Distributed Carrier Aggregation in Small Cell Networks: A Game-theoretic Approach

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Abstract

In this paper, we investigate the problem of achieving global optimization for distributed carrier aggregation (CA) in small cell networks, using a game theoretic solution. To cope with the local interference and the distinct cost of intra-band and inter-band CA, we propose a non-cooperation game which is proved as an exact potential game. Furthermore, we propose a spatial adaptive play learning algorithm with heterogeneous learning parameters to converge towards NE of the game. In this algorithm, heterogeneous learning parameters are introduced to accelerate the convergence speed. It is shown that with the proposed game-theoretic approach, global optimization is achieved with local information exchange. Simulation results validate the effectivity of the proposed game-theoretic CA approach.

Keywords: Carrier aggregation, small cell network, game theory, inter-band cost

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1. Introduction

Small cell is the most promising approach for providing a thousand-fold mobile traffic over the next decade [1]. Compared to the macrocell, small cell has lower power and smaller coverage areas. They can operate in licensed and unlicensed spectrum. Thus, more spectrum bands can be utilized by small cells, e.g., Super high frequency (SHF) and Extremely high frequency (EHF). However, as exponential growth of the number of devices and high data rate in future mobile communication systems [2]-[4], the demand of high bandwidth for high data rate is urgent. Carrier aggregation (CA) allows a cell to aggregate multiple channels for a wider bandwidth to transmit simultaneously. It is necessary to exploit CA to increase the data rate in small cell networks [5]-[6]. Thus, it is promising important to study the problem of resource allocation for distributed CA in dense small cell networks.

Actually, to be different from traditional cellular system, channel allocation for distributed CA in dense small cell networks faces a challenge that the mutual interference is more serious. Moreover, the impact caused by the distinct cost of intra-band and inter-band CA should be considered. The reason is that inter-band CA needs multiple FFT and multiple RF front-end in contrast that intra-band needs only one [7]. For the problem of distributed CA in small cell networks, the key task is to determine the aggregated channels among multiple small cells, which is a combinatorial majorization problem and hard to solve.

Generally, there are centralized gateways [8] in small cell networks that make centralized optimization possible. If we apply a centralized optimization to address this problem, e.g., [9]-[11], as the deployment of small cells become dense, this optimization problem is extremely complicated. For example, consider a network with 20 small cells and two band with two channels in each band. Consider a simple scenario in which each small cell aggregates at most two channels for CA, the corresponding number of all possible strategy selection profiles is 10^{20}, which is hardly possible to achieve the optimal solutions. To solve this problem, we resort to game theory, which is a powerful optimization tool involving multiple interactive decision-makers [12]-[13]. In this paper we propose a game-theoretic solution for solving the problem of distributed CA in small cell networks. To the best of our knowledge, such an investigation has not been addressed effectively in existing researches.

To summarize, the main contributions of this paper are as follows:

1) We formulate the problem of distributed CA in small cell networks as a non-cooperative game. In particular, the utility function in the game takes into account local interference and the distinct cost of intra-band and inter-band CA. It is proved that the game is an exact potential game with the defined potential function serving as the potential function. It is shown that the strategy profile of achieving the optimal potential function can make the network throughput better.

2) We propose a spatial adaptive play algorithm with heterogeneous learning parameters (SAP-H) to converge towards Nash equilibrium (NE) of the game. In this algorithm, we introduce heterogeneous learning parameters to accelerate the convergence speed. Thus, compared with the conventional SAP algorithm, the proposed algorithm converges rapidly while keeping the network capacity. Moreover, the performance of the proposed SAP-H is close to the best Nash equilibria.

3) We compare the average throughput for each small cell when varying the available spectrum resource and the degree of flexibility in performing CA respectively. We draw some meaningful conclusions.

The rest of the article is organized as follows. In Section 2, we present the related work. In Section 3, we give the system model and formulate the problem. In Section 4, we model the problem of CA as a non-cooperative game and investigate the properties of its NE. And we propose a spatial adaptive play algorithm with heterogeneous learning parameters. In Section 5, simulation results are presented and conclusion is drawn in Section 6.

2. Related Work

The problem of CA was studied in some works. The authors studied the UE energy saving by applying carrier aggregation in [14]. In [15] a novel carrier-aggregated modulator structure was proposed. In [16] a fully matched LTE-A carrier aggregation quadplexer based on bulk acoustic wave and surface acoustic wave technologies was proposed. In [17] an efficient carrier aggregation receiver architecture was described,which employed one receive path and a single synthesizer. These works [14]-[17] aimed to study the performance of a single user with CA. Compared with the existing studies, the network performances of multiple users with CA are studied in this work.

Recently, there were some researches on CA for multiple users [18]-[24]. In [17], to improve the performance of the cognitive Ad Hoc networks, based on the proposed Channel-Aggregation Diversity technology the authors proposed two joint power-channel allocation schemes. In [18], to balance the energy efficiency (EE) among multiple users, joint bandwidth and power allocation for both the base station and users was studied. In [19], a joint uplink-downlink algorithm was presented based on a utility function. Although good performance can be achieved with the utilizing methods in [18]-[19], the computation cost was heavy especially for dense small cell networks. In [22], a inter-cell CA technique was proposed to mitigate the non-uniform transmission performance. However, the mitigation of the non-uniform transmission performance was limited. To provide further mitigation against the non-uniform transmission performance, an enhanced inter-cell CA scheme using spread spectrum transmission with variable spreading factor was given in [23]. Note that these methods on CA were all implemented in a centralized manner and we study a distributed game-based approach in this paper.

Besides, many game-based approaches were investigated [25]-[30]. For instance, a pricing game for spatial spectrum sharing-based carrier aggregation was proposed in [27]. In [28], the authors modeled the inter-network CA problem of two networks as a Bayesian game with incomplete information and proposed a distributed algorithm that approaches a neighborhood of the Bayesian NE of the system. But it needed mobile network operators to control the dynamic aggregation of their component carriers. In [29], to alleviate cross-tier and inner-tier interference in heterogeneous networks, a distributed two-dimensional (2D) scheme based on game theory was presented. In [30], the knowledge of the users' positions was combined with Q-learning and game-theoretic approached to enhance the dynamic physical resource allocation for CA in a semi-and uncoordinated deployment of heterogeneous networks. However, for these studies, the different transmission characteristics for the channels in discrete bands was not taken into account. Specifically, for different CA types, i.e., intra-band and inter-band CA, their distinct costs should be considered when aggregating different channels.

The most related work [6] took into account the cost associated with inter-band CA. CA for autonomous networks operating in shared spectrum was studied and a game-based approach was proposed. However, the defined utility function in [6] was not rational to reflect the throughput, e.g., for player n, if the measured interference in one channel was larger than specified interference threshold, this channel can not be utilized for communication, i.e., n's obtained throughput should be zero rather than a minus value calculated by [6]. In addition, due to the limited transmitting power of base stations, especially for lower power of small cell base stations, the mutual interference between cells should occur in a local area. However, the authors ignored the characteristic of local interference in the design of utility function in [6]. On the contrary, we not only overcome the aforementioned disadvantages, but also define a new utility function to capture the throughput from a different perspective.

