

Game Theory based Dynamic Spectrum Allocation for Secondary Users in the Cell Edge of Cognitive Radio Networks

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Abstract

Cognitive Radio (CR) has very promising potential to improve spectrum utilization by allowing unlicensed Secondary Users (SUs) to access the spectrum dynamically without disturbing licensed Primary Users (PUs). Mitigating interference is a fundamental problem in CR scenarios. This is particularly problematic for deploying CR in cellular networks, when users are located at the cell edge, as the inter-cell interference mitigation and frequency reuse are critical requirements for both PUs and SUs. Further cellular networks require higher cell edge performance, then SUs will meet more challenges than PUs. To solve the performance decrease for SUs at the cell edge, a novel Dynamic Spectrum Allocation (DSA) scheme based on Game Theory is proposed in this paper. Full frequency reuse can be realized as well as inter-cell interference mitigated according to SUs' sensing, measurement and interaction in this scheme. A joint power/channel allocation algorithm is proposed to improve both cell-edge user experience and network performance through distributed pricing calculation and exchange based on game theory. Analytical proof is presented and simulation results show that the proposed scheme achieves high efficiency of spectrum usage and improvement of cell edge SUs' performance.

Keywords: Dynamic Spectrum Allocation; Game Theory; Nash Equilibrium; Pricing.

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1. Introduction

Today, spectrum is one of the most valuable natural resource. In order to utilize spectrum fully, Dynamic Spectrum Allocation (DSA) is a promising approach to increase efficiency for wireless networks. The approach has attracted a great deal of attention and has been widely researched [1][2]. A key technology of the approach is cognitive radio (CR) [3][4], which provides unlicensed users capability of sharing the wireless channels with licensed users in an negotiated or opportunistic manner. It is realized by SUs' sensing the "idle" channels. There are varying sensing methods for SUs such as energy detection and matched-filtering sensing. After sensing, the data of channels are used for channel selection by SUs. And then, the SUs decide to grant access or not. However, the same channel could be used by a PU or SU simultaneously due to limited range of detection and frequency reuse. As a result, interferences between PUs and SUs might be occurred. An important interference is the inter-cell interference. In order to mitigate the interference and improve spectrum efficiency, it is necessary to improve the DSA algorithm.

Traditionally, a network-wide spectrum assignment is carried out by a central server. Recently, distributed spectrum allocation approaches have been studied to share spectrum efficiently that is based on solely on local observations. In [5], the research challenges of spectrum management in cognitive radio networks are introduced. In [6][7], game theory approaches are presented to deploy DSA. In [8], Markov models are used for DSA. Graph coloring methods are proposed in [9]. This work mostly focuses on ad hoc scenarios, but seldom refers to cellular networks.

Because of complex channel characteristics and interference in multi-user cellular networks, DSA is more difficult to design as it is constrained by inter-cell interference mitigation considerations and frequency reuse requirements. Also, future cellular networks require a higher number of cell edge users throughput [10]. In order to improve cell edge performance as well as suppress inter-cell interference, dynamic frequency allocation schemes have been proposed, such as Soft Frequency Reuse (SFR) [11] and Fractional Frequency Reuse (FFR) [12]. In these schemes, cell-edge users can only use part of the total frequency bands, thereby reducing the inter-cell interference and improving cell edge data rate. However, it comes at a cost of bandwidth reduction.

1.1 Related works

In this paper, we focus on the scenario where SUs with cognition ability coexist with PUs and SUs share channels in the cell edge, which is shown in Fig. 1. The PUs are licensed to access the cellular network, and SUs continuously sense the channels and exploit spectrum "holes" for their transmissions, then access the network as unlicensed users.

There are some previous work address here. The reference [13] assumed that SUs' transmissions do not interfere with each other, i.e., only one SU can operate over a given channel in a given neighborhood. Consequently, there is no spectrum sharing among SUs. Such schemes limit the number of access users, especially when the number of channels is small. Makki and Eriksson introduced the an interference indicator signal, which can get further potential benefits for data transmission of SUs. The ergodic achievable rates of CR based spectrum sharing networks are also researched. And this paper didn't implement the standard inter-cell interference avoiding methods, which proposed that the SU's activity is not restricted within the PU's inactive periods [14]. The reference [15-16] researched on the cognitive radio networks with Relay scenario and cooperative communication techniques

implemented scenario separately. The spectrum sharing performances are evaluated with different service types. But the interferences for SUs at the cell edge are not involved.

Considering co-channel scenarios in cell edge, we allow multiple SUs in adjacent cell edges to share a particular channel in our work to improve frequency utilization. After sensing a spectrum opportunity, SUs will measure the signal-to-interference plus noise ratio (SINR) and then determine whether they are cell edge users according to predefined threshold. If SUs are cell edge users, they need to share channels with other cell edge SUs using the same channels. Interference is measured and interference information is exchanged to mitigate inter-cell interference and improve spectrum utilization.

1.2 Contributions

In this article, we propose a game theory based DSA scheme to formulate the interactions and achievable utilities of cell edge SUs. The main contributions of this article are summarized as follows.

- 1) The proposed utility function is defined to measure the reward SUs received from the network. SUs on the edge of cells cooperatively and competitively share the channels to maximize their own utilities. A user-dependent pricing function is presented and SUs exchange their pricings to indicate the “cost” of relative interferences.
- 2) We also propose a price-based iterative algorithm, in which we derive the user-dependent water filling levels according to the SU’s pricings to achieve locally optimal Nash Equilibrium (NE) and mitigate interference after iterations. Such a pricing function can be determined by allowing each SU to cooperatively acquire its neighborhood information via signaling exchanges with a small group of neighborhood SUs.
- 3) The SUs-to-SUs and SUs-to-PU’s interference are treated respectively through setting corresponding protection factors to further reduce SUs-to-PU’s interference.

