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QoE Driven Decentralized Spectrum Sharing in 5G Networks: Potential Game Approach

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***Abstract*—This paper studies spectrum sharing for providing better quality of experience (QoE) in 5G networks, which are characterized by multi-dimensional heterogeneity in terms of spectrum, cells, and user requirements. Specifically, spectrum access, power allocation, and user scheduling are jointly investigated and an optimization problem is formulated with the objective of maximizing the users' satisfaction across the network. In order to reduce the complexity and overhead, decentralized solutions with local information are required. To this end, we employ game-theoretic approach and interference graph to solve the problem. The proposed game is proved to have at least one Nash Equilibrium (NE), corresponding to either the globally or locally optimal solution to the original optimization problem. A concurrent best-response iterative (CBSI) algorithm is first devised to find the solution, which can converge to an NE, but may not be globally optimal. Therefore, a spatial adaptive play iterative (SAPI) learning algorithm is further proposed to search the global optimum. Theoretical analysis demonstrates that the SAPI algorithm can guarantee to find the globally optimal solution with an arbitrary large probability, when the learning step is set to be sufficiently large. Simulation results are provided to validate the performance of the proposed algorithms.**

***Index Terms*—5G network, next generation wireless network, quality of experience, spectrum sharing, small cell networks, spectrum access, user scheduling, power allocation, game theory**

I. Introduction

Mobile traffic is predicted to increase 1000 times over the next decade, due to the proliferation of connected devices. For instance, the number of connected devices will reach 50 billions in 2020, including smart phones, connected vehicles, and Internet of Things (IoT). In addition to such a 1000$\times$ data challenge, a wide range of applications will emerge with different service requirements, such as augmented reality, e-health, and e-banking [1]. Consequently, next generation (5G) wireless network has to improve the network capacity significantly to support massive mobile traffic, and meanwhile satisfy distinct service requirements from various applications.

5G network needs to boost the capacity significantly to accommodate the mobile traffic surge and diverse services. *Firstly*, more spectrum is required. As the licensed spectrum is quite limited, cellular networks are now expanding to utilize the unlicensed bands (e.g., LTE-Unlicensed or LTE-U), such as 5GHz and 60GHz [2]. Excessive efforts from both industry and academia have been made to enable LTE to operation in 5GHz bands [3]–[5]. Besides, the under-utilized spectrum from other systems such as TV white space (TVWS) can be harvested and reused in cellular systems to increase network capacity opportunistically, through advanced cognitive radio technologies [6]. Then, the network will deal with a heterogenous spectrum pool in terms of availability, bandwidth, etc. *Secondly*, spatial spectrum reuse should be effectively improved across the network by deploying diverse small base stations (SBSs) [7]–[10]. However, densely deployed SBSs can suffer from severe inter-cell interference, which will degrade both the network capacity and user experience. To effectively improve the network capacity and satisfy users' requirements, efficient spectrum sharing among cells plays a critical role. However, spectrum sharing in 5G networks mainly faces the following challenges: i) since different cells have different traffic loads with diverse applications, spectrum sharing should satisfy the differentiated quality of service (QoS) requirements with heterogeneous and dynamic resources; and ii) inter-cell spectrum sharing and intra-cell user scheduling should be jointly optimized, which are also coupled with power allocation. Existing works on spectrum sharing are mostly based on central optimization which usually incurs extremely high complexity, or only provide suboptimal solutions. In addition, the differentiated-QoS requirements and heterogeneity of spectrum are seldom considered [11]–[13].

In this paper, we study spectrum sharing in 5G networks for efficient service provisioning, where different types of SBSs are deployed to exploit a heterogenous spectrum pool consisting of licensed and harvested spectrums. To efficiently improve users' quality of experience (QoE) [14], spectrum access, power allocation, and user scheduling are jointly investigated. Specifically, we consider that users have diverse service requirements in terms of throughput. An optimization problem is formulated, with the objective of maximizing the users' satisfaction degree across the network. To solve the problem, we employ a game-theoretic approach and interference graph. The utility function of each player (i.e., SBS) and the associated strategy set are carefully designed. Then,

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we prove that the proposed game is a potential game which has at least one Nash Equilibrium (NE), corresponding to the globally or locally optimal solution to the original optimization problem. To find the NE, we first propose a concurrent best-response iterative (CBSI) algorithm. Since the NE obtained might be locally optimal, a spatial adaptive play iterative (SAPI) learning algorithm is proposed to search the global optimum. Through theoretical analysis, the SAPI algorithm can guarantee to reach the global optimal solution with an arbitrary large probability, when the learning step is set to be sufficiently large. Extensive simulations are conducted for performance evaluation, which demonstrate the efficiency and optimality of the proposed algorithms.

In a nutshell, the contributions of this work can be summarized as follows:

- A joint optimization framework of spectrum access, user scheduling, and power allocation are formulated, with objective of maximizing the satisfaction of users in the network.
- A local interaction game is formulated and proved to have NE, corresponding to either the local or global optimum of the original optimization problem.
- Two algorithms are devised to converge to NE, either being the locally or globally optimal solution. The SAP learning based iterative algorithm is proved to converge to the globally optimal solution with an arbitrary large probability, given a large learning step.

The remainder of the paper is organized as follows. Related works are presented in Section II. The detailed description of the system model and problem formulation are given in Section III. The game model and proposed solutions are presented in Section IV and Section V, respectively. Simulation results are provided in Section VI, followed by concluding remarks in Section VII.

II. Related Works

To accommodate the massive mobile data, the network capacity of 5G should be increased accordingly. The network capacity can be approximately expressed as follows:

$$C = \sum_i \sum_j W_j \log_2(1 + \Upsilon_{i,j}), \tag{1}$$

where $\Upsilon_{i,j}$ is the signal-to-interference-plus-noise ratio (SINR) in cell i on channel j and W_j is the bandwidth for channel j. From this expression, we can improve network capacity from the following aspects:

- add more spectrum resources through spectrum harvesting or expanding the network in unlicensed bands;
- enhance spectrum efficiency (SINR improvement), through advanced PHY/MAC layer techniques, such as relaying, device-to-device (D2D) [15], [16], massive MIMO [17];
- improve network densification through densely deploying SBSs [18].

Since the gain obtained from spectrum efficiency improvement is very limited due to the log function, significant efforts are devoted to the other two aspects. In the aspect of spectrum expansion, LTE-Unlicensed (LTE-U) and different spectrum harvesting techniques (e.g., spectrum sensing [19], TVWS database, spectrum leasing) can bring more spectrum to the network. However, the key is how to share those spectrum across the network. With SBSs to fully reuse spectrum, the main limiting factor for network capacity is intercell interference. Therefore, in the following, we will mainly present the related work on each aspect, particularly on spectrum sharing and interference mitigation in small cell networks.

When different spectrum bands are available, spectrum sharing is important to network capacity [20] and different schemes are proposed for efficient sharing spectrum among different network entities. In [21], the spectrum resources are simply shared among users with equal probability. In [11], the spectrum sharing strategy is proposed based on multi-channel ALOHA protocol and the theory of potential games. In [22], the authors study spectrum sharing among multiple cellular operators in the unlicensed spectrum using Stackelberg game. In [23], spectrum sharing is studied using stable marriage game, which aims to find the most stable pairings between the users and spectrum bands. A congestion game approach is proposed to allow users to autonomously select a spectrum bands for access to maximize its own utility in [6], [24]. However, those approaches are mainly for dynamic spectrum access and cannot be applied directly to 5G networks, considering the heterogenous SBSs and users' requirements.

With densely deployed SBSs, the main limiting factor for network capacity is inter-cell interference, which has received much attention recently. In order to mitigate interference and improve network capacity, user scheduling and power control are usually jointly studied. The centralized iterative scheme is proposed to jointly optimize the user scheduling and power allocation in the multicell networks [25]. However, it is not suitable when SBSs are densely deployed, due to the high complexity and the heavy overhead for information exchange. To overcome this issue, clustering based approaches are proposed [13], [26], where power control and channel allocation are studied within each small cluster. However, it is still difficult to decide the optimal cluster size and the number of clusters. An algorithm combining Lagrangian duality and dynamic programming is proposed in [12]. In [27], joint channel and power allocation is decomposed into two subgames and then solved accordingly. However, the obtained solutions in [12], [27] are suboptimal.