3. System Model and Problem Formulation

Consider a small cell network with N small cell base stations (SCBSs). For presentation, we use $N = \{1,...,N\}$ to represent the set of SCBSs. Motivated by [31], assume that SCBSs can exchange information (e.g., location, strategy and utility) through the gateway (See Fig.1). There are B frequency bands available ($B = \{1,...,B\}$) in this network area and for each band the number of orthogonal channels available is K_b ($1 \leq b \leq B$). It is assumed that each channel has the same bandwidth and all SCBSs can aggregate different channels in different bands, which means that each SCBS can simultaneously operate on multiple contiguous and non-contiguous channels in the same band or different bands. We denote M_i as the maximum number of channels that SCBS i can simultaneously operate on, and $M = \sum_{j=1}^{B} K_j$ as the total number of available channels [6]. Therefore，the cardinality of SCBS i's strategy space is：
$|A_i| = \sum_{n=1}^{M_i} \binom{M}{n} = \sum_{n=1}^{M_i} \frac{M(M-1)\cdots(M-n+1)}{n(n-1)\cdots 1}$, where A_i is the set of all available strategy of SCBS i.

As is shown in Fig.1, seven SCBSs are deployed in a geographic area randomly. All SCBSs can exchange information with each other through the gateway. Besides, there are three bands available for the network. Using a proper approach, each SCBS decides the aggregated channels in a distributed manner.

According to Shannon equation, when SCBS i communicates in a channel, e.g., c, the channel capacity in c can be calculated:

$$C_i(c) = B(c) \times \log_2 \left(1 + \frac{P_i(c)}{\sigma^2 + I_i(c)} \right), \tag{1}$$

where $B(c)$ is the bandwidth of c. $P_i(c)$ is the transmitting power of the SCBS in c. σ^2 is the power of the background noise. $I_i(c)$ is the interference caused by other cells transmitting in c. However, depending on CA technology, the SCBS i may not transmit on only one channel but aggregate more channels for communication. Note that CA is different from the multiple channel selection. When aggregating channels for CA, we must take whether these channels are in different bands and how many bands they cross into account. The reason is that CA with contiguous component carriers needs only one fast Fourier transform (FFT), comparatively CA with non-contiguous component carriers requires separate FFT. In addition, the degree of flexibility in performing CA should also be taken into account. Therefore, in order to present its payoff when SCBS i selects the strategy a_i, we define the payoff of SCBS i as follows:

$$R_i(a_i) = \sum_{c_j \in a_i} C_i(c_j) / \Delta - \frac{(b(a_i)-1)}{b_M} \delta, \tag{2}$$

where a_i is the set of channels that SCBS i aggregates. c_j is one of channels in the strategy a_i. $C_i(c_j)$ is given by equation(1). Δ is the normalization factor. $b(a_i)$ is the number of bands that SCBS i accesses when selecting strategy a_i, and $|b(a_i)| \le |a_i|$. b_M is a constant that denotes the maximum number of bands that SCBS i can simultaneously deploy (**Fig. 1**). δ is the parameter that each base station can tune to reflect its degree of flexibility in performing CA [6], and smaller δ represents smaller cost when aggregating channels in different bands.
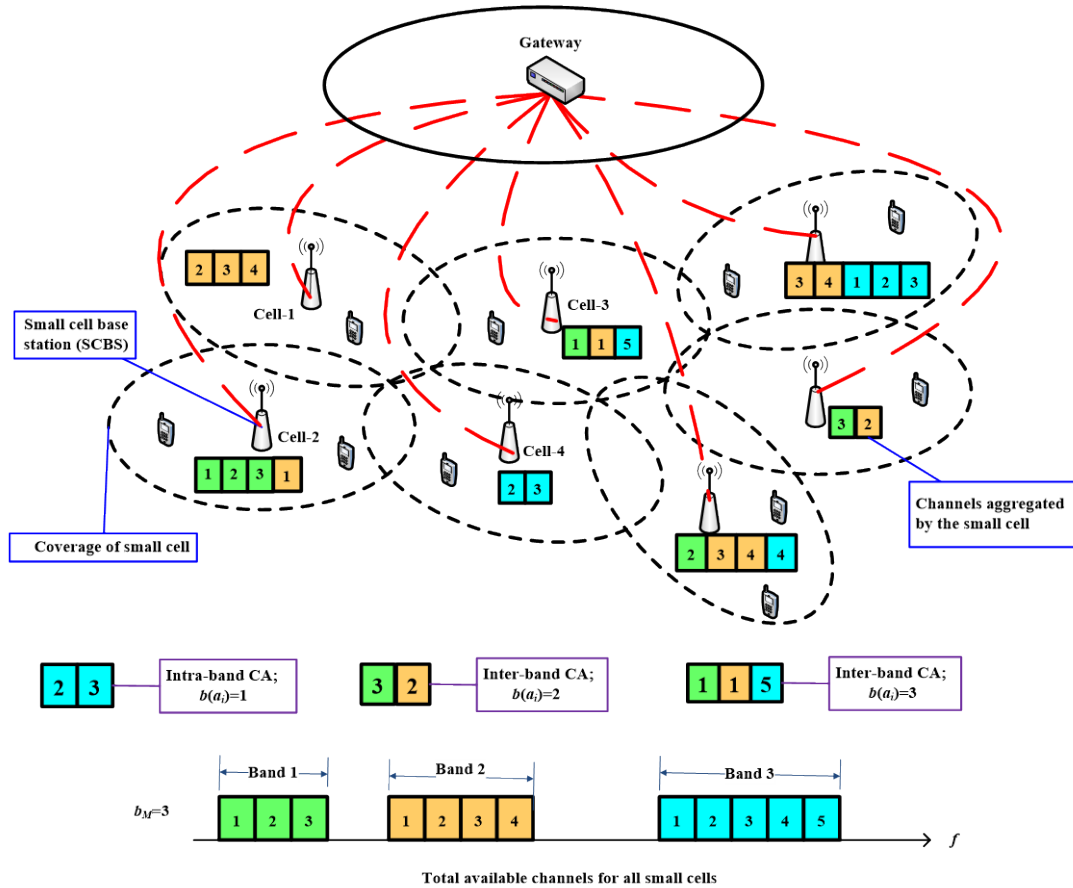

Fig. 1. An example of network model. Different colors represent different frequency bands. Each small rectangle represents a channel. Networks can transmit on multiple channels in the same frequency band (intra-band CA) or in multiple frequency bands (inter-band CA). The red broken lines represent the virtual connection between small cells and the gateway.

For an individual SCBS i, the payoff $R_i(a_i)$ should be maximized. From a network-centric perspective, the total payoff of all the SCBSs, which is regarded as the network throughput, i.e., $\sum_{i=1}^{N} R_i(a_i)$, should be maximized. Therefore, we formulate the problem of CA in cognitive small cell networks as follows:

$$P1: \quad \max \sum_{i=1}^{N} R_i\left(a_i\right) \tag{3}$$

According to equation (1), (2) and (3), in order to improve the capacity of the network, we must mitigate mutual interference among the small cells while other parameters stay. Thus, we model the problem $P1$ as a congest game as follows.

