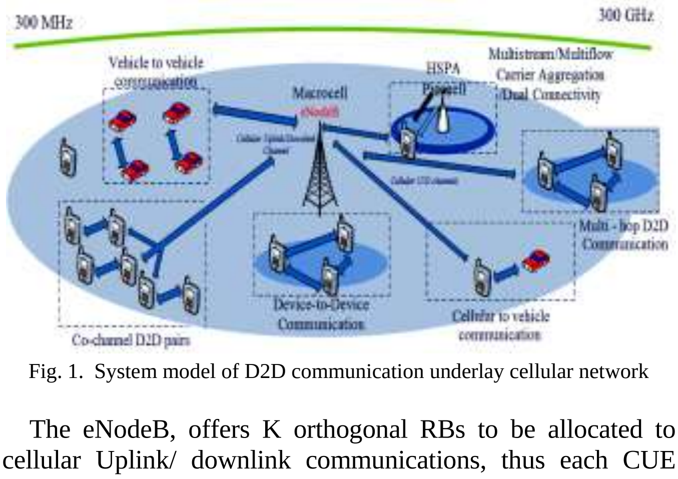

Fig. 1. System model of D2D communication underlay cellular network

The eNodeB, offers K orthogonal RBs to be allocated to cellular Uplink/ downlink communications, thus each CUE occupies a set of RBs from the available bandwidth B. However interference cannot occur between cellular UEs due to OFDM orthogonality.

Let $c \in \xi = \{The\ set\ of\ available\ RBs\}$ be the set of Resource Blocks assigned to a UE, it can be either cellular or D2D communicating pair.

The achievable data rate of the i^{th} UE in the RB c can be expressed as:

$$R_i^c = w.\log_2(1 + S_i^c), \tag{1}$$

where, w is the channel bandwidth (in hertz) and S_i^c is the SINR of the ith receiver at the RB c.

For a given i^{th} cellular UE, interferences occur only from co-channel D2D pairs. Whereas, for a D2D UE interferences came from other co-channel D2D pairs as well as the primary CUE allocating this RB. The SINR at the i^{th} cellular UE and D2D receivers are respectively represented by S_i^c and S_i^d.

$$S_i^c = \frac{p_i^c g_i^c}{\sum_{j=1, j\neq i}^{N} \gamma_{j,c} p_j^d g_j^d + N_0}, \tag{2}$$

$$S_i^d = \frac{p_i^d g_i^d}{\sum_{j=1, j\neq i}^{N} \gamma_{j,d} p_j^d g_j^d + p_j^c g_j^c + N_0}, \tag{3}$$

We note g_i^d the channel gain of the i^{th} D2D pair in RB c and g_j^d the interference channel gain between the i^{th} D2D receiver and other co-channel j^{th} D2D transmitters. g_i^c represents the channel gain of the i^{th} cellular UE in the RB c and g_j^c is the interference channel gain between the i^{th} D2D receiver and j^{th} cellular transmitter.

Taking into account the large scale fading effects, the channel gains between transmitter and receiver can be modelled as $g_i^c = |h_{i,j}|^2 d_i^{-\alpha}$ where d_i is the distance between the transmitter and the receiver and α represents the path-loss exponent for multipath fading and shadowing.

$g_j^c = |h_{i,j}|^2 d_j^{-\alpha}$ where d_j represents the distance between the receiver and other co-channel transmitters, and $h_{i,j}$ is a complex Gaussian channel coefficient satisfying $h_{i,j} \sim CN(0,1)$.

$\gamma_{i,c} \in \{0,1\}$ is a variable indicating if the RB c is allocated by the i^{th} link. i.e $\gamma_{i,c} = 1$ if RB c is occupied by i^{th} link, 0 if not.

p_i^c and p_j^c are respectively the transmission powers of i^{th} transmitter at RB c, and other interfering transmitters.

For a D2D receiver $p_j^c g_j^c$ denotes the interference from the cellular UE and $\sum_{j=1, j\neq i}^{N} \gamma_{j,d} p_j^d g_j^d$ is the interference from cellular and other D2D pairs allocating the same RB c, whereas N_0 models the power of the thermal noise.