To sum up, existing works either only obtain suboptimal solution or incur high complexity due to the centralized operation. Moreover, most of them do not consider the heterogeneity of spectrum and users' requirements. Different from these works, we aim to jointly optimize spectrum sharing, user scheduling, and power allocation in a decentralized manner based on local information, to improve user experience in 5G networks. Furthermore, the heterogeneities of spectrum, cells and user requirements are all considered.

III. System Model and Problem Formulation

In this section, the system model and problem formulation are presented.

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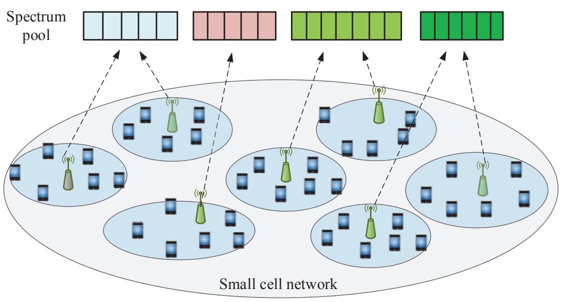

Figure 1. Network architecture with heterogenous spectrum pool.

A. System Model

We consider a heterogenous network with different small cell base stations (SBSs). The set of SBSs is denoted by $\mathcal{M} = \{1, 2, ..., M\}$, which are spatially distributed to serve their own users in the respective coverage area. Let $\mathcal{N}$ denote the user set, i.e., $\mathcal{N} = \{1, 2, ..., N\}$. The users served by SBS m is denoted by $\mathcal{N}_m$ and $\bigcup_{m\in\mathcal{M}} \mathcal{N}_m = \mathcal{N}$. In this paper, we mainly focus on downlink transmission from SBSs to users. Users are considered to have certain rate requirements and denote by $R'_{m,n}$ the rate required by user n associated with SBS m, which may vary for different users. The SBSs share a heterogenous spectrum pool consisting of the licensed bands and unlicensed bands[1]. SBSs can access the unlicensed bands in an opportunistic fashion. Each band consists of a number of channels. Let $\mathcal{K}$ be the band set, e.g., $\mathcal{K} = \{1, 2, ..., K\}$. Denote $\mathcal{C}_k$ for the channel set in band k, with size of J_k. SBSs schedule their users to different channels for service and the scheduled users from the same SBS access channels orthogonally. Licensed channels are always available while unlicensed channels are available with certain probabilities[2]. Define the channel availability probability $p_{k,i}$ for channel $c_{k,i}$ to be available, where $c_{k,i}$ is the ith channel in band k. For licensed channels, $p_{k,i} = 1$. The channels are with different bandwidths, and denote by $W_{k,i}$ the bandwidth of channel $c_{k,i}$. The average channel gain from SBS m to user n on channel $c_{k,i}$ is $h^{k,i}_{m,n}$.

SBSs select a spectrum band and schedule users to different channels in the selected band. Let $\eta^{k,i}_{m,n}$ indicate whether or not SBS m selects channel $c_{k,i}$ to serve user n, i.e., $\eta^{k,i}_{m,n} = 1$ when SBS m chooses channel $c_{k,i}$ to serve user n. Then, the SINR for user n can be given by

$$\Upsilon^{k,i}_{m,n} = \frac{\eta^{k,i}_{m,n} P^{k,i}_m h^{k,i}_{m,n}}{\sum_{j\in\mathcal{M}, j\neq m} \eta^{k,i}_{j,l} P^{k,i}_j h^{k,i}_{j,n} + \sigma^2}, \tag{2}$$

where σ^2 is the noise power, while $P^{k,i}_m$ and $P^{k,i}_j$ are the transmission power of SBS m and j for channel j in band k, respectively. Assume that the SBSs apply equal power allocation for all the channels in a selected band, to reduce the computational complexity. The channel gain can be calculated as follows:

$$h^{k,i}_{m,n} = \frac{\varsigma}{d^{\mu}_{m,n}}, \tag{3}$$

where ς represents the rayleigh fading, $d_{m,n}$ is the distance between SBS m and user n, while μ is the path loss exponent.

The expected transmission rate for user n in SBS m when selecting channel $c_{k,i}$ can be expressed as follows:

$$R^{k,i}_{m,n} = p_{k,i} W_{k,i} \log_2(1 + \Upsilon^{k,i}_{m,n}). \tag{4}$$

Considering users have certain transmission rate requirement, the satisfaction degree is adopted as the performance metric to measure user's experience, which is similar to the conception of quality of experience (QoE). Specifically, when the transmission rate $R^{k,i}_{m,n}$ is greater than $R'_{m,n}$, the satisfaction of user n will increase slowly. When $R^{k,i}_{m,n}$ is lower than $R'_{m,n}$, the satisfaction will decrease dramatically. To estimate the satisfaction, we define the following function, similar to [28]:

$$\Gamma_{m,n} = 1 - \exp(-\alpha \frac{R^{k,i}_{m,n}}{R'_{m,n}}), \tag{5}$$

where α is the factor representing the steepness of the satisfactory curve. The value of satisfaction ranges from 0 to 1. Moreover, the marginal rate of the satisfactory improvement is diminishing, following the law of the diminishing marginal benefit in economics. Fig. 2 shows the degree of satisfaction versus the transmission rate for the given the required rate of 4Mbps, under different values of α.

Table I
SUMMARY OF IMPORTANT SYMBOLS.

Symbol	Definition
$\mathcal{M}$	The set of SBSs
$\mathcal{K}$	The set of spectrum bands
$\mathcal{N}$	The set of user
$\mathcal{N}_m$	The users served by SBS m
B	The spectrum band selection vector for all SBSs
P	The power selection vector for all SBSs
S	The user scheduling vector for all SBSs
$h^{k,i}_{m,n}$	The channel gain for user n in SBS m on channel i in band k
$\Upsilon^{k,i}_{m,n}$	The SINR for user n in SBS m on channel i in band k
$R^{k,i}_{m,n}$	The data rate for user n in SBS m on channel i in band k
$R'_{m,n}$	The required data rate for user n in SBS m
$p_{k,i}$	Availability for channel i in band k
$W_{k,i}$	Bandwidth for channel i in band k
$\eta^{k,i}_{m,n}$	Indicator for user n in SBS m to access channel i in band k
$\mathcal{Z}_m$	The neighboring SBSs of SBS m
Φ	The potential function
U_m	The utility of SBS m
Q_m	The overall strategy for SBS m
$\tilde{\mathbf{Q}}_m$	The subset strategy of SBS m
$\tilde{\mathrm{M}}$	The set of SBSs selected for updating policy

B. Problem Formulation

Define power selection vector $\mathbf{P} := \{P_1, P_2, ..., P_M\}$ for all SBSs. For an SBS, it will equally allocate the selected power to the selected channels. We consider that the SBSs choose discrete power levels, similar to that in

[1]Unlicensed bands correspond to the spectrum resources that are not assigned to the HetNet, such as spectrum around 5GHz and spectrum harvested from other systems.

[2]The availability probabilities can be obtained through spectrum sensing or learning on other systems.

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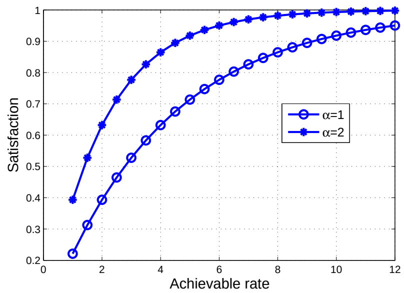

Figure 2. The satisfaction function with respect to transmission rate.

3GPP LTE standard [29]. Suppose that there exist L different power levels. The SBSs can choose the power level from $\mathcal{P} := \{\mu_1 P_{max}, \mu_2 P_{max}, ..., \mu_L P_{max}\}$, where $\mu_1 < \mu_2, ..., < \mu_L = 1$. Define the spectrum band selection vector $\mathbf{B} := \{B_1, B_2, ..., B_M\}$, where B_m respects the band selection of SBS m, i.e., $B_m \in \mathcal{K}$ and $B_m = \{k : \eta_{m,n}^{k,i} = 1\}$. Define user scheduling vector $\mathbf{S} := \{\mathcal{S}_1, \mathcal{S}_2, ..., \mathcal{S}_M\}$, where $\mathcal{S}_m$ represents the user scheduling of SBS m over the selected band and $\mathcal{S}_m = \{n : \eta_{m,n}^{k,i} = 1, \forall i \in \mathcal{C}_k\}$.