4. Game Model and Spatial Adaptive Play Algorithm with Heterogeneous Learning Parameters

4.1 Game Model

Due to the fact that small cells have lower transmission power and smaller coverage, a SCBS only interferes with its adjacent ones in a limited range rather than interacts with all SCBSs in a given network [32]. Specifically, if the distance d_{ij} between SCBS i and j is smaller than a predefined threshold d_0, then they interfere with each other when transmitting on the same channel. That is to say, if the distance d_{ij} between SCBS i and j is larger than a predefined threshold d_0, they can reuse the spectrum, i.e., transmit on the same channels simultaneously without mutual interference, to improve the spectrum efficiency. For presentation, we denote the neighboring SCBS set of SCBS i as J_i, i.e., $\mathsf{J}_i = \left\{ j \in \mathsf{N} : d_{ij} < d_0 \right\}$. When two or more neighboring small cells transmit on the same channel, they collide with each other and mutual interference occur, i.e., we only consider co-channel interference. When SCBS i chooses the strategy a_i we define corresponding collision level as follows:

$$f_i\left(a_i, a_{\mathsf{J}_i}\right) = \sum_{c_j \in a_i} f_i\left(c_j, a_{\mathsf{J}_i}\right), \tag{4}$$

where $f_i\left(c_j, a_{\mathsf{J}_i}\right)$ is the following indicator function:

$$f_i\left(c_j, a_{\mathsf{J}_i}\right) = \left| I_i\left(c_j, a_{\mathsf{J}_i}\right) \right|, \quad I_i\left(c_j, a_{\mathsf{J}_i}\right) = \left\{ k \in \mathsf{J}_i : c_j \in a_k \right\} \tag{5}$$

Accordingly, a quantitative characterization of the network collision level is given as follows:

$$I_0 = \frac{1}{2} \sum_{i \in \mathsf{N}} f_i\left(a_i, a_{\mathsf{J}_i}\right), \tag{6}$$

where a_{J_i} is the strategy profile of i's adjacent SCBSs.

It is noted that $f_i\left(c_j, a_{\mathsf{J}_i}\right)$ denotes the number of adjacent SCBSs who also select channel c_j while $c_j \in a_i$. For the reason that every small cell prefers aggregating more spectrum resources, a lower collision level and less inter-band cost for better payoff. This motivates us to define the utility function as following:

$$u_i\left(a_i, a_{-i}\right) = \left| a_i \right| - f_i\left(a_i, a_{\mathsf{J}_i}\right) - \frac{\left(b\left(a_i\right) - 1\right)}{b_M} \delta, \tag{7}$$

where a_{-i} is the strategy selection profile of all SCBSs except i. $\left| a_i \right|$ is the cardinality of the channel set a_i. $f_i\left(a_i, a_{\mathsf{J}_i}\right)$ is given by (4). $\left(b\left(a_i\right) - 1\right) * \delta / b_M$ represents the cost of inter-band CA with the same as the last part in (2). If a_i crosses only one band this item will be zero, i.e., no cost is taken for CA. If a_i crosses two or more bands this item will be greater than zero

which means that cost is taken for CA. For example, in Fig.1, Cell-2 interfers with Cell-1, Cell-3 and Cell-4. When Cell-2 aggregates the channels shown in Fig.1, $|a_2| = 4$, $f_2\left(a_2, a_{J_2}\right) = 2$, $b(a_i) = 2$, the utility of Cell-2 is equal to 1.5 (assume that $\delta = 1.5$).

Formally, the game model can be denoted as:

$$G = \left(N, \{A_i\}_{i \in N}, \{u_i\}_{i \in N} \right) \tag{8}$$

where $N = \{1, ..., N\}$ is a set of players (SCBSs), A_i is the set of player i's available strategies (set of channels), and u_i is the utility function defined by (6). Due to the limited interference range, the utility function can also be expressed as $u_i\left(a_i, a_{J_i}\right)$, i.e.:

$$u_i\left(a_i, a_{-i}\right) = u_i\left(a_i, a_{J_i}\right) \tag{9}$$

where a_i is the strategy of player i and a_{J_i} is the strategy profile of i's neighboring players.

Then the proposed channel selection game can be expressed as:

$$G: \max_{a_i \in A_i} u_i\left(a_i, a_{J_i}\right) \tag{10}$$

To analyze the properties of the formulated game, we first present the concept of Nash equilibrium, which is the most well-known stable solution for non-cooperative game model.

Definition 1(NE). A strategy selection profile $a^* = (a_1^*, ..., a_N^*)$ is a pure strategy NE if and only if no player can improve its utility by deviating unilaterally, i.e.,

$$u_i(a_i^*, a_{-i}^*) \geq u_i(a_i, a_{-i}^*), \quad \forall i \in N, \forall a_i \in A_i, a_i \neq a_i^* \tag{11}$$

Definition 2 (Exact potential game [33]**).** A game is an exact potential game if there exists an ordinal potential function $\Phi: A_1 \times \cdots \times A_N \to R$ such that for all $i \in N$, all $a_i \in A_i$ and $a_i' \in A_i$, the following holds:

$$u_i\left(a_i, a_{-i}\right) - u_i\left(a_i', a_{-i}\right) = \Phi\left(a_i, a_{-i}\right) - \Phi\left(a_i', a_{-i}\right) \tag{12}$$

i.e., the change in the utility function caused by the unilateral action change of an arbitrary player is exactly the same with that in the potential function.

The given definitions are straightforwardly obtained from game theory [33]. The properties of the proposed game are characterized by the following theorem.

Theorem 1. G is an exact potential game which has at least one pure strategy NE.

Proof: In order to prove G to be an exact potential game, we construct a potential function as follows:

$$\Phi\left(a_i, a_{-i}\right) = \sum_{i=1}^{N} |a_i| - \frac{1}{2} \sum_{i=1}^{N} f_i\left(a_i, a_{J_i}\right) - \sum_{i=1}^{N} \frac{(b(a_i) - 1)}{b_M} \delta \tag{13}$$

If player i changes its selected strategy unilaterally from $a_i = \{c_1, c_2, ..., c_h\}$ to $a_i^* = \left\{c_1^*, c_2^*, ..., c_H^*\right\}$, the amount of change in its utility function is given by:

$$u_i\left(a_i^*,a_{-i}\right)-u_i\left(a_i,a_{-i}\right)$$

$$=u_i\left(a_i^*,a_{\mathsf{J}_i}\right)-u_i\left(a_i,a_{\mathsf{J}_i}\right)$$

$$=\left|a_i^*\right|-\left|a_i\right|+f_i\left(a_i,a_{\mathsf{J}_i}\right)-f_i\left(a_i^*,a_{\mathsf{J}_i}\right)+\frac{\left(b(a_i)-1\right)}{b_M}\delta-\frac{\left(b\left(a_i^*\right)-1\right)}{b_M}\delta \qquad (14)$$

$$=\left|a_i^*\right|-\left|a_i\right|+\sum_{c_j\in a_i}f_i\left(c_j,a_{\mathsf{J}_i}\right)-\sum_{c_j\in a_i^*}f_i\left(c_j,a_{\mathsf{J}_i}\right)+\frac{\left(b(a_i)-1\right)}{b_M}\delta-\frac{\left(b\left(a_i^*\right)-1\right)}{b_M}\delta$$