We assume that a cellular UE can allocate a cellular RB, whereas any i^{th} D2D link can allocate simultaneously many RBs already assigned to different CUEs. Thus its total achievable rate is the sum of all allocated RB rates:

$$\sum_{i=1}^{c} R_i = \sum_{i=1}^{c} \sum_{c \in \xi} \gamma_{i,c}. R_i^c, \tag{4}$$

$$\sum_{i=1}^{C} \sum_{c \in \xi} \gamma_{i,c}. W. \log_2 \left(1 + \frac{p_i^c g_i^c}{\sum_{j=1, j\neq i}^{N} \gamma_{j,c} p_j^c g_j^c + N_0}\right). \tag{5}$$

The system Capacity is maximized if transmitted signal arrives at the receiver with the maximum achievable SINR.

The SE (bits/s/Hz) and EE (bits/Hz/J) of the i^{th} cellular UE at the k^{th} RB are respectively presented by:

$$SE_i^c = \log_2 \left(1 + \frac{p_i^c g_i^c}{\sum_{j=1}^{N} \gamma_{j,c} p_j^d g_j^d + N_0}\right) \tag{6}$$

$$EE_i^c = \frac{\log_2 \left(1 + \frac{p_i^c g_i^c}{\sum_{j=1}^{N} \gamma_{j,c} p_j^d g_j^d + N_0}\right)}{\frac{1}{\eta} p_h^k + p_{cc}} \tag{7}$$

The SE (bits/s/Hz) and EE (bits/Hz/J) of the i^{th} D2D UE at the k^{th} RB are respectively presented by:

$$SE_i^d = \log_2 \left(1 + \frac{p_i^d g_i^d}{\sum_{j=1, j\neq i}^{N} \gamma_{j,c} p_j^d g_j^d + p_i^c g_i^c + N_0}\right) \tag{8}$$

$$EE_i^d = \frac{\log_2 \left(1 + \frac{p_i^d g_i^d}{\sum_{j=1, j\neq i}^{N} \gamma_{j,d} p_j^d g_j^d + p_i^c g_i^c + N_0}\right)}{\frac{1}{\eta} p_h^k + p_{dtc} + p_{drc}} \tag{9}$$

where N_0 represents the thermal noise power, η is the power amplifier efficiency, with $0 < \eta < 1$. p_{cc}, p_{dtc} $and p_{drc}$ represent respectively the circuit power of the cellular, the D2D transmitter and receiver of the communicating pair.

B. Mathematical Formulation

In this section we formulate the joint SE/EE algorithm based on optimal RB allocation for D2D communication underlay cellular network. We analyse all D2D pairs and CUEs resource allocation inside the cell. Our goal is to allocate the appropriate RB that simultaneously minimizes the total received interference for the D2D receiver as well as the amount of energy consumed by the transmitter to route its data.

Each cellular UE allocates an orthogonal channel from eNodeB while D2D links reuse these RBs with the primary cellular links. As a result, co-channel interference can occur to every link allocating a shared RB between one cellular and one or more D2D pairs.

Consequently, our SE/EE maximisation problem can be formulated as a mixed integer programming with N D2D pairs and K RBs.

$$\max \sum_{i=1}^{N} \frac{\sum_{h=1}^{K} \log_2 \left(1 + \frac{p_i^d g_i^d}{\sum_{j=1, j\neq i}^{N} \gamma_{j,c} p_j^d g_j^d + p_i^c g_i^c + N_0}\right)}{\sum_{h=1}^{K} \frac{1}{\eta} p_h^k} \tag{10}$$

$$\min \sum_{h=1}^{K} \sum_{c \in \xi} \gamma_{i,c} p_i^c g_i^c + N_0 \tag{11}$$

Subject to: $0 \leq p_i^c \leq p_{max}^c;\ \forall c \in C;\ i \in K \cup N$ (a)

$SE_i^c \geq SE_{min}^c; \forall i \in K;\ \forall c \in C$ (b1)

$SE_i^d \geq SE_{min}^d. \forall i \in N;\ \forall c \in C$ (b2)

$EE_i^c \geq EE_{min}^c. \forall i \in N;\ \forall c \in C$ (c1)

$EE_i^d \geq EE_{min}^d. \forall i \in N;\ \forall c \in C$ (c2)

The above problem aims to maximize the total SE/EE for all UEs inside the cell under the constraints (a), (b) and (c). (a) Specify the maximum transmitted power values. (b1) and (b2) concern the minimum SE requirements at the i^{th} receiver, while (c1) and (c2) represent the EE lower bound required respectively to cellular and D2D pairs.