The objective is to maximize the network utility, which is defined as the aggregate user satisfaction across the network. It is a function of $(\mathbf{B}, \mathbf{P}, \mathbf{S})$:

$$U(\mathbf{B}, \mathbf{P}, \mathbf{S}) = \Sigma_{m \in \mathcal{M}} \Sigma_{n \in \mathcal{N}_m} \Gamma_{m,n}. \tag{6}$$

To find the optimal solution, we can formulate the following optimization problem:

$$\begin{aligned} (\mathbf{B}^*, \mathbf{P}^*, \mathbf{S}^*) &= \arg\max U(\mathbf{B}, \mathbf{P}, \mathbf{S}) \\ s.t. \quad & \mathbf{B} \in \mathbb{K}, \mathbf{P} \in \mathbb{P}, \mathbf{S} \in \mathbb{S} \end{aligned} \tag{7}$$

Note that $\mathbb{K}$, $\mathbb{S}$, and $\mathbb{P}$ are the band selection, power selection, and user scheduling space for all SBSs.

The above problem is a combinatorial optimization problem and is NP-hard to find the optimal solution [29].

IV. Local Interaction Game

To solve the above problem, we exploit a game theoretical approach in this section. A local interaction game is proposed and through analyzing the game, solutions are devised accordingly.

A. Game Model

Since all SBSs share the same spectrum pool, there might be inter-cell interference. Considering that the users are mainly interfered by a small number of neighboring cells [30], we adopt the interference graph to represent the potential interference relationship among SBSs. The interference graph is a unidirectional graph $G = (\mathcal{M}, \xi)$, where $\mathcal{M}$ and ξ are the vertex and edge set. $\mathcal{M}$ corresponds to the SBS set, while ξ represents the potential mutual interference relationship between two nodes. The interference graph only represents the potential mutual interference relationship based on distance. The actual interference also depends on whether the two SBSs select the same channel or not. For instance, when the distance

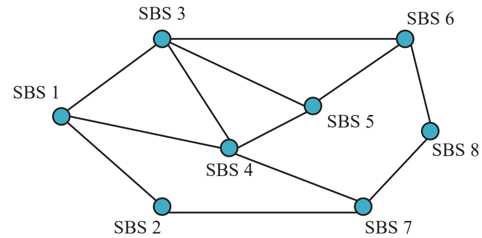

Figure 3. Interference graph.

between two SBSs is greater than a predefined threshold[3], they have the potential interference when using the same spectrum band. In the interference graph, nodes with edge connected can interfere with each other's transmission if using the same channel. Denote by $\mathcal{Z}_m := \{i \in \mathcal{M}, (i, m) \in \xi\}$ the neighboring SBSs set of SBS m. Fig. 3 shows an example of interference graph. In this figure, $\mathcal{Z}_4 = \{1, 3, 5, 7\}$.

We define a local interaction game $\mathcal{G} = \{\mathcal{M}, \{\mathbf{B}_m \bigotimes \mathbf{P}_m \bigotimes \mathbf{S}_m\}_{m \in \mathcal{M}}, \{U_m\}_{m \in \mathcal{M}}\}$, where $\mathcal{M}$ is the player set, $\{\mathbf{B}_m \bigotimes \mathbf{P}_m \bigotimes \mathbf{S}_m\}$ is the strategy set for player m, and U_m is the utility function of player m. In our case, the players are the SBSs and the utility function U_m is defined as follows:

$$U_m(Q_m, \mathbf{Q}_{\mathcal{Z}_m}) = \Gamma_m + \sum_{j \in \mathcal{Z}_m} \Gamma_j, \tag{8}$$

where Q_m and $\mathbf{Q}_{\mathcal{Z}_m}$ are the strategies of SBS m and its neighboring SBSs, while Γ_m is the aggregate user satisfaction in SBS m when adopting the strategy Q_m and $\mathbf{Q}_{\mathcal{Z}_m}$. Note that the neighboring SBSs of SBS m are those who has connection with SBS m in the interference graph. Specifically, $Q_m := \{B_m, P_m, S_m\}$. From (8), the utility of player m consists of two parts: its own user satisfaction and the aggregate user satisfaction from its neighbors. By designing the utility functions in such a way, we could obtain the maximum network utility when each SBS aims to maximize its utility. For each player, it aims to select the best strategy to maximize its utility function.

Definition *1:* A strategy profile $\mathbf{Q}_{m \in \mathcal{M}}^* = (B_1^*, B_2^*, \ldots, B_M^*, P_1^*, P_2^*, \ldots, P_M^*, S_1^*, S_2^*, \ldots, S_M^*,)$ is an Nash Equilibrium (NE) if and only if

$$U_m(Q_m^*, \mathbf{Q}_{-m}^*) \geq U_m(Q_m, \mathbf{Q}_{-m}^*), \forall m \in \mathcal{M}, \tag{9}$$

where $\mathbf{Q}_{-m}^*$ are the strategies selected by all the other players except m. NE means no one has the intention to change its strategy since it cannot increase its utility unilaterally. Since NEs are the solutions to the game $\mathcal{G}$, in the following, we will analyze the game to obtain NEs.

B. Game Analysis

Theorem *1:* The proposed game $\mathcal{G}$ has at least one pure NE strategy.

[3]The selection of threshold can balance the complexity and performance. For instance, a smaller threshold indicates more SBSs will be considered as interference sources for a given BS, which is more accurate but with high complexity.

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In what follows, we provide the proof for Theorem 1, based on the theory of potential games. To this end, the definition for a special type of game: exact potential game, is given first.

***Theorem** 2:* A game is an exact potential game if there exists a potential function Φ which satisfies the following condition:

$$U_i(s_i', s_{-i}) - U_i(s_i, s_{-i}) = \Phi(s_i', s_{-i}) - \Phi(s_i, s_{-i}), \quad (10)$$

where U_i is the utility function of player i, while s_i and s_{-i} are the strategy for player i and other players, respectively.

For an exact potential game, if any player changes its strategy, e.g., from s_i to s_i', the change in its own utility equals to the change in the potential function. It is well known that there exist at least one pure NE in exact potential games. Therefore, in the following, we prove the proposed game $\mathcal{G}$ is an exact potential game, similar to [29], [31].

Proof: Define the potential function Φ as follows:

$$\Phi(Q_m, \mathbf{Q}_{-m}) = \sum_{m \in \mathcal{M}} \Gamma_m(Q_m, \mathbf{Q}_{-m}). \quad (11)$$

Note that $Q_m := \{S_m, C_m, P_m\}$, which is the strategy set for SBS m.

Since $\Gamma_m(Q_m, \mathbf{Q}_{-m}) = \Gamma_m(Q_m, \mathbf{Q}_{\mathcal{Z}_m})$, we have

$$\begin{aligned}\Phi(Q_m, \mathbf{Q}_{-m}) =& \Gamma_m(Q_m, \mathbf{Q}_{\mathcal{Z}_m}) + \sum_{j \in \mathcal{Z}_m} \Gamma_j(Q_m, \mathbf{Q}_{\mathcal{Z}_j}) \\ &+ \sum_{n \neq m, n \notin \mathcal{Z}_m} \Gamma_n(Q_n, \mathbf{Q}_{\mathcal{Z}_n})\end{aligned}$$

Considering that each player has three decision variables, any change in band selection, transmission power, and user scheduling will cause the change of its strategy set. Therefore, we will investigate the effect in potential function and player's individual utility function when any change is made in the strategy set. Suppose that an arbitrary player, e.g., SBS m, changes its band selection decision from B_m to B_m'. Then, the change in potential function $\Phi(Q_m, \mathbf{Q}_{-m})$ is given by (12).

$$\begin{aligned}&\Phi(Q_m', \mathbf{Q}_{-m}) - \Phi(Q_m, \mathbf{Q}_{-m}) \\ &= \Phi(B_m', P_m, S_m, \mathbf{Q}_{-m}) - \Phi(B_m', P_m, S_m, \mathbf{Q}_{-m}) \\ &= \Gamma_m(B_m', P_m, S_m, \mathbf{Q}_{\mathcal{Z}_m}) - \Gamma_m(B_m, P_m, S_m, \mathbf{Q}_{\mathcal{Z}_m}) \\ &+ \sum_{j \in \mathcal{Z}_m} [\Gamma_j(B_m', P_m, S_m, \mathbf{B}_{\mathcal{Z}_j,}', \mathbf{P}_{\mathcal{Z}_j}, \mathbf{S}_{\mathcal{Z}_j}) \\ &- \Gamma_m(B_m, P_m, S_m, \mathbf{B}_{\mathcal{Z}_j,}, \mathbf{P}_{\mathcal{Z}_j}, \mathbf{S}_{\mathcal{Z}_j})] \\ &+ \sum_{n \neq m, n \notin \mathcal{Z}_m} \Gamma_n(Q_n, \mathbf{Q}_{\mathcal{Z}_n}) - \sum_{n \neq m, n \notin \mathcal{Z}_m} \Gamma_n(Q_n, \mathbf{Q}_{\mathcal{Z}_n})\end{aligned} \quad (12)$$