Accordingly, the amount of change in the potential function caused by the unilateral change $\left(a_i\to a_i^*\right)$ is given by:

$$\Phi\left(a_i^*,a_{-i}\right)-\Phi\left(a_i,a_{-i}\right)$$

$$=\sum_{i=1}^N\left|a_i^*\right|-\sum_{i=1}^N\left|a_i\right|+\frac{1}{2}\sum_{i=1}^N f_i\left(a_i,a_{\mathsf{J}_i}\right)-\frac{1}{2}\sum_{i=1}^N f_i\left(a_i^*,a_{\mathsf{J}_i}\right)+\sum_{i=1}^N\frac{\left(b(a_i)-1\right)}{b_M}\delta-\sum_{i=1}^N\frac{\left(b\left(a_i^*\right)-1\right)}{b_M}\delta \qquad (15)$$

$$=\left|a_i^*\right|-\left|a_i\right|+\frac{1}{2}\sum_{i=1}^N\left[\sum_{c_j\in a_i}f_i\left(c_j,a_{\mathsf{J}_i}\right)-\sum_{c_j^*\in a_i^*}f_i\left(c_j^*,a_{\mathsf{J}_i}\right)\right]+\frac{\left(b(a_i)-1\right)}{b_M}\delta-\frac{\left(b\left(a_i^*\right)-1\right)}{b_M}\delta$$

Compare (14) with (15), we know that proving (12) is equal to proving the following expression:

$$\frac{1}{2}\sum_{i=1}^N\left[\sum_{c_j\in a_i}f\left(c_j,a_{\mathsf{J}_i}\right)-\sum_{c_j^*\in a_i^*}f\left(c_j^*,a_{\mathsf{J}_i}\right)\right]=\sum_{c_j\in a_i}f\left(c_j,a_{\mathsf{J}_i}\right)-\sum_{c_j^*\in a_i^*}f\left(c_j^*,a_{\mathsf{J}_i}\right) \qquad (16)$$

For presentation, without loss of generality the change $a_i\to a_i^*$ can be seen as the change of corresponding channels, i.e., $\left\{c_j\to c_j^*,c_j\in a_i,c_j^*\in a_i^*\right\}$.

Therefore,

$$\sum_{i=1}^N\left[\sum_{c_j\in a_i}f\left(c_j,a_{\mathsf{J}_i}\right)-\sum_{c_j^*\in a_i^*}f\left(c_j^*,a_{\mathsf{J}_i}\right)\right]$$

$$=\sum_{c_j\in a_i}f\left(c_j,a_{\mathsf{J}_i}\right)-\sum_{c_j^*\in a_i^*}f\left(c_j^*,a_{\mathsf{J}_i}\right)+\sum_{k\in\mathsf{J}_i}\left[\sum_{c_k\in a_k}f\left(c_k,a_{\mathsf{J}_i}\right)-\sum_{c_k\in a_k}f\left(c_k,a_{\mathsf{J}_i}^*\right)\right]$$

$$=\sum_{c_j\in a_i}f\left(c_j,a_{\mathsf{J}_i}\right)-\sum_{c_j^*\in a_i^*}f\left(c_j^*,a_{\mathsf{J}_i}\right)+\sum_{c_j\to c_j^*,c_k\in a_k}\sum_{k\in\mathsf{J}_i}\left[f\left(c_k,a_{\mathsf{J}_k}\right)-f\left(c_k,a_{\mathsf{J}_k}^*\right)\right] \qquad (17)$$

$$=\sum_{c_j\in a_i}f\left(c_j,a_{\mathsf{J}_i}\right)-\sum_{c_j^*\in a_i^*}f\left(c_j^*,a_{\mathsf{J}_i}\right)+\sum_{k\in\mathsf{J}_i}\sum_{c_j\to c_j^*,c_k\in a_k}\left[f\left(c_k,a_{\mathsf{J}_k}\right)-f\left(c_k,a_{\mathsf{J}_k}^*\right)\right]$$

$$=\sum_{c_j\in a_i}f\left(c_j,a_{\mathsf{J}_i}\right)-\sum_{c_j^*\in a_i^*}f\left(c_j^*,a_{\mathsf{J}_i}\right)+\sum_{k\in I_i\left(c_j,a_{\mathsf{J}_i}\right)}\sum_{c_j\to c_j^*,c_k\in a_k}\left[f\left(c_k,a_{\mathsf{J}_k}\right)-f\left(c_k,a_{\mathsf{J}_k}^*\right)\right]$$

$$+\sum_{k\in I_i\left(c_j^*,a_{\mathsf{J}_i}\right)}\sum_{c_j\to c_j^*,c_k\in a_k}\left[f\left(c_k,a_{\mathsf{J}_k}\right)-f\left(c_k,a_{\mathsf{J}_k}^*\right)\right]+\sum_{k\in\kappa,k\neq i}\sum_{c_j\to c_j^*,c_k\in a_k}\left[f\left(c_k,a_{\mathsf{J}_k}\right)-f\left(c_k,a_{\mathsf{J}_k}^*\right)\right]$$

where $\kappa=\mathsf{J}_i\setminus\left\{I_i\left(c_j,a_{\mathsf{J}_i}\right)\cup I_i\left(c_j^*,a_{\mathsf{J}_i}\right)\right\}$, and $A\setminus B$ means to delete the set B from the set A. $f\left(c_k,a_{\mathsf{J}_k}^*\right)$ is the collision level of player k in channel c_k after player i unilaterally changes

its strategy. Due to the strategy change of player i only impacts its neighboring player, following results can be obtained:

$$\begin{cases} f\left(c_k, a_{\mathsf{J}_k}\right) - f\left(c_k, a^*_{\mathsf{J}_k}\right) = 1, & \forall k \in I_i\left(c_j, a_{\mathsf{J}_i}\right) \\ f\left(c_k, a_{\mathsf{J}_k}\right) - f\left(c_k, a^*_{\mathsf{J}_k}\right) = 1, & \forall k \in I_i\left(c^*_j, a_{\mathsf{J}_i}\right) \\ f\left(c_k, a_{\mathsf{J}_k}\right) - f\left(c_k, a^*_{\mathsf{J}_k}\right) = 0, & \forall k \in \kappa, k \neq i \end{cases} \tag{18}$$

Then, according to (18) we can derive:

$$\sum_{i=1}^{N}\left[\sum_{c_j \in a_i} f\left(c_j, a_{\mathsf{J}_i}\right) - \sum_{c^*_j \in a^*_i} f\left(c^*_j, a_{\mathsf{J}_i}\right)\right]$$

$$= \sum_{c_j \in a_i} f\left(c_j, a_{\mathsf{J}_i}\right) - \sum_{c^*_j \in a^*_i} f\left(c^*_j, a_{\mathsf{J}_i}\right) + \sum_{c_j \in a_i} f\left(c_j, a_{\mathsf{J}_i}\right) - \sum_{c^*_j \in a^*_i} f\left(c^*_j, a_{\mathsf{J}_i}\right) \tag{19}$$

$$= 2\left[\sum_{c_j \in a_i} f\left(c_j, a_{\mathsf{J}_i}\right) - \sum_{c^*_j \in a^*_i} f\left(c^*_j, a_{\mathsf{J}_i}\right)\right]$$

Thus, (16) is derived and the following holds:

$$u_i\left(a^*_i, a_{-i}\right) - u_i\left(a_i, a_{-i}\right) = \Phi\left(a^*_i, a_{-i}\right) - \Phi\left(a_i, a_{-i}\right) \tag{20}$$

i.e., when an arbitrary player changes its selected strategy unilaterally, the change in the individual utility function caused by any player's unilateral deviation is the same as the change in the potential function. According to Definition 2, G is an exact potential game with network utility serving as the potential function.