The main goal of this research is to maximize the number of connecting users by providing a maximum simultaneous throughput for all communications inside the cell. This requires cellular resources management as well as costs, energy and interferences minimization.

Tin this context; many 5G approaches have been proposed to deal with these issues; as mm waves, massive multiple antennas (MIMO) and new ways of spectrum allocation. Thus, to fairly meet users' demands, the first ideas were to strategically centralize the resource management in the eNodeB; A macro cellular base station designed to serve many users and thereby justifies this choice. However, with the integration of D2D, multiple simultaneous communicating pairs have to be efficiently served which further increases the complexity and the management of the network, especially when jointly optimizing more than one parameter simultaneously. It is not often achievable and many parameters may conflict with each other leading to a divergence of proposed solutions. In addition joint SE/EE problems are NP-hard and imply high capital and operating costs.

More recently, the concept of distributed approaches was introduced, in which multiple simultaneous users have to be automatically served via smart mathematical algorithms in order to reduce the complexity and expanses of traditional approaches. However the main issue with these solutions is that convergence is not always hold. So it is a main requirement to get a real estimation and the best model to ensure the convergence with correct and full results.

Mixed strategy is a good application when a D2D can use a set of shared RB. According to John Forbes Nash "There is at least an equilibrium for every finite Mixed Strategy game". Thus, we propose a distributed resource allocation algorithm based on Mixed Strategy game theory, which ensures convergence at MSNE point. We use approximation methods to divide the problem into sub-problems, and then we investigate the MSNE vectors. Finally assign the best RB for each UE in the network.

B.1. Mixed Strategy Game Theory Formulation

Our problem is modelled as a Mixed Strategy a non-cooperative game with N players. Each player selects the best strategy that maximizes its utility function U_i. Each UE is a player, it acts independently from all other users to maximize its own payoff.

Firstly, we identify the parameters of our game:

G = {N,S,U}

Players: N is the set of players i.e. the set of User equipments inside the cell: Cellular UEs and D2D UEs.

Strategies: D2D UE must choose the strategy that maximizes its payoff presented by the set of RBs supporting its data.

For any i^{th} player in a game, its mixed strategy is the probability distribution over the pure strategies space S^i.

The mixed strategies space of this player is: $\delta^i=\left\{\sigma^i \in \mathbb{R}^{m^i} \mid \sum_{j=1}^{m^i} \sigma_j^i = 1\right\}$, where σ_j^i is the probability assigned to pure strategy S_j^i, given $\sigma^i \in \delta^i$.

$\delta = \prod_{i\in N} \delta^i$ is the strategy space of the game. i.e when a UE plays a mixed strategy σ, the probability that the pure strategies combinations $=\left(S_{j^1}^1, S_{j^2}^2, \dots, S_{j^n}^n\right)$ occurs is defined by $\sigma(s)=\prod_{i\in N} \sigma_j^i$.

Mixed strategies payoff: In game theory approaches, every player is supposed rational and tries to maximize his own payoff independently from other players. In a pure strategy the player makes only one choice which involves no chance or probability. Whereas in MS its payoff as well as its opponents becomes random variables noted as $u^i(\sigma)=\sum_{s\epsilon S} u^i(s)\,\sigma(s)$, where $u^i(s)$ is the players' payoff at the pure strategy space $S\{N\}$. The strategy taken by the i^{th} player depends not only on its own strategy but also on the strategies taken by others UEs in $S\backslash\{i\}$. Thus, the mixed strategies σ is a combination between σ^i and σ^{-i} .

B.2. Mixed Strategy Nash Equilibrium

The MSNE is an equilibrium point, where no player in the game can maximize its payoff by unilaterally changing his strategies while the other players keep their unchanged.

According to Nash, there is at least one Mixed Strategy Equilibrium for any game in a normal form.