The change in the individual utility is expressed as follows:

$$\begin{aligned}&U_m(Q_m', \mathbf{Q}_{-m}) - U_m(Q_m, \mathbf{Q}_{-m}) \\ &= \Gamma_m(B_m', P_m, S_m, \mathbf{Q}_{\mathcal{Z}_m}) - \Gamma_m(B_m, P_m, S_m, \mathbf{Q}_{\mathcal{Z}_m}) \\ &+ \sum_{j \in \mathcal{Z}_m} [\Gamma_j(B_m', P_m, S_m, \mathbf{B}_{\mathcal{Z}_j,}', \mathbf{P}_{\mathcal{Z}_j}, \mathbf{S}_{\mathcal{Z}_j}) \\ &- \Gamma_m(B_m, P_m, S_m, \mathbf{B}_{\mathcal{Z}_j,}, \mathbf{P}_{\mathcal{Z}_j}, \mathbf{S}_{\mathcal{Z}_j})]\end{aligned} \quad (13)$$

■

When SBS m changes its band selection decision from B_m to B_m', the transmission rate for SBS n will not change, where $n \neq m, n \notin \mathcal{Z}_m$. Therefore, from (12) and (13), the following equation holds:

$$\begin{aligned}&\Phi(B_m', P_m, S_m, \mathbf{Q}_{-m}) - \Phi(B_m', P_m, S_m, \mathbf{Q}_{-m}) \\ &= U_m(B_m', P_m, S_m, \mathbf{Q}_{-m}) - U_m(B_m, P_m, S_m, \mathbf{Q}_{-m}).\end{aligned} \quad (14)$$

Due to the symmetry of B_m and P_m, when SBS m changes its power selection decision from P_m to P_m', the same result can be obtained. Next, we will analyze the case when SBS m changes its user scheduling strategy from S_m to S_m'. Given the spectrum band selection and power selection vector, the change in user selection decision does not affect the neighboring cells for downlink transmission. The reason is that the transmission rate of a generic SBS does not depend on the other SBSs' user scheduling decision, when power and channel selection are given. Therefore, when SBS m changes its power selection decision from P_m to P_m', we have

$$\begin{aligned}&\Phi(B_m, P_m, S_m', \mathbf{Q}_{-m}) - \Phi(B_m, P_m, S_m, \mathbf{Q}_{-m}) \\ &= \Gamma_m(C_m, P_m, S_m', \mathbf{Q}_{-m}) - \Gamma_m(B_m, P_m, S_m, \mathbf{Q}_{-m}) \\ &= U_m(B_m', P_m, S_m, \mathbf{Q}_{-m}) - U_m(B_m, P_m, S_m, \mathbf{Q}_{-m})\end{aligned} \quad (15)$$

From above analysis, we can find that the change in potential function is the same as the change in the SBS's utility function when the SBS unilaterally changes its strategy (e.g., B_m, P_m, S_m for a generic SBS m). According to Definition 2, the game $\mathcal{G}$ is an exact potential game with the potential function defined in (11). Therefore, the game $\mathcal{G}$ has at least one pure NE strategy. Theorem 1 has been proved.

***Theorem** 3:* The NE of the proposed game $\mathcal{G}$ can maximize the aggregate user satisfaction locally or globally.

According to [32], the NE of potential game correspond to the local or global maximizer of the associated potential function. In our case, the potential function Φ is the aggregate user satisfaction. Therefore, Theorem 3 is proved. Note that the best NE is the globally optimal solution to the original optimization problem.

V. Iterative Algorithms to Find NEs

According to Theorem 2, to maximize the objective, it is necessary to devise efficient algorithms to find the NEs or even the best NE. In this section, we first study the optimal user scheduling given power allocation and band selection. Then, by incorporating the obtained user scheduling strategy, we propose a concurrent best response iterative (CBSI) algorithm to find an NE, which serves as an benchmark solution. Although CBSI algorithm can help achieve the NE, the outcome might be a locally optimal solution. Therefore, we propose a spatial adaptive play iterative (SAPI) learning algorithm to find the best NE, which globally maximizes the potential function, i.e., the aggregate user satisfaction.

A. User Scheduling

As aforementioned, the user scheduling in SBSs is independent with other SBSs, given the power allocation and band selection. Without loss of generality, we take a generic SBS

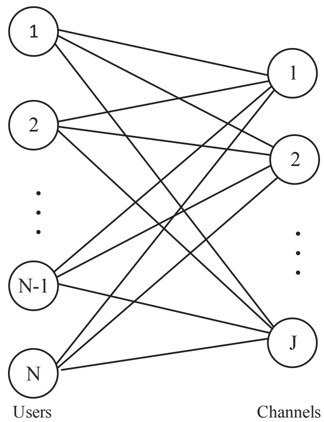

Figure 4. Matching based user scheduling.

to study the user scheduling. Suppose the SBS has N users to serve and the selected band has J channels to explore. The SBS determines the optimal user scheduling, with the objective of maximizing the aggregate user satisfaction. Specifically, denote by $I_{i,j}$ the indicator which indicates whether user i is scheduled to channel j or not. Then, we have

$$I_{i,j} = \begin{cases} 1 & \text{if user } i \text{ accesses channel } j \\ 0 & \text{otherwise.} \end{cases} \tag{16}$$

User scheduling is equivalent to determining all the indicators $I_{i,j}$, where $i \in \{1, 2, ..., N\}$ and $j \in \{1, 2, ..., L\}$, which can be formulated as follows:

$$\begin{aligned} &\max \sum_{i=1}^{N} \sum_{j=1}^{J} I_{i,j} \Gamma_i(i,j) \\ &s.t. \sum_{i} I_{i,j} \leq 1, \forall i = 1, 2, ..., N \\ &\sum_{j} I_{i,j} \leq 1, \forall j = 1, 2, ..., J \\ &I_{i,j} \in \{0,1\}, \forall i \in \{1, 2, ..., N\}, \forall j \in \{1, 2, ..., J\} \end{aligned} \tag{17}$$

Note that $\Gamma_i(i,j)$ is the satisfaction degree for user i if scheduled to channel j, which can be calculated by (4) and (5).

The above problem can be transformed into the maximum weight bipartite matching problem, which can be solved in polynomial time [33]. Fig. 4 shows the bipartite graph, where the weight $w_{i,j}$ on each edge represents the user satisfaction degree if the corresponding user i accesses channel j (represented by vertices). Finding the optimal user scheduling is equivalent to finding the maximum weight matching in Fig. 4.To this end, Hungarian algorithm [34] can be adopted, which is a well known algorithm to find the matching to maximize the sum of the weights in polynomial time. By doing so, the best matching can be determined such that the aggregate user satisfaction of the SBS is maximized.

B. Concurrent Best Response Iterative Algorithm

For a potential game with finite strategy sets, it possesses the finite improvement property (FIP). With FIP, unilateral improvement dynamics will converge to an NE in a finite number of steps. Since the game $\mathcal{G}$ has finite strategy sets, we can employ the basic best response technique to find the NE strategy of the proposed game. Furthermore, considering the characteristics of our optimization, i.e., multi-dimensional strategies and interference graph, we propose CBSI algorithm in the following. Define the subset of strategy $\tilde{\mathbf{Q}}_m$ for SBS m, $\forall m \in \mathcal{M}$, where $\tilde{\mathbf{Q}}_m := \mathbf{B}_m \bigotimes \mathbf{P}_m$ and $\tilde{Q}_m = (B_m, P_m)$.