Exact potential game belongs to potential games, which have been widely applied to wireless communication systems. Potential game exhibits several nice properties and the most important two are as follows [32]-[33].

1) Every potential game has at least one pure strategy NE.
2) Any global or local maxima of the potential function constitutes a pure strategy NE.

Based on the first property, theorem 1 is proved.   □

We note that this potential function (13) has strong relevance with the network utility according to (6) and (7). Moreover, the utility function (7) is bound up with the payoff level. The reason is that higher collision level causes the utility smaller as well as the payoff level. Therefore, the network utility can reflect the level of total network throughput, so can the potential function. We conclude that the strategy profile corresponding to the global or local maxima of the potential function can make the network throughput better.

4.2 Spatial Adaptive Play Algorithm with Heterogeneous Learning Parameters

Because the distributed CA problem has been now formulated as an exact potential game, the spatial adaptive play (SAP) algorithm [34]-[36] can be applied to achieve a pure NE of the game that maximizes the potential function with arbitrarily high probability. However, it has been shown that the convergence speed of conventional SAP algorithm is slow [32].

The learning parameter β of SAP balances the tradeoff between exploration and exploitation. Smaller implies that the CR users are more willing to choose an suboptimal action to explore, whereas higher implies that they are prone to choose the best response action. Motivated by the idea proposed in [37], we introduce a heterogeneous learning parameter, i.e., $\beta|\mathsf{J}_i| / \min_{n \in \mathsf{N}}\left(|\mathsf{J}_n|\right)$, where $|\mathsf{J}_i|$ is the number of small cell i's neighboring cells, to balance the

tradeoff between exploration and exploitation and accelerate the converging speed. The reason is that small cells are usually deployed randomly, the density of small cells is distinct in different local areas. For a given small cell network, $\min_{n \in \mathsf{N}}(|\mathsf{J}_n|)$ is a constant, and $|\mathsf{J}_i|$ is larger for the denser area. Note that $\beta|\mathsf{J}_i|/\min_{n \in \mathsf{N}}(|\mathsf{J}_n|)$ is larger than the homogeneous learning parameter β and in the denser area $\beta|\mathsf{J}_i|/\min_{n \in \mathsf{N}}(|\mathsf{J}_n|)$ is larger for a fixed β. During the learning period, players (small cells) with the larger learning parameter $\beta|\mathsf{J}_i|/\min_{n \in \mathsf{N}}(|\mathsf{J}_n|)$ will have the higher probability (defined by (21)) to choose better actions. Thus, accelerate the process of choosing the optimal actions for every players, i.e., improve the converging speed.

Therefore, we propose a spatial adaptive play algorithm with heterogeneous learning parameters (SAP-H). The specific algorithm is described in Algorithm 1.

Algorithm 1. *Spatial adaptive play algorithm with heterogeneous learning parameters (SAP-H).*

Initialization: Set the iteration index $k = 0$, let each player n, $\forall n \in \mathsf{N}$, randomly select an available strategy $a_n(0)$ from the set of its available strategies with equal probability.

Step 1: All players exchanges information with their adjacent players through the gateway.

Step 2: Select a player i randomly.

Step 3: Player i calculates the utility functions over its all available strategies, i.e., $u_i(\bar{a}_i, a_{\mathsf{J}_i}(k))$, $\forall \bar{a}_i \in \mathsf{A}_i$, while all other players repeat their selections, i.e., $a_{-i}(k+1) = a_{-i}(k)$. Then, player i updates its mixed strategy:

$$q_i^{a_i}(k+1) = \frac{\exp\left\{\left[|\mathsf{J}_i|/\min_{n \in \mathsf{N}}(|\mathsf{J}_n|)\right]\beta u_i\left(a_i, a_{J_i}(k)\right)\right\}}{\sum_{\bar{a}_i \in \mathsf{A}_i} \exp\left\{\left[|\mathsf{J}_i|/\min_{n \in \mathsf{N}}(|\mathsf{J}_n|)\right]\beta u_i\left(\bar{a}_i, a_{J_i}(k)\right)\right\}}, \tag{21}$$

where $q_i^{a_i}(k+1)$ is the probability when play i select the strategy a_i at iteration $k+1$. $\beta = 1 + 5k/1000$; $|\mathsf{J}_i|$ is the number of neighboring player of player i; $|\mathsf{J}_i|/\min_{n \in \mathsf{N}}(|\mathsf{J}_n|)$ is a dynamic factor which can vary according to the density of small cells deployed. Player i selects a new strategy $a_n(k+1)$ according to the mixed strategy $q_n(k+1)$.

Step 4: If k exceeds predefined maximal number of learning, end; otherwise return to Step 2.

Theorem 2. In a potential game in which all players adhere to SAP-H, the unique stationary distribution $\mu(a) \in \Delta(\mathsf{A})$ of the joint action profiles, $\forall \beta > 0$, is given as

$$\mu(\mathrm{a}) = \frac{\exp\left\{\left[|\mathsf{J}_i|/\min_{n \in \mathsf{N}}(|\mathsf{J}_n|)\right]\beta\Phi(a)\right\}}{\sum_{s \in \mathsf{A}} \exp\left\{\left[|\mathsf{J}_i|/\min_{n \in \mathsf{N}}(|\mathsf{J}_n|)\right]\beta\Phi(s)\right\}}, \tag{22}$$

where $\Phi(\ )$ is the potential function of the games specified by (13), A is the set of available selection profiles of all players, i.e., $\mathsf{A} = \mathsf{A}_1 \otimes \mathsf{A}_2 \otimes \cdots \otimes \mathsf{A}_N$.

Proof: The following proof follows the proof lines given in [32] [34].

In the considered network scenario, once the network topology is fixed, $|\mathsf{J}_i| / \min_{n \in \mathsf{N}}(|\mathsf{J}_n|)$ is a constant for a fixed SCBS i but distinct for different SCBSs. Consequently, it is rational to replace $\left[|\mathsf{J}_i| / \min_{n \in \mathsf{N}}(|\mathsf{J}_n|)\right]\beta$ with β_i. Thus, (22) can be written as:

$$\mu(\mathrm{a}) = \frac{\exp\{\beta_i \Phi(a)\}}{\sum_{s \in \mathsf{A}} \exp\{\beta_i \Phi(s)\}} \tag{23}$$

Denote the action selection profile at the kth iteration by $a(k) = \{a_1(k),...,a_N(k)\}$, where $a_n(k)$ is the action of player n. Note that an action selection profile corresponds to a network state. Because the network state $a(k+1)$ just depends on $a(k)$ rather than the network states before the kth iteration. Therefore, we can interpret the learning process as a discrete time Markov process, which is irreducible and aperiodic. According to the nature of the discrete time Markov process, an unique stationary distribution can be found.