This MSNE denoted s* is mathematically represented by the combination of the optimal strategies for all players in the game $s^*= (s_i^{d*}, s_{-i}^{d*}, s_k^{c*}, s_{-k}^{c*})$, where

$$U_{i,EE}\left(s_i^{d*}, s_{-i}^{d*}, s_k^{c*}, s_{-k}^{c*}\right) \geq U_{i,EE}\left(s_i^{d}, s_{-i}^{d*}, s_k^{c*}, s_{-k}^{c*}\right) \forall\, i \;\; N, \forall\, s_i \in \; S_i$$

it represents the optimal resource block allocation for all UEs in the cell that maximises the joint SE/EE.

IV. SPECTRAL AND ENERGY EFFICIENT D2D ALGORITHM

Our proposed approach is summarized in the following algorithm. We assume that all cellular UEs already allocated orthogonal channels from eNodeB. There is a set of D2D pairs already preformed according to distance and maximum transmission power constraints, and new pairs can sequently access to the cell. All DUEs are competing to allocate the best RBs. Each of them is a rational player and aims to maximize its own payoff given by the equation (10). Any UE knows its coordinates in the cell, and the eNodeB broadcasts the locations and RB allocations of CUEs to D2D in the pair discovery step. Thus every DUE can calculate the interference coming from each cellular link as well as from co-channel D2D pairs.

Given that the utility function (10) of the i^{th} link depends not only on its own strategy, we iterate our algorithm step by step until reaching the best one that gives the maximum payoff. Let it_i the iteration index. For any given D2D pair and at each iteration, the optimal resource allocation is obtained by solving the equation (10).

Once the algorithm sufficiently converges to the optimum EE, i.e. when the condition $c_{it_i}^*(\sigma^i, \sigma -^i)$- $c_{it_{i-1}}^*(\sigma^i, \sigma -^i) \leq \Delta$ is satisfied (Δ is the maximum tolerance), the transmitter identifies its best mixed strategy. Consequently we move to the next D2D pair. Finally the algorithm terminates when all

D2D pairs reach their maximum payoff and leads to the MSNE matrix.

As the best strategy of any UE depends on the strategies of others, the strategy sets must be broadcasted to all UEs. However, this information can be simply extracted from co-channel interferences. In this way, each D2D pair has to estimate only the interference on all available channels to determine the power optimization rather than knowing the exact strategies of other UEs. Accordingly, for the k^{th} cellular UE the BS estimates the interference from D2D pairs on the k^{th} channel and feeds it back to the cellular UE. Thus, UEs sequentially update their strategies and the MSNE matrix which is proved to exist by Nash is finally obtained.

TABLE I
SPECTRAL AND ENERGY EFFICIENT D2D ALGORITHM

ALGORITHM: Spectral and Energy Efficient D2D algorithm
Assign the CUEs resource allocation vector CRB=[1]x[k]
Variable $c^* = [0]$, n=1, it_i=1, $it_{max} = 30$, D = 40, K = 17,
Dp=20, S= 3 , CD_Dist = [D]x[K], MSNE=[D][S]
$d_{th} = 30, c_{rd} = 500$
D2D_Dist = [Dp]x[Dp] and $\Delta = 10^{-3}$
Generate PPP random distribution for k cellular and N
D2D pairs
Calculate Distances: Fill CD_Dist and D2D_Dist from
generated PPP distribution
While n≤ Dp do;
While $it_i \le it_{max}$do;
$c^*_{it_i}(\sigma^i, \sigma -^i)$=arg $\max_c$ $U_{it_i}(\sigma^i, \sigma^{-i})$
if $c^*_{it_i}(\sigma^i, \sigma -^i)$- $c^*_{it_{i-1}}(\sigma^i, \sigma -^i) \le \Delta$
then MSNE [n] [1]= σ^i And n=n + 1;
else: $it_i = it_i + 1$;
End while.
End while.

V. SIMULATION RESULTS

In this section, we investigate the results of our joint "SE/EE" algorithm through computer simulations. We used "Matlab" as numerical computing environment. The communication channels between cellular UEs and eNodeB and between D2D pairs are small scales Rayleigh fading with path loss and log-normal shadowing, and the average power gain over all channels is equal to 1. We calculate the gain using: $g = |h|^2 d^{-\alpha}$, where h is a Rayleigh random variable, α= 4 and d represents the distance between the transmitter and receiver. All UEs coordinates are randomly generated through PPP distribution with $\lambda_d = D$ and $\lambda_c = K$ representing respectively D2D and cellular UEs intensities. Thus we can simply fill the distances tables CD_Dist and D2D_Dist representing the distances matrix respectively between cellular and D2D and between D2D pairs. For each simulation, we can set dynamically different intensities and regenerate new locations of cellular and D2D UEs.