1) **Initialization**: Set the iteration counter $t := 0$. Each SBS, randomly selects a spectrum band, transmission power level, and user scheduling policy, i.e., initialize $B_m(t=0), P_m(t=0), S_m(t=0), \forall m \in \mathcal{M}$. Based on the initial condition, each SBS calculates the user's satisfaction.
2) **SBS selection**: A set of non-neighboring SBSs $\tilde{\text{M}}$ is randomly selected, where these SBSs are not neighbors of each other. Each SBS m in $\tilde{\text{M}}$ calculates its utility $U_m(t)$ using (8) through communication with neighboring nodes.
3) **Best response**: Given that the other SBSs keep their strategies, each SBS m in $\tilde{\text{M}}$, calculates its utility function over all the possible strategies, i.e., $U_{m,i}(S_m, \tilde{Q}_{m,i}, \mathbf{Q}_{-m})$, $\forall\ \tilde{Q}_{m,i} \in \tilde{\mathbf{Q}}_m$ and $\forall\ m \in \tilde{\text{M}}$. Then, SBS m in $\tilde{\text{M}}$, selects the best strategy such that the utility function is maximized:
$$\tilde{\text{Q}}_m^* = \arg\max U_{m,i} \tag{18}$$
4) **Best user scheduling**: Based on the new selected strategy, SBS m in $\tilde{\text{M}}$ and the corresponding neighboring SBSs select the best user scheduling such that the utility in (8) is maximized. Since the user scheduling is independent among SBSs, given the power and band selection vector, the best user selection can be performed independently. Each selected SBS just applies Hungarian algorithm to obtain the optimal user scheduling.
5) **Stop**: If the stopping criterion is satisfied (e.g., the maximum number of iterations is reached), then stop; otherwise increase the iteration counter t by 1, and reiterate from step 2.

C. Convergence and Optimality Analysis

The CBSI algorithm allows multiple non-interfering SBSs to concurrently improve their utilities. According to the FIP feature, after a finite number of iterations, the CBSI algorithm can converge to a stable solution, i.e., an NE. As for the optimality, according to Theorem 2, the solution obtained by CBSI algorithm is at least locally optimal.

D. Spatial Adaptive Play Iterative Algorithm

Although CBSI algorithm can find NE of the game, the solution might be locally optimal. In order to find the best NE, we devise SAPI learning algorithm. The SAPI learning algorithm adopts mixed strategy to search the best NE and will

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converge to the best NE with an arbitrarily large probability. Its main idea is to iteratively update the mixed strategy to maximize the potential function. For each player, its mixed strategy is the probability mass function (p.m.f) over the strategy set, i.e., $p_{m,i}(t)$, which denotes the probability that SBS m choose i-th strategy at iteration t. Algorithm 1 presents the detailed procedure with four main steps as follows.

1) **Initialization**: Set the iteration counter $t := 0$. For each SBS, the mixed strategy is initialized as a uniform distribution, i.e., $p_{m,i}(t=0) = 1/\Lambda$, where Λ is the size of $\tilde{\mathbf{Q}}_m, \forall m \in \mathcal{M}$. Then, each SBS initializes $B_m(t=0), P_m(t=0), S_m(t=0), \forall m \in \mathcal{M}$, and calculates the user's satisfaction.
2) **SBS selection**: A set of non-neighboring SBSs $\tilde{\mathrm{M}}$ is randomly selected. Each SBS m in $\tilde{\mathrm{M}}$ calculates its utility $U_m(t)$ using (8) through communication with neighboring nodes.
3) **Exploration and mixed policy update**: Given that the other SBSs keep their strategies, SBS m in $\tilde{\mathrm{M}}$, calculates the utility function over all the possible strategies, i.e., $U_{m,i}(S_m, \tilde{Q}_{m,i}, \mathbf{Q}_{-m}), \forall \tilde{Q}_{m,i} \in \tilde{\mathbf{Q}}_m$ and $\forall m \in \tilde{\mathrm{M}}$. Update the mixed strategy as follows:
$$p_{m,i}(t+1) = \frac{\exp\{\beta U_{m,i}\}}{\Sigma_{\tilde{Q}_{m,i} \in \tilde{\mathbf{Q}}_m} \exp\{\beta U_{m,i}\}}, \qquad (19)$$
where β is the learning parameter[4], which is positive. SBS m randomly selects its strategy according to the updated mixed strategy. Based on the new selected strategy, SBS m and the corresponding neighboring SBSs selects the best user scheduling such that the utility in (8) is maximized. Since given the power and band selection vector, the user scheduling is independent among SBSs. Therefore, the best user selection can be performed independently. Each selected SBS just applies Hungarian algorithm to obtain the optimal user scheduling.
4) **Stop**: If the stopping criterion is satisfied (e.g., the maximum number of iterations is reached), then stop; otherwise increase the iteration counter t by 1, and reiterate from step 2.

E. Convergence and Optimality Analysis

1) Convergence Analysis:

Theorem 4: SAPI algorithm can converge to a stationary distribution $\pi(\mathbf{B}, \mathbf{S}, \mathbf{P})$ given by
$$\pi(\mathbf{B}, \mathbf{P}, \mathbf{S}) = \frac{\exp\{\beta \Phi(\mathbf{B}, \mathbf{P}, \mathbf{S})\}}{\Sigma_{\mathbf{B} \in \mathbb{K}, \mathbf{P} \in \mathbb{P}} \exp\{\beta \Phi(\mathbf{B}, \mathbf{P}, \mathbf{S})\}}, \qquad (20)$$
where user scheduling vector $\mathbf{S}$ can be determined, given $\mathbf{B}, \mathbf{P}$.

Proof: Given the band selection and power selection vectors $\mathbf{B}$ and $\mathbf{P}$, namely $\tilde{\mathbf{Q}}_m, \forall m \in \mathcal{M}$, user scheduling vector $\mathbf{S}$ can be uniquely determined. Define $\tilde{\mathbf{Q}} := \{\tilde{\mathbf{Q}}_m, \forall m \in \mathcal{M}\}$, then $\mathbf{S} = f(\tilde{\mathbf{Q}})$. In the following analysis, we will mainly focus on the strategy set $\tilde{\mathbf{Q}}$. Denote the strategy adopted in the t-th iteration $\tilde{\mathbf{Q}}(t) = \{\tilde{Q}_1(t), \tilde{Q}_2(t), ..., \tilde{Q}_M(t)\}$. Since the strategy space is discrete and the future strategy does not

[4] β balances the tradeoff between exploration and exploitation.

Algorithm 1 SAPI algorithm

Require: $\mathcal{M}, T, N, \alpha, \beta, h_s^m, \forall m \in \mathcal{M}, s \in \mathcal{N}$.
Ensure: $\mathbf{S}^*, \mathbf{C}^*, \mathbf{P}^*$

(**Initialization**): Set mixed strategy $p_{m,i}(t=0) = 1/\Lambda$, where $\Lambda = M \cdot L, \forall m \in \mathcal{M}$ and $\forall i, \tilde{Q}_{m,i} \in \tilde{\mathbf{Q}}_m$. Generate samples of the strategy vector.
for $t \leftarrow 1$ to T **do**
  Randomly generate non-interfering SBSs set $\tilde{\mathrm{M}}$
  Calculate utility according to (5)
  for Each $m \in \tilde{\mathrm{M}}$ **do**
    Calculate $U_{m,i}(S_m, \tilde{Q}_{m,i}, \mathbf{Q}_{-m}), \forall \tilde{Q}_{m,i} \in \tilde{\mathbf{Q}}_m$ and $\forall m \in \tilde{\mathrm{M}}$
    Update mixed strategy: $p_{m,i}(t+1) = \frac{\exp\{\beta U_{m,i}\}}{\Sigma_{\tilde{Q}_{m,i} \in \tilde{\mathbf{Q}}_m} \exp\{\beta U_{m,i}\}}$
    Generate samples of the strategy vector
    Each SBS determines user scheduling strategy independently
  end for
  Stop when maximum of iterations is reached
end for
return

---

depend on the past strategy selection given the current strategy, $\tilde{\mathbf{Q}}(t)$ is a discrete time Markov process. Moreover, it is a irreducible and aperiodic process. Thus, there exists an unique stationary distribution for $\tilde{\mathbf{Q}}(t)$, which should satisfy the balanced equations. To prove Theorem 3, we can justify that the distribution given by (20) satisfies the balanced equations. To this end, we first define two arbitrary states for the above process, A and B, where $A, B \in \tilde{\mathbf{Q}}$. Then, we justify that distribution in (20) satisfy: $\pi(A)p(B|A) = \pi(B)p(A|B)$.