In order to show that (23) is the mentioned unique stationary distribution, we can verify that (23) deduces to the balanced equations of the Markov process. The details are as follows:

Denote any two arbitrary neighboring network state by a and b, $a,b \in \mathsf{A}$, and the transmission probability from a to b, by $P_{ab} = \Pr\left[a(k+1) = b \mid a(k) = a\right]$. Since in one iteration only exactly one node is selected to update its selection in the proposed algorithm, there is at most one element that can be changed in the network states between any two successive iterations. Thus, there are only two nontrivial cases: 1) a and b differ by exactly one element, or 2) $a=b$.

For case 1), specifically, we suppose that a and b differ by the ith element. Since node has a probability $1/N$ of being chosen in any given iteration, it follows that

$$\mu(\mathrm{a}) P_{ab} = \left(\frac{1}{N}\right) \times \left(\frac{\exp\{\beta_i \Phi(a)\}_{i \in \mathsf{N}}}{\sum_{s \in \mathsf{A}} \exp\{\beta_i \Phi(s)\}_{i \in \mathsf{N}}}\right) \times P_{ab}, \tag{24}$$

where the the iteration index k is omitted and that has no effect.

Note that

$$P_{ab} = \left(\frac{\exp\{\beta_i u(b_i, b_{-i}(k))\}_{i \in \mathsf{N}}}{\sum_{\bar{b}_i \in \mathsf{A}_i} \exp\{\beta_i u(\bar{b}_i, b_{-i}(k))\}_{i \in \mathsf{N}}}\right), \tag{25}$$

where $u(b_i, b_{-i}(k))$ is the utility function of node b under the network state b at the kth iteration.

Thus,

$$\mu(\mathrm{a}) P_{ab} = \left(\frac{1}{N}\right) \times \left(\frac{\exp\{\beta_i \Phi(a)\}_{i \in \mathsf{N}}}{\sum_{s \in \mathsf{A}} \exp\{\beta_i \Phi(s)\}_{i \in \mathsf{N}}}\right) \times \left(\frac{\exp\{\beta_i u(b_i, b_{-i}(k))\}_{i \in \mathsf{N}}}{\sum_{\bar{b}_i \in \mathsf{A}_i} \exp\{\beta_i u(\bar{b}_i, b_{-i}(k))\}_{i \in \mathsf{N}}}\right) \tag{26}$$

Letting

$$\lambda = \frac{1/N}{\left(\sum_{s \in \mathsf{A}} \exp\{\beta_i \Phi(s)\}_{i \in \mathsf{N}}\right) \times \left(\sum_{\bar{b}_i \in \mathsf{A}_i} \exp\{\beta_i u_i(\bar{b}_i, b_{-i})\}_{i \in \mathsf{N}}\right)}$$

$$= \frac{1/N}{\left(\sum_{s \in \mathsf{A}} \exp\{\beta_i \Phi(s)\}_{i \in \mathsf{N}}\right) \times \left(\sum_{\bar{a}_i \in \mathsf{A}_i} \exp\{\beta_i u_i(\bar{a}_i, a_{-i})\}_{i \in \mathsf{N}}\right)} \tag{27}$$

According to the fact that the network states a and b differ by the ith element, i.e., $a_{-i}(k) \equiv b_{-i}(k)$, the following equation can be obtained:

$$\mu(a)P_{ab} = \lambda \exp\{\beta_i \Phi(a) + \beta_i u_i(b_i, b_{-i})\}_{i \in \mathsf{N}} \tag{28}$$

Due to symmetry,

$$\mu(b)P_{ba} = \lambda \exp\{\beta_i \Phi(b) + \beta_i u_i(a_i, a_{-i})\}_{i \in \mathsf{N}} \tag{29}$$

Therefore,

$$\frac{\mu(a)P_{ab}}{\mu(b)P_{ba}} = \exp\{\beta_i [\Phi(a) - \Phi(b)] + \beta_i [u_i(b_i, b_{-i}) - u_i(a_i, a_{-i})]\}_{i \in \mathsf{N}} \tag{30}$$

Using (12) in Theorem 1, we obtain

$$\mu(a)P_{ab} = \mu(b)P_{ba} \tag{31}$$

For case 2), i.e., $a=b$, (31) naturally holds.

Thus,

$$\sum_{a \in \mathsf{A}} \mu(a)P_{ab} = \sum_{a \in \mathsf{A}} \mu(b)P_{ba} = \mu(b) \sum_{a \in \mathsf{A}} P_{ba} = \mu(b), \tag{32}$$

which is exactly the balanced stationary equation of the Markov process. Since SAP-H has unique distribution and the distribution (22) satisfies the balanced equations of its Markov process, we conclude that its stationary distribution must be (22).

Therefore, Theorem 2 is proved.   □

Theorem 3: With a sufficiently large β, SAP-H achieves the maximum potential function values with an arbitrarily high probability, where the potential function is defined by (13).

Proof: Theorem 4 in [32] had proved that with a sufficiently large β, SAP could achieve the maximum potential function value of the game with an arbitrarily high probability. Similarly, as mentioned in the proof of Theorem 2, we replace $\left[|\mathsf{J}_i| / \min_{n \in \mathsf{N}}(|\mathsf{J}_n|)\right]\beta$ with β_i. Then, (21) can be rewritten as:

$$q_i^{a_i}(k+1) = \frac{\exp\{\beta_i u_i(a_i, a_{J_i}(k))\}}{\sum_{\bar{a}_i \in \mathsf{A}_i} \exp\{\beta_i u_i(\bar{a}_i, a_{J_i}(k))\}}, \tag{33}$$

which is similar to (30) in [32]. In addition, $\beta \to \infty$ is equal to $\beta_i \to \infty$ due to the limited value of $|\mathsf{J}_i| / \min_{n \in \mathsf{N}}(|\mathsf{J}_n|)$, and the updating processes of SAP-H and SAP are the same. Thus, we deduce that the two algorithms have the same converging result, i.e., with a sufficiently large β, SAP-H also achieves the maximum potential function value of the game with an arbitrarily high probability.

Therefore, Theorem 3 is proved.   □

For the proposed game, even though the optimal strategy profile may oscillate [36], the maximum potential function value can be achieved with arbitrarily high probability with a sufficiently large β. Then, according to the strong relevance between the potential function and the network throughput, as specified by Theorem 3, the strategy profile of achieving the optimal potential function can make the network throughput better. Thus, it is a desired learning algorithm because a better solution for problem P1 are achieved via just local information exchange between neighbors.

5. Simulation Results and Discussion

In the following simulation study, we consider a homogeneous small cell network that all SCBSs are randomly located in a 200m×200m square region. The direct connectivity between the core network and the SAP is maintained by the small-cell gateway. Together with signaling protocol and channel conversions, the small-cell gateway aggregates and integrates traffic from a large number of small cells into the existing mobile networks [8]. In addition, the small-cell gateway can allow the information exchanging among small cells. For the convenience of simulation and presentation, we assume that each small cell has the same transmitting power and the same coverage[1]. An example of the simulated random topology is given by **Fig. 2**. The coverage distance of each small cell is 20m, and the interference distance of co-channel communications is set to 60m. The transmitting power of each small cell is 40mW. We assume that in the network there are several different bands available, and the transmitting characteritic for different channels in different bands are same. All the channels have the same bandwidth $5\,\mathrm{MHz}$. The background noise is -174dbm/Hz. The path loss is proportional to square of the transmitting distance.