The variable n represents the DUE index $1 \le n \le D$. n is initialized to 1 and incremented by 1 if the n^{th}DUE payoff converged to its optimal strategy, and consequently until finding the best strategies for all D UEs. it_i, represents the iteration index, initialized at it_0=1, $it_{max}$is the maximum number of iterations used to ensure the convergence of the algorithm. But, if the optimum EE is reached before, the loop terminates and we move to the next D2D pair.

$\Delta = 10^{-3}$ is used to ensure the convergence of our algorithm. We compare the difference between the obtained EE at the actual i^{th} iteration with that founded at the previous iteration i^{th-1}. If the difference is less than Δ, then our algorithm reaches the convergence.

At the end, the MSNE variable designs the mixed strategy Nash equilibrium matrix at the convergence of the algorithm. $c^*_{it_i}(\sigma -^i)$=arg $\max_c$ $U_{it_i}(\sigma^i, \sigma^{-i})$ means that the MSNE point representing the best resource block allocation combination for the n^{th}DUE is reached at the i^{th} iteration. Contrarily to our previous work cited in [2] considering two steps algorithm; one for resource allocation and a second for power control, we investigate a joint SE/EE algorithm that allocates the best resource block simultaneously providing minimum interference, maximum spectrum and energy efficiency. All these parameters are efficiently managed at the same utility function. Thus, at the equilibrium point, all D2D and CUEs reach the maximum SE/EE ratio. The second strong point in our algorithm is that it operates with sequential UEs access in the cell, contrarily to other state of art solutions constrain that all D2D must be pre formed before executing the algorithm, which is quite far from reality.

Also a main concern of our approach is the reduced number of iterations needed to the convergence. After executing our algorithm on a set of random combination and various PPP intensities, an average number of 10 runs was needed to reach the convergence. The total average time taken from generating random cellular environment to obtaining the final MSNE matrix is 39.669342 seconds.

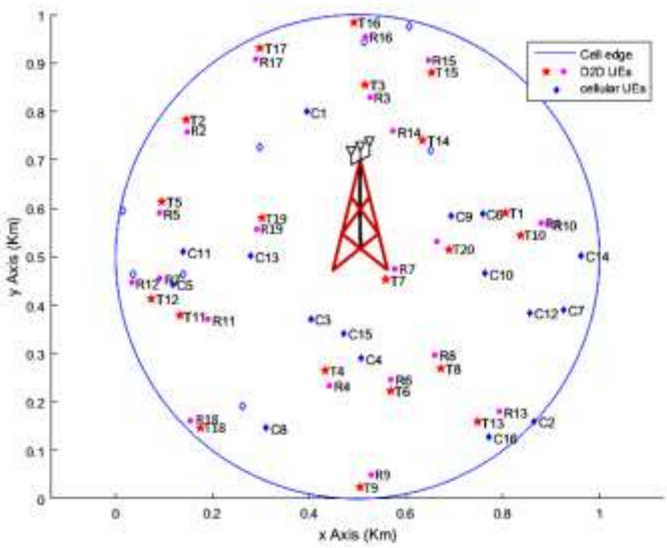

Fig. 2. The locations of K CUEs and N D2D UEs: (D = 40, K = 17, the cell radius is 500 m, max D2D distance=30 m)

In this section, the performance of our algorithm is investigated through computer simulations. There is a total number of 56 UE randomly generated by PPP. We set $\lambda_d =$ 40 D2D UE and $\lambda_c = 16$ CUE. The maximum D2D transmission distance d_{th} =30 m to preserve the quality of communication between pairs. All UEs are randomly distributed inside a cell of c_{rd} =500 m radius and centred by the eNodeB. Active cellular UE are represented by blue diamonds, while D2D transmitters are marked by red stars and receivers by pink points. The numbers behind each symbol indicate UE type and id.

To evaluate the joint SE/EE resource block allocation, we start by presenting in Table II the default random allocation vs. new MSNE allocation obtained through our algorithm. We observe that D2D links change their random RB selection and allocate optimal ones given by MSNE equilibrium. Each D2D pair can reuse k cellular RBs in this example k is set to 3. The 20 D2D pairs compete all for 16 available RBs, their MSNE matrix is presented in table III.