Suppose that state A is given by $\{\tilde{Q}_1, \tilde{Q}_2, ..., \tilde{Q}_M\}$. Let the set of randomly selected SBSs be $\tilde{\mathrm{M}} := \{1, 2, ..., |\tilde{\mathrm{M}}|\}$, where $|\tilde{\mathrm{M}}|$ is the number of elements of $\tilde{\mathrm{M}}$. The associated probability for selecting $\tilde{\mathrm{Q}}'_{|\tilde{\mathrm{M}}|}$ is denoted by ϱ. Define state B as $\{\tilde{Q}'_1, \tilde{Q}'_2, ..., \tilde{Q}'_{|\tilde{\mathrm{M}}|}, \tilde{Q}'_{|\tilde{\mathrm{M}}|+1}, ..., \tilde{Q}_M\}$. Then, the conditional probability $p(B|A)$ is
$$p(B|A) = \prod_{i \in \tilde{\mathrm{M}}} \frac{\exp\{\beta U_i(\tilde{Q}'_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}, f(\tilde{Q}'_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}))\}}{\sum_{\tilde{\mathbf{Q}}_i} \exp\{\beta U_i(\tilde{Q}_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}, f(\tilde{Q}_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}))\}} \qquad (21)$$

Based on that, we have
$$\begin{aligned} &\pi(A)p(B|A) \\ &= \lambda \exp\{\beta \Phi(A, f(A))\} \cdot \prod_{i \in \tilde{\mathrm{M}}} \exp\{\beta U_i(\tilde{Q}'_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}, f(\tilde{Q}'_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}))\} \\ &= \lambda \exp\{\beta \Phi(A, f(A)) + \beta \prod_{i \in \tilde{\mathrm{M}}} U_i(\tilde{Q}'_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}, f(\tilde{Q}'_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}))\}, \end{aligned}$$
where $\lambda = \frac{\varrho}{\Sigma_{A \in \tilde{\mathbf{Q}}} \exp\{\beta \Phi(A, f(A))\}} \cdot \prod_{i \in \tilde{\mathrm{M}}} \frac{1}{\sum_{\tilde{Q}_i} \exp\{\beta U_i(\tilde{Q}_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}, f(\tilde{Q}_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}))\}}$.

Similarly, we have
$$\begin{aligned} &\pi(B)p(A|B) \\ &= \lambda \exp\{\beta \Phi(B, f(B)) + \beta \prod_{i \in \tilde{\mathrm{M}}} U_i(\tilde{Q}_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}, f(\tilde{Q}_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}))\}. \end{aligned}$$

Comparing state B with A, there are $\tilde{\mathrm{M}}$ elements changed. Define $A(i)$ to be the new state with changes up to the i-th

Table II
PARAMETERS USED IN THE SIMULATIONS

Parameters	Value
Maximum transmission power	2 W
Power levels	[2 4 8]
σ^2	-90 dB
Path loss exponent μ	3.5
Cell radius	200 m
Required throughput	[1 1.5 2 2.5]Mbps
Learning parameter β	[20 40 60]
Interference distance	[350 450 550] m
α	[0.8 1 1.2]

element in state A. Then, state B can be considered as $A(|\tilde{\mathbf{M}}|)$, while state $A = A(0)$. Then, we can have

$$\begin{aligned} &\Phi(B, f(B)) - \Phi(A, f(A)) \\ &= \Phi\{A(|\tilde{\mathbf{M}}|), f(A(|\tilde{\mathbf{M}}|))\} - \Phi\{A(0), f(A(0))\} \\ &= \Sigma_{i=1}^{|\tilde{\mathbf{M}}|}\{\Phi(A(i), f(A(i))) - \Phi(A(i-1), f(A(i-1)))\} \end{aligned} \tag{22}$$

Since the proposed game is an exact potential game, we have

$$\begin{aligned} &\Sigma_{i=1}^{|\tilde{\mathbf{M}}|}\{\Phi(A(i), f(A(i))) - \Phi(A(i-1), f(A(i-1)))\} \\ &= \Sigma_{i=1}^{|\tilde{\mathbf{M}}|}\{U_i(A(i), f(A(i))) - U_i(A(i-1), f(A(i-1)))\} \\ &= U_i(\tilde{Q}'_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}, f(\tilde{Q}'_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i})) - U_i(\tilde{Q}_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i}, f(\tilde{Q}_i, \tilde{\mathbf{Q}}_{\mathcal{Z}_i})). \end{aligned} \tag{23}$$

The last equation holds because all the SBSs in $\tilde{\mathbf{M}}$ are not neighboring nodes. Therefore, the stationary distribution $\pi(\mathbf{B}, \mathbf{P}, \mathbf{S})$ given in (20) satisfies the balanced equations. ■

2) Optimality Analysis:

***Theorem** 5:* SAPI algorithm can achieve the globally optimal solution with an arbitrarily large probability, given a sufficiently large value of β.

Proof: Suppose that the globally optimal solution is $(\mathbf{B}^*, \mathbf{P}^*, \mathbf{S}^*)$, which can maximize $\Sigma_{m=1}^{M} R_{m,n}^k$, or the potential function Φ. Then, we have $\Phi(\mathbf{B}^*, \mathbf{P}^*, \mathbf{S}^*) > \Phi(\mathbf{B}, \mathbf{P}, \mathbf{S})$ for any other strategy set rather than the optimal one. If we set β to be sufficiently large, we have

$$\exp\{\beta\Phi(\mathbf{B}^*, \mathbf{P}^*, \mathbf{S}^*)\} \gg \exp\{\beta\Phi(\mathbf{B}, \mathbf{P}, \mathbf{S})\}, \tag{24}$$

for any $(\mathbf{B}, \mathbf{P}, \mathbf{S}) \neq (\mathbf{B}^*, \mathbf{P}^*, \mathbf{S}^*)$. Then the stationary probability $\lim_{\beta\to\infty} \pi(\mathbf{B}^*, \mathbf{P}^*, \mathbf{S}^*) = 1$ ■

Remark: Computational complexity of SAPI algorithm: in each iteration, each selected SBS calculates the utility based on the current strategy with a computational complexity of O(1). Then, each selected SBS calculates the potential utility for all possible strategy space of spectrum bands and power levels with a computational complexity of $O(|\mathcal{K}| \cdot |\mathcal{P}|)$. Each selected SBS needs a random number to choose the spectrum band and power level with a computational complexity of O(1). After that, the selected SBS decides the best user assignment with a complexity of $O(|\mathcal{N}_m| \cdot |\mathcal{C}_k|)$. Therefore, in total, the computational complexity for each selected SBS is $O(\max(|\mathcal{K}| \cdot |\mathcal{P}|, |\mathcal{N}_m| \cdot |\mathcal{C}_k|))$. Similarly, the computational complexity of CBSI algorithm can be obtained, which is the same to that of SAPI algorithm.

VI. SIMULATION RESULTS

In this section, the simulation results are provided to evaluate the performance of the proposed algorithms. The simulation is set up as follows. As shown in Fig. 5, in a 1 km×1 km area, there is a set of SBSs located, each with a cell radius of 200 m. A number of spectrum bands are shared by SBSs, which have different availabilities and bandwidth. In each cell, a number of users are randomly generated, with transmission rate requirement randomly selected from [1 1.5 2 2.5] Mbps. The power of noise is set to -90 dB. The path loss exponent μ is set to 3.5, and unit rayleigh fading is adopted. The channels are with different availabilities ranging from 0.8 to 1. Detailed simulation parameters are given in Table II.

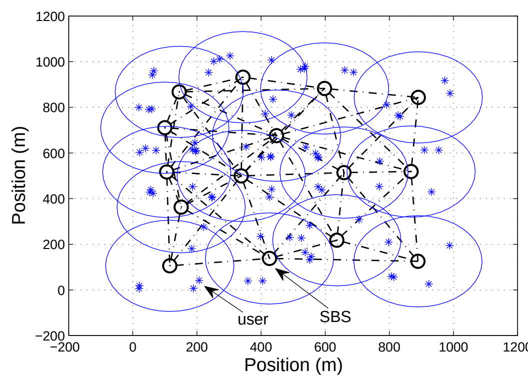

Figure 5. Simulation scenarios.