5.1 Comparison of Convergence Speed

For the random network topology which is shown in **Fig. 2**, there are 20 SCBSs deployed. We consider that there are *two* frequency bands, i.e., $B = 2$, that can be used dynamically and each band has *three* channels [6], i.e., $K_b = 3$. Therefore, there are *six* channels available in the network. The maximum number of channels that each SCBS can simultaneously operate on is *three*, i.e., $M_i = 3$. The maximum number of bands that each SCBS can simultaneously deploy is *two*, i.e., $b_M = 2$.

On one hand, in **Fig. 3** we compare the convergence speed of the proposed SAP-H and the conventional SAP in different network scenarios. The results are obtained by taking 1000 independent trials and then taking expectation for a network topology. It is noted that in the network with 20 small cells the proposed SAP-H converges after about 400 iterations while the conventional SAP does after 900 iterations, and in the network with 40 small cells the proposed SAP-H converges after about 600 iterations while the conventional SAP does after 950 iterations. Therefore, the iterations needed for converging of the proposed SAP-H algorithm is significantly decreased compared with the conventional SAP algorithm.

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[1] However, it should be emphasized that the proposed game-theoretic solution is general and can be applied to scenarios with heterogeneous converge.
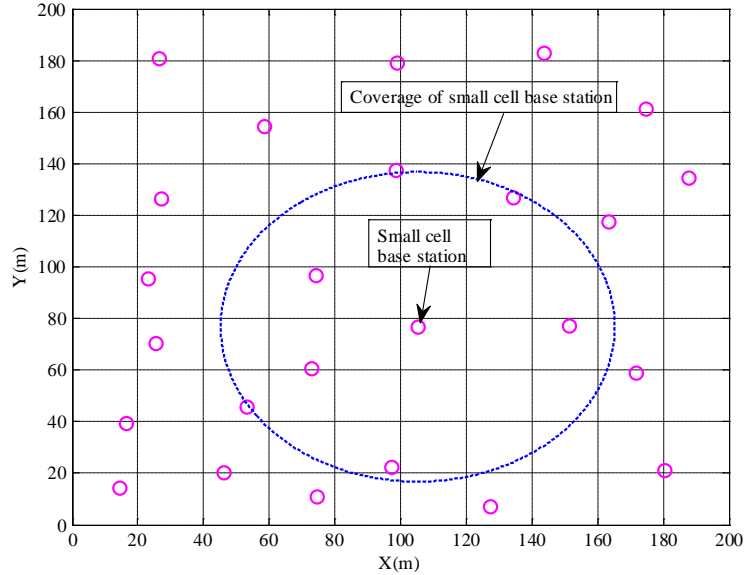
Fig. 2. An example of simulated random network topology with 20 SCBSs. (The small solid circles represent the SCBSs while the large dashed circles represent the region of co-channel interference.)
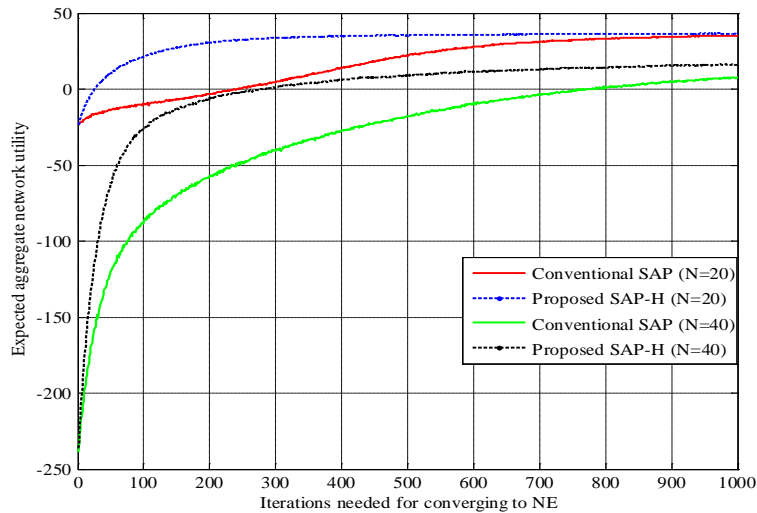

Fig. 3. Comparison of the convergence speed between the conventional SAP and the proposed SAP-H (N represents the number of SCBSs in the considered network).

On the other hand, in **Fig. 4**, we compare the relevance among the network utility, the potential function and the network throughput. It is noted that as the potential function increases, the network utility and the network throughput increases. This result confirms that the relevance among the network utility, the potential function and the network throughput is robust. It is further validated that the strategy profile of achieving the optimal potential function can also make the network utility and the network throughput optimal. Besides, our defined utility function is rational, which can reflect the network capacity.
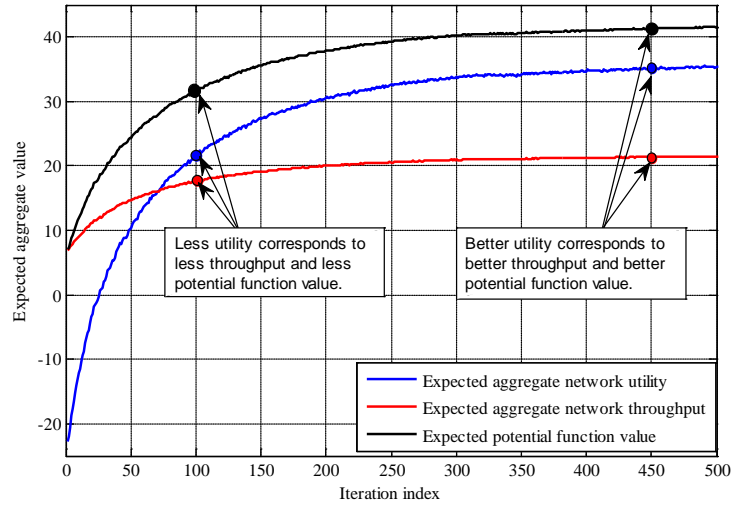
Fig. 4. The relevance among the network utility, the potentialfunction and the network throughput.
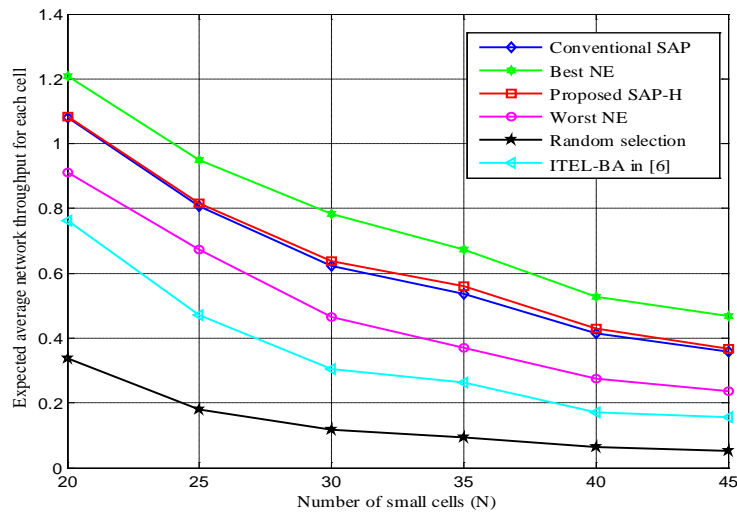
5.2 Throughput Performance

Fig. 5. The expected average throughput for each small cell when varying the number of small cells $\left(B = 2, K_b = 3, M_i = 3, b_M = 2\right)$.