TABLE II
RANDOM VS FINAL RB ALLOCATION OF ALL LINKS OF THE NETWORK

D2D pair	Random RBs		
D2D 1	C_6	C_9	-
D2D 2	C_{12}	C_1	-
D2D 3	C_1	-	-
D2D 4	C_4	C_{15}	C_3
D2D 5	C_{12}	C_{11}	C_3
D2D 6	C_4	C_{15}	C_3
D2D 7	C_5	C_{11}	C_{13}
D2D 8	C_4	C_{16}	-
D2D 9	C_8	C_{16}	-
D2D 10	C_6	C_{14}	C_9
D2D 11	C_5	C_{13}	-
D2D 12	C_5	C_{11}	-
D2D 13	C_{16}	C_2	-
D2D 14	C_1	C_9	-
D2D 15	C_1	-	-
D2D 16	C_1	-	-
D2D 17	C_1	-	-
D2D 18	C_8	-	-
D2D 19	C_{13}	C_{11}	-
D2D 20	C_9	C_6	C_{10}

D2D pair	MSNE RBs		
D2D 1	C_4	C_{15}	C_3
D2D 2	C_5	C_{13}	C_{11}
D2D 3	C_{14}	C_9	C_6
D2D 4	C_2	C_{16}	C_8
D2D 5	C_8	C_4	-
D2D 6	C_{11}	C_{13}	-
D2D 7	C_4	C_8	C_{17}
D2D 8	C_6	C_9	C_{13}
D2D 9	C_{13}	C_5	C_3
D2D 10	C_{16}	C_2	C_7
D2D 11	C_{12}	C_8	C_4
D2D 12	C_4	C_8	C_{15}
D2D 13	C_{13}	C_9	C_3
D2D 14	C_{11}	C_{13}	C_{12}
D2D 15	C_{14}	C_{10}	C_6
D2D 16	C_{13}	C_9	C_6
D2D 17	C_{11}	C_{13}	C_{12}
D2D 18	C_{12}	C_{11}	C_{13}
D2D 19	C_6	C_9	C_1
D2D 20	C_{11}	C_{13}	C_3

In our previous work [1] we remark that at the convergence to the MSNE and in order to reduce interferences, each DUE chooses the RB(s) occupied by cellular links located far from it. It applies the same approach when many D2D UEs pre allocate the same RB. This assumption matches very well with analytical formulas; where interferences depend on distances between D2D communicating pair and CUE as well as between co-channel D2D pairs. However, in this research the joint SE/EE depends on various parameters. Each D2D UE tries to allocate the RB that maximizes its SE and simultaneously minimizes transmitter power. To satisfy the SE requirement, interferences must be reduced, while transmitter signal and channel gain must be enhanced compared to the interference channel gain. This condition is met when the considered D2D pair is close to each other and far from other cellular and D2D interferers. However this assumption does not match with EE maximization, because when reducing interference by reducing energy consumption or increasing co-channel UE distance, the overall EE of the cell became much lower due to the low signal channel gain caused by transmission distance in cellular resource blocks.

TABLE III
FINAL NASH EQUILIBRIUM MIXED STRATEGIES MATRIX OF 20 D2D PAIR SHARING 16 CELLULAR RB

D2D pair	MSNE Matrix		
D2D 1	0,4652	0,2784	0,2563
D2D 2	0,4971	0,2985	0,2042
D2D 3	0,7732	0,1884	0,0383
D2D 4	0,4894	0,3526	0,1578
D2D 5	0,4802	0,3950	0,1247
D2D 6	0,6418	0,1882	0,1699
D2D 7	0,6165	0,2315	0,1519
D2D 8	0,5059	0,4266	0,0674
D2D 9	0,3986	0,3380	0,2633
D2D 10	0,3460	0,3300	0,3239
D2D 11	0,5072	0,3806	0,1121
D2D 12	0,6306	0,2453	0,1239
D2D 13	0,4214	0,2920	0,2865
D2D 14	0,4321	0,3713	0,1964
D2D 15	0,4026	0,3983	0,1990
D2D 16	0,4224	0,4009	0,1765
D2D 17	0,5192	0,3227	0,1580
D2D 18	0,6824	0,2309	0,0865
D2D 19	0,3658	0,3623	0,2717
D2D 20	0,3728	0,3137	0,3133