Fig. 6 shows the convergence of the proposed CBRI and SAPI algorithms. The exhausted search (E-S) is employed as the performance benchmark, which can achieve the optimal result. However, due to time complexity of exhausted search, we consider a small scale network with 5 SBSs, 4 power levels, and 4 bands with 3 channels in each band. It can be seen that the network utilities obtained by the proposed algorithms are updated iteratively. After a number of iterations, both algorithms converge and the SAPI converges to the optimal solution. Note that the CBRI algorithm converges fast since the SAPI algorithm adopts stochastic strategy to search the optimal solution. However, the CBRI algorithm may be tracked at a local optimal solution, while the SAPI algorithm can find the global optimal solution with an arbitrary large probability.

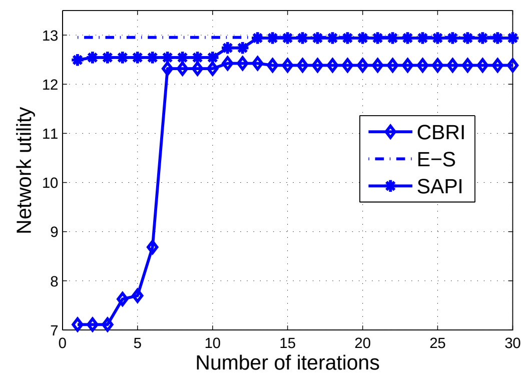

Figure 6. Convergence of the proposed algorithms.

Fig. 7 and Fig. 8 show the evolution of power allocation and spectrum band access strategy for SAPI algorithm, since it can help achieve the global optimum result, compared with the CBRI algorithm. The evolution of power levels for 4 SBSs is shown in Fig. 7. It can be seen that the power allocation strategies keep unchanged after 7 iterations, with 4 SBSs selecting power level 4 and 1 SBS selecting power level 1. It also further validates the convergence of the proposed algorithm. The evolution of band selection for 5 SBSs is shown in Fig. 8. It can be seen that the band selection strategies keep unchanged after around 15 iterations.

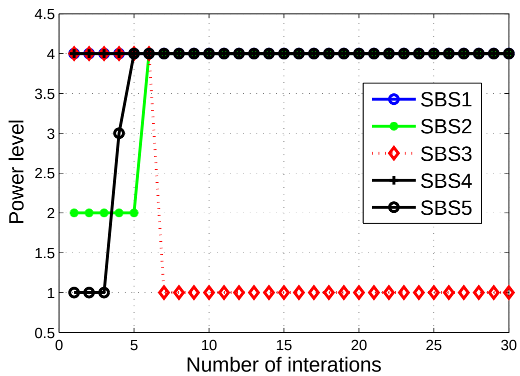

Figure 7. Power strategy convergence of SAPI.

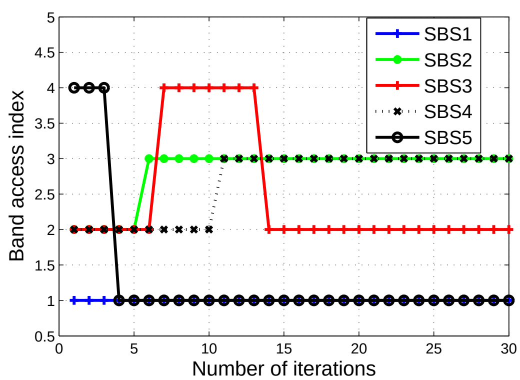

Figure 8. Channel strategy convergence of SAPI.

Fig. 9 compares the convergence speed between CBRI and best response (BR) algorithms for different power levels. We consider a network consisting of 15 SBSs serving 6 users in each SBS, 8 power levels, and 5 bands with 5 channel in each band in the following simulations. It can be seen that the CBRI converges faster than BR algorithm since CBRI allows the non-interfering users concurrently updates their strategies. Moreover, with more power levels to choose, the network utility can be slightly improved.

Fig. 10 compares the network utility for different algorithms. It can be seen that the proposed algorithms converge fast. Moreover, the network utility obtained from the SAPI algorithm is better than that from the CBRI algorithm. The reason is that, although both can converge to NEs, which correspond to either locally or globally optimal solutions, the SAPI can avoid to be tracked in a local optimum by adopting stochastic updating policy.

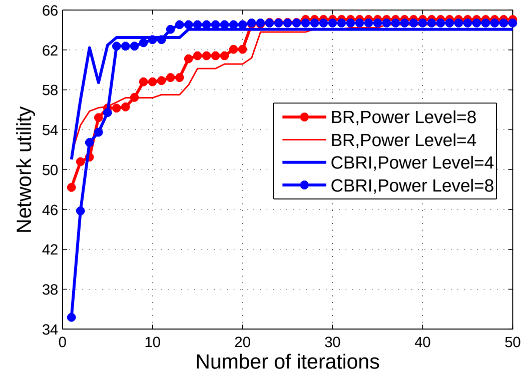

Figure 9. Comparison between CBRI and BR.

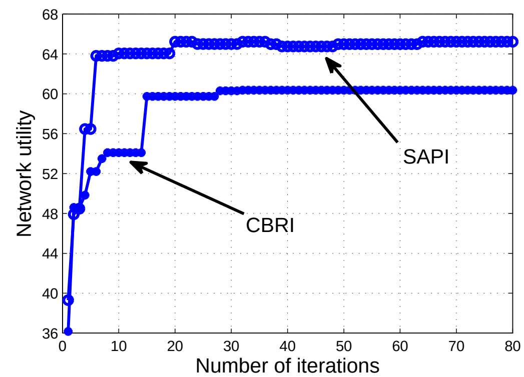

Figure 10. Network utility with respect to iterations for different algorithms.

Fig. 11 shows the network utility with respect to transmission rate requirement under different learning parameter β. For simplicity, we consider all users have the same data rate requirement. It can be seen that with a higher rate requirement, the network utility is lower. In addition, it can been seen that a large β can lead to a higher network utility, because it helps to converge to the globally optimal solution.

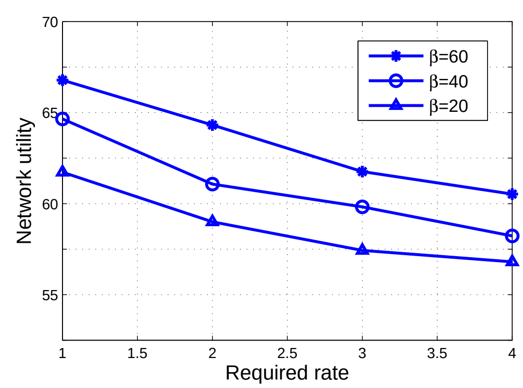

Figure 11. Network utility versus user requirement for different β.

Fig. 12 shows the network utility with respect to transmission rate requirement under different satisfaction parameter α. It can be seen that with a higher rate requirement, the network utility is lower. Moreover, it can also be seen that a larger α can improve the network utility, since it brings more satisfaction for the same amount increase in transmission rate.

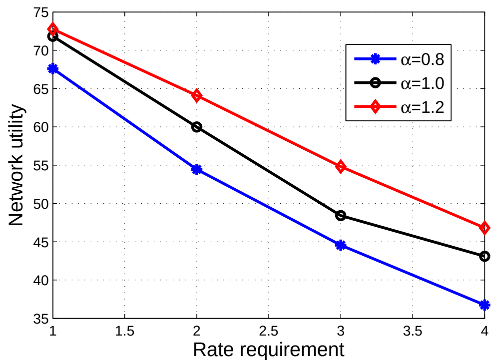

Figure 12. Network utility versus user requirement for different α.

VII. Conclusion

In this paper, we have investigated spectrum access, power allocation, and user scheduling jointly in 5G networks to improve users' service of experience. A local interaction game has been established based on interference graph. Two decentralized algorithms have been devised, namely CBSI and SAPI algorithms, to converge to NE, corresponding to either the local or global maximizer of the aggregate user satisfaction across the network. The SAPI algorithm can find the global optimal solution with an arbitrary large probability, when a learning parameter is set to be sufficiently large. For the future work, we will consider user association, which can further improve service experience through allocating users to suitable SBSs and spectrum bands. Additionally, when energy harvesting technologies are employed at SBSs to improve energy efficiency, the users' quality of experience might be disturbed due to intermittent arrival of renewable energy [35]. Therefore, it is necessary to consider the energy status of SBSs when performing spectrum sharing.

References

[1] A. Osseiran, F. Boccardi, V. Braun, K. Kusume, P. Marsch, M. Maternia, O. Queseth, M. Schellmann, H. Schotten, H. Taoka *et al.*, "Scenarios for 5g mobile and wireless communications: the vision of the metis project," *IEEE Communications Magazine*, vol. 52, no. 5, pp. 26–35, 2014.