The average throughput for each small cell when varying the number of small cells is shown in **Fig. 5**. It is noted that as the number of small cells increases, i.e., the network density deployed increases, the average throughput for each cell decreases and the tendencies are almost the same for different algorithms. We obtain the best NE and the worst NE by taking 1000 independent trials and then taking the maximum and minimum throughput after convergence for different network layouts, respectively. Note that the performance of the proposed SAP-H algorithm is close to the best NE and has approximate 10% improvement than the worst NE. The gap among them is nearly uniform. Also, the several learning

algorithms significantly outperform the random selection methods. Particularly, SAP-H has a great improvement in terms of the throughput than random selection methods especially for the networks deployed with sparse cells, e.g., 20 small cells. More importantly, compared to conventional SAP, its performance have a little improvement. In addition, the performance of our proposed SAP-H has about 25% improvement than the ITEL-BA algorithm proposed in [6]. The reason is that the defined utility function in [6] was not rational to reflect the throughput, e.g., for player n, if measured interference in one channel was larger than specified interference threshold, this channel could not be utilized for communication, i.e., n's obtained throughput should be zero rather than a minus value calculated by [6].
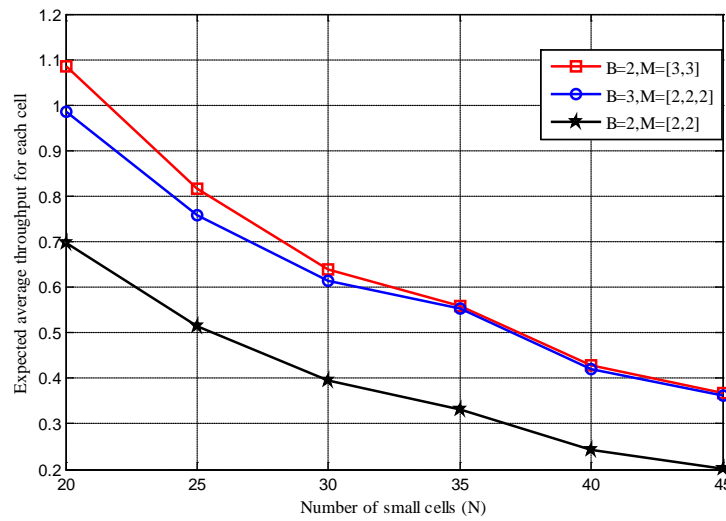

Fig. 6. The comparison of expected average throughput for each small cell with different spectrum resource available (B denotes the number of bands available, M shows the number of channels in each band).

In order to study the impact on the network performance with different spectrum available, we compare the average throughput with different spectrum resources available in **Fig. 6**. For $M = [3,3]$ and $M = [2,2,2]$, there are both 6 channels available. It is noted that in a network with 20 cells the throughput for $M = [3,3]$ has 10% improvement than $M = [2,2,2]$. That is to say, with the same channel available, the more number of bands in which these channels locate, the less throughput can be achieved. The reason is that more bands cause more cost in performing CA. However, as the number of the small cells increases, the gap between the red line and the blue line decreases. Especially for the small cell network with 35 or more cells, the average throughput is about the same for $M = [3,3]$ and $M = [2,2,2]$. The reason is that as the density of small cells becomes larger, the mutual interference is more severe which plays a more important part than inter-band cost in selecting channels for CA. And when small cells are denser enough, e.g., there are 35 or more cells in the network, the mutual interference is so severe that the inter-band cost is negligible according to (7). In addition, the network performance for $M = [3,3]$ is significantly improved compared with $M = [2,2]$ and the gap between the blue line and the black line is almost uniform for different number of cells. It is rational that the more channels are available, the more throughput can be achieved correspondingly. The presented results also imply that searching more available spectrum resources is a good way to improve the network capacity.

In **Fig. 7**, we compare the throughput performance under different δ. From the simulation result it is noted that as δ increases the expected average throughput for each small cell decreases firstly and then increases. The reason is that when δ is less than 2.5, it is beneficial to aggregate a white channel according to the defined utility function (6), but larger δ takes more cost which make the throughput less according to equation (2). And when δ outnumbers 2.5, it is not beneficial to aggregate a white channel according to (6), it is more likely that small cells aggregate intra-band channels rather than inter-band channels. Consequently, the throughput increases. Besides, when $\delta = 0$, such an CA model has also been applied for multiple channel selection in small cell networks.
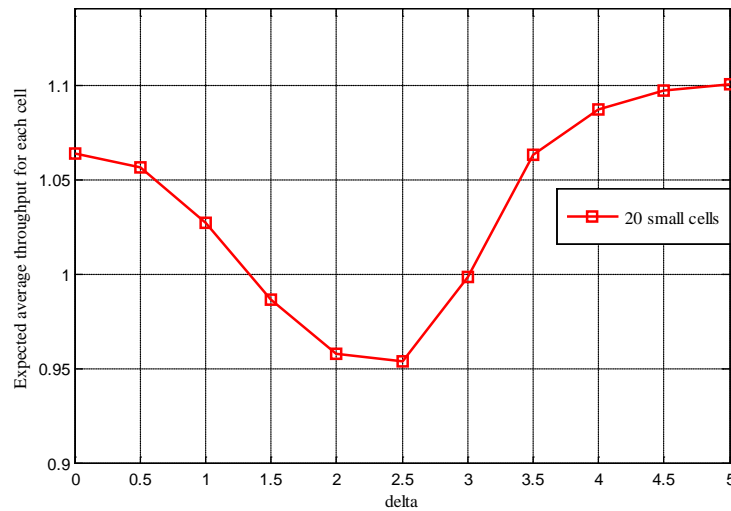

Fig. 7. The expected average network throughput for each small cell when varying the degree of flexibility in performing CA, i.e., δ (larger δ means that greater cost would be paid for performing CA) $\left(B = 3, K_b = 2, M_i = 3, b_M = 3 \right)$

6. Conclusion

To cope with the local interference and the distinct cost of intra-band and inter-band CA, we proposed a non-cooperation game which was proved to be an exact potential game. Furthermore, we proposed a spatial adaptive play algorithm with heterogeneous learning parameters (SAP-H) to converge towards NE of the game. In this algorithm, heterogeneous learning parameters were introduced to accelerate the convergence speed. It is shown that with the proposed game-theoretic approach, global optimization is achieved with local information. Simulation results validated the effectivity of the proposed game-theoretic CA approach. In addition, we studied other factors to affect the network throughput in performing CA and obtained some meaningful conclusions. In future, we plan to study QoS-aware CA in heterogeneous wireless communication system.

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