A main advantage in our algorithm is that it provides a list of ranked RBs for each D2D pair according to SE/EE maximization. Therefore, each pair can allocate simultaneously k resource blocs and divide its data according to the probability obtained at the equilibrium point, contrarily to previous works investigating pure strategies and therefore providing one cellular RB per D2D pair. Even if the transmitter achieves its data only through the first allocated RB, it is not obliged to repeat the algorithm each time slot as pure strategies approaches does; it can simply choose the second strategy obtained by MSNE. This approach highly decreases convergence time: An average of 10 iterations is needed to reach the convergence even with a high UES number.

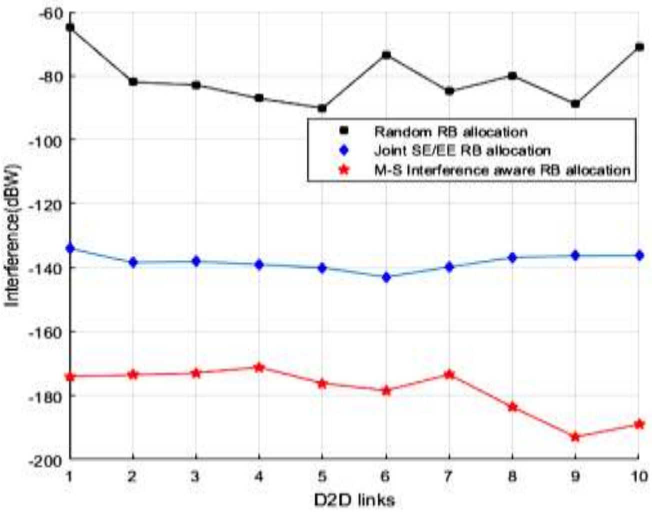

Fig. 4. Average Interference of active D2D pairs in the cell

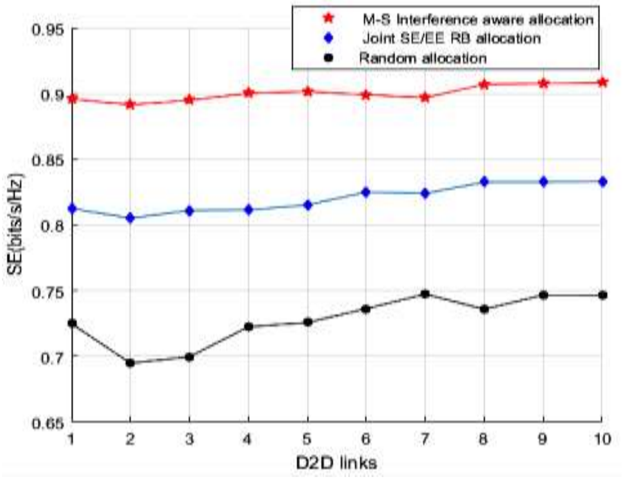

Fig. 5. The Averaged SE of active D2D links in the cell

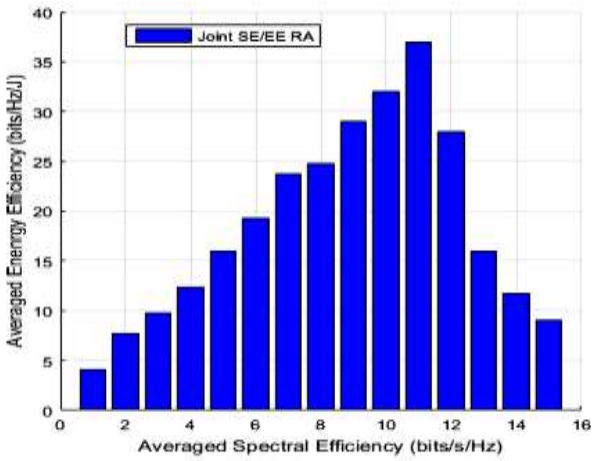

Fig. 6. The averaged EE/SE tradeoff of “SE/EE algorithm”