[2] A. Al-Dulaimi, S. Al-Rubaye, Q. Ni, and E. Sousa, "5g communications race: pursuit of more capacity triggers lte in unlicensed band," *IEEE Vehicular Technology Magazine*, vol. 10, no. 1, pp. 43–51, 2015.

[3] E. Almeida, A. M. Cavalcante, R. C. Paiva, F. S. Chaves, F. M. Abinader, R. D. Vieira, S. Choudhury, E. Tuomaala, and K. Doppler, "Enabling lte/wifi coexistence by lte blank subframe allocation," in *Proceedings of IEEE ICC*, 2013.

[4] N. Zhang, S. Zhang, S. Wu, J. Ren, J. Mark, and X. Shen, "Beyond coexistence: traffic steering in lte networks with unlicensed bands," *IEEE Wireless Communications*, vol. 6, pp. 40–46, 23, 2016.

[5] C. Cano and D. J. Leith, "Coexistence of wifi and lte in unlicensed bands: A proportional fair allocation scheme," in *Proceedings of IEEE ICC*, 2015.

[6] N. Zhang, H. Liang, N. Cheng, Y. Tang, J. W. Mark, and X. Shen, "Dynamic spectrum access in multi-channel cognitive radio networks," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 11, pp. 2053–2064, 2014.

[7] J. G. Andrews, S. Buzzi, W. Choi, S. V. Hanly, A. Lozano, A. C. Soong, and J. C. Zhang, "What will 5g be?" *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 6, pp. 1065–1082, 2014.

[8] H. Zhang, C. Jiang, R. Q. Hu, and Y. Qian, "Self-organization in disaster-resilient heterogeneous small cell networks," *IEEE Network*, vol. 30, no. 2, pp. 116–121, 2016.

[9] Z. Zhang, L. Song, Z. Han, and W. Saad, "Coalitional games with overlapping coalitions for interference management in small cell networks," *IEEE Transactions on Wireless Communications*, vol. 13, no. 5, pp. 2659–2669, 2014.

[10] N. Zhang, N. Cheng, A. T. Gamage, K. Zhang, J. Mark, and X. Shen, "Cloud assisted hetnets toward 5g wireless networks," *IEEE Communization Magazine*, vol. 53, no. 6, pp. 59 – 65, 2015.

[11] K. Cohen, A. Leshem, and E. Zehavi, "Game theoretic aspects of the multi-channel aloha protocol in cognitive radio networks," *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 11, pp. 2276–2288, 2013.

[12] L. Lei, D. Yuan, C. Ho, and S. Sun, "Joint optimization of power and channel allocation with non-orthogonal multiple access for 5g cellular systems," in *Proceedings of IEEE GLOBECOM*, 2015.

[13] X. Hu, E. Ngai, H. Zhao, S. Wang, J. Wei, and V. Leung, "A dynamic graph-based scheduling and interference coordination approach in heterogeneous cellular networks," *IEEE Transactions on Vehicular Technology*, 2015, dOI:10.1109/TVT.2015.2435746.

[14] M. Dong, K. Takashi, S. Komei, and Z. Koji, "Quality-of-experience (qoe) in emerging mobile social networks," *IEICE TRANSACTIONS on Information and Systems*, vol. 97, no. 10, pp. 2606–2612, 2014.

[15] L. Wei, R. Q. Hu, Y. Qian, and G. Wu, "Energy efficiency and spectrum efficiency of multihop device-to-device communications underlaying cellular networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 1, pp. 367–380, 2016.

[16] K. Doppler, M. Rinne, C. Wijting, C. B. Ribeiro, and K. Hugl, "Device-to-device communication as an underlay to lte-advanced networks," *IEEE Communications Magazine*, vol. 47, no. 12, pp. 42–49, 2009.

[17] E. Larsson, O. Edfors, F. Tufvesson, and T. Marzetta, "Massive mimo for next generation wireless systems," *IEEE Communications Magazine*, vol. 52, no. 2, pp. 186–195, 2014.

[18] M. Bennis, S. M. Perlaza, P. Blasco, Z. Han, and H. V. Poor, "Self-organization in small cell networks: A reinforcement learning approach," *IEEE transactions on wireless communications*, vol. 12, no. 7, pp. 3202–3212, 2013.

[19] E. Axell, G. Leus, E. G. Larsson, and H. V. Poor, "Spectrum sensing for cognitive radio: State-of-the-art and recent advances," *IEEE Signal Processing Magazine*, vol. 29, pp. 101–116, 2012.

[20] Y. Pei and Y.-C. Liang, "Cooperative spectrum sharing with bidirectional secondary transmissions," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 1, pp. 108–117, 2015.

[21] X. Hao, M. Cheung, V. Wong, and V. Leung, "Hedonic coalition formation game for cooperative spectrum sensing and channel access in cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 11, pp. 3968 – 3979, 2012.

[22] H. Zhang, Y. Xiao, L. X. Cai, D. Niyato, L. Song, and Z. Han, "A hierarchical game approach for multi-operator spectrum sharing in lte unlicensed," in *Proceedings of IEEE GLOBECOM*, 2015.

[23] A. Leshem, E. Zehavi, and Y. Yaffe, "Multichannel opportunistic carrier sensing for stable channel access control in cognitive radio systems," *IEEE Journal on Selected Areas in Communications*, vol. 30, no. 1, pp. 82–95, 2012.

[24] N. Cheng, N. Zhang, N. Lu, X. Shen, and J. W. Mark, "Opportunistic spectrum access for cr-vanets: A game theoretic approach," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 1, pp. 237–251, 2013.

[25] T. Wang and L. Vandendorpe, "Iterative resource allocation for maximizing weighted sum min-rate in downlink cellular ofdma systems," *IEEE Transactions on Signal Processing*, vol. 59, no. 1, pp. 223–234, 2011.

[26] E. Pateromichelakis, M. Shariat, A. Quddus, and R. Tafazolli, "Graph-based multicell scheduling in ofdma-based small cell networks," *IEEE Access*, vol. 2, pp. 897–908, 2014.

[27] L. Liang and G. Feng, "A game-theoretic framework for interference coordination in ofdma relay networks," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 1, pp. 321–332, 2012.

[28] N. G. Mankiw, *Principles of Economics (Mankiw)*. Cengage Learning, 2011.

[29] J. Zheng, Y. Cai, Y. Liu, Y. Xu, B. Duan, and X. Shen, "Optimal power allocation and user scheduling in multicell networks: Base station cooperation using a game-theoretic approach," *IEEE Transactions on Wireless Communications*, vol. 13, no. 12, pp. 6928–6942, 2014.

[30] E. Björnson, N. Jaldén, M. Bengtsson, and B. Ottersten, "Optimality properties, distributed strategies, and measurement-based evaluation of coordinated multicell ofdma transmission," *IEEE Transactions on Signal Processing*, vol. 59, no. 12, pp. 6086–6101, 2011.

[31] Y. Xu, J. Wang, Q. Wu, A. Anpalagan, and Y.-D. Yao, "Opportunistic spectrum access in cognitive radio networks: Global optimization using

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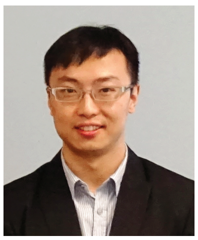
local interaction games," *IEEE Journal of Selected Topics in Signal Processing*, vol. 6, no. 2, pp. 180–194, 2012.

[32] D. Monderer and L. S. Shapley, "Potential games," *Games and economic behavior*, vol. 14, no. 1, pp. 124–143, 1996.

[33] Y. Liu and M. Tao, "Optimal channel and relay assignment in ofdm-based multi-relay multi-pair two-way communication networks," *IEEE Transactions on Communications*, vol. 60, no. 2, pp. 317–321, 2012.

[34] D. B. West *et al.*, *Introduction to graph theory*. Prentice hall Englewood Cliffs, vol. 2, 2001.

[35] S. Zhang, N. Zhang, S. Zhou, J. Gong, Z. Niu, and X. Shen, "Energy-aware traffic offloading for green heterogeneous networks," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 5, pp. 1116 – 1129, 2016.



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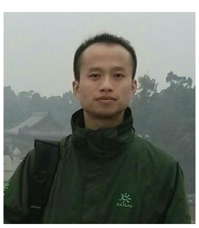

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