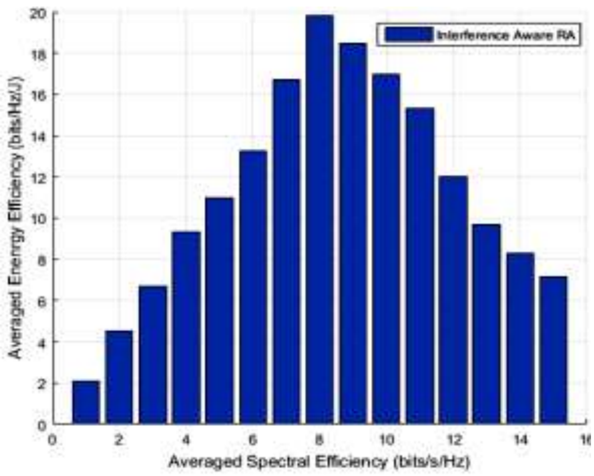

Fig. 7. The averaged EE/SE tradeoff of “Interference Aware algorithm”

For each averaged transmitted power, the corresponding SE is obtained by the proposed algorithm. Simulation results show that the maximum achievable SE increases as interferences decrease, which agrees very well with our mathematical formulas. However, the EE firstly increases with SE then decreases as power consumption needed to route data increases. When trying to reduce this energy, EE increases firstly but it decreases monotonically due to the decrease of spectral efficiency affected by power minimization. Simulation results show also that both of the maximum EE and SE are limited due to (5a) and (5b) constraints.

The figure 4 presents the interferences plots of three RB allocation approaches: Random RB allocation, Joint SE/EE RB allocation and M-S Interference Aware allocation. The results are averaged through a total number of 10 different simulations and normalized by the maximum value. It is clear that our previous work [1] considering only interference aware allocation outperforms others in term of Interference minimization. This is evident since this approach doesn’t take into consideration power consumption; its interference range is between [-190,-170] dBW. The Joint SE/EE approach minimizes the interferences compared to the random approach which is obvious, however it gives a mean range between [142,-138] dBW where in random allocation interferences are always between -90 and -62 dBW.

In the figure 5, we compare the SE approach of our proposed approach against the same approaches mentioned in figure 4, in term of Spectrum efficiency. In the interference aware approach each UE is self-interested and wants to maximize its own SE by minimizing interferences. However in Joint SE/EE, the SE fluctuates around the mean between the first approach and Random approach. The results are also averaged through a total number of 10 simulations and normalized by the maximum value. UEs distributions are randomly modelled according to PPP.

The averaged SE of our proposed mixed strategy algorithm converges to 0.83, while in the interference Aware it converges to 0.91 and in the random algorithm it between 0.7 and 0.73. The random algorithm has the worst SE performance among the three because interference is completely ignored in the optimization process, which is also proven by the figure 4.

The figures 6 and 7, draw the tradeoff between EE and SE. D2D UEs are assumed to transmit with their optimal power and allocate the best RBs. The corresponding EE is obtained by (10). Simulation results show that the EE firstly increases with SE and then decreases monotonically as the consumed power increases, which agrees with analytical equations.

Compared with Fig 7 representing SE/EE tradeoff of the “Interference Aware” algorithm, it is clear that our approach outperforms the second where each DUE is interested to maximize its own SE rather than EE, thus the energy consumption is completely ignored in the algorithm. The results are averaged through a total number of 100 simulations and normalized by the maximum value. The maximum average EE of the Joint SE/EE algorithm is around 38 bits/Hz/J, whereas the maximum achievable EE of the Interference Aware algorithm is 19 bits/Hz/J.

Although the little spectrum efficiency loss our proposed algorithm brings significant EE improvement. it outperforms other algorithms in terms of Energy efficiency, simultaneous D2D communicating pairs, and convergence time even with high UEs number. This was not feasible especially with pure strategy approaches supporting only reduced UEs number.

VI. Conclusion and Perspectives

In this paper, we proposed a joint spectral and energy efficient resource allocation algorithm for D2D communications by exploiting distributed game theory in mixed strategy form. We analyzed SE and EE maximization through computer simulations. Results prove that our method outperforms previous approaches in terms of results and performances as supported UE numbers and convergence time. As perspective, the algorithm can be followed by a complementary approach to support multihop D2D, where communication capabilities need to be enhanced and relays should be efficiently selected for a long and efficient data exchange.

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