Based on the analytical proof and simulation results, the proposed joint power/channel allocation algorithm can effectively improve both cell-edge user experiences and network performances.

The remainder of the paper is organized as follows: the system model is described in section 2. In section 3, the improved DSA scheme is formulated and analyzed based on the game theory. Performance evaluation results are provided in section 4. Section 5 concludes the paper.

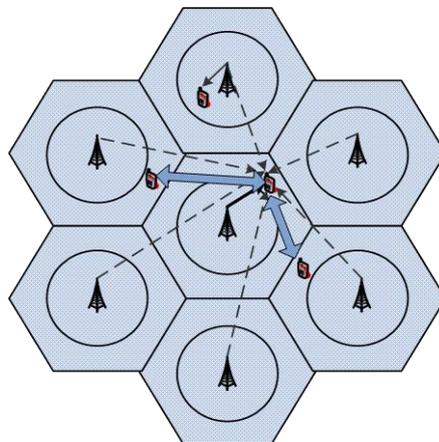


Fig. 1. System scenarios in Cognitive Radio Networks

2. System Model

We assume that a cellular network consists of PUs and SUs. PUs are licensed users, who have priority to access the network. SUs are unlicensed users and work on unutilized spectrum temporally.

In this paper, the total spectrum contains K orthogonal frequency sub-channels, which are shared by all the users, including the PUs and SUs. In other words, one sub-channel cannot be occupied by different users at the same time in the same cell. But for the multi-cell environments, the adjacent cell users could be allocated with the same sub-channels, which may cause the resource collisions and inter-cell interferences. $\mathcal{N}=\{1,2,\dots,N\}$, $\mathcal{K}=\{1,2,\dots,K\}$ and $\mathcal{B}=\{B_1,B_2,\dots,B_N\}$ denote the sets of SUs, channels and Base Stations (BS), respectively. The main differences of the obtained information for the PUs and SUs come from that PUs have the right for licensed spectrum access and also the channel state information, interference information from neighbor cells on the channels they allocated. The SUs need to carry on the spectrum sensing for available spectrums, which will leads to information loss of above signaling exchanges in the actual network.

For simplify the analytical scenario, we assume that each SU has the ability to sense the spectrum hole exactly and measure interference over all channels. $I_{i,k}^{Total}$ denotes the total noise-plus-interference level SU i measures over channel k . This value includes the PU-to-SU interference, the SU-to-SU interference and the thermal noise. $\mathbf{I}_i \square [I_{i,1}^{Total}, I_{i,2}^{Total}, \dots, I_{i,K}^{Total}]$, which is used by SU i to perform channel selection, power control and rate allocation.

We assume that the interferences between cell center SUs can be ignored and no interaction is needed. Because when the users located in the cell center, the interferences actually can be alleviated by two ways, which are the transmission power control/allocation policy and the relatively further distances from adjacent base stations. According to the definition of ‘‘cell edge’’ by the 3GPP, the 5% tile cell throughput CDF will be the cell edge user performance. In this article, the differences of the user received signals strength from the neighboring base stations will be the criteria of cell edge and cell center. If the differences of the user received signal strength are big than the threshold, the user will be regarded as the cell center. And vice versa, the users are regarded as the cell edge users. The criteria are also associated with the frequency reuse strategy.

The transmission power vector of an SU i in B_i over all channels is denoted as $\mathbf{P}_i^{B_i} = [P_{i,1}^{B_i}, P_{i,2}^{B_i}, \dots, P_{i,K}^{B_i}]$, where $P_{i,k}^{B_i}$ is the transmission power of SU i over channel k . If channel k belongs to SU i , $P_{i,k}^{B_i} > 0$; otherwise $P_{i,k}^{B_i} = 0$.

To ensure available spectrum sharing and consider practical deployment, we impose the following constraints:

- 1) Maximum transmission power constraints: The total transmission power of an SU over all the selected channels should not exceed P_{\max} , i.e., $\sum_{k \in \mathcal{F}_i} P_{i,k}^{B_i} \leq P_{\max}, \forall i \in \mathcal{N}$, where \mathcal{F}_i denotes the set of utilized channels of SU i . Here, we assume that the total power constraint is the same for all users. It is easy to extend the treatment to the case where P_{\max} is user-dependent.

- 2) Power mask constraints: The transmission power of SU i on channel k should fulfill $P_{i,k}^{B_i} \leq P_{mask}^k$, where P_{mask}^k is the power mask on channel k . The power mask is often specified by a radio management agent, e.g., the Federal Communications Commission (FCC). However, because the number of SUs that share a given channel varies in time and space, it is impractical to define an independent power mask. We use the vector $\mathbf{P}_{mask} = [P_{mask}^1, P_{mask}^2, \dots, P_{mask}^K]$ to denote the power mask on all channels.

SUs are assumed to be either static or be moving slowly compared to the convergence time of the resource assignment algorithm. In addition, SUs are homogeneous, meaning that they follow the same operation rules and have the same system constraints.

3. DSA Scheme Simulation

In a CR network, each SU is interested in maximizing its own achievable rate. Such self-serving behavior can be modeled using game theory. Game theory analyzes the interactions of players in decision-making processes. Based on the aforementioned system model, a game can be formulated as follows: The players in this game are the SUs $\mathcal{N} = \{1, 2, \dots, N\}$, the strategy of each player is the transmission power vector, i.e., the strategy of SU i is denoted by $\mathbf{P}_i^{B_i} = [P_{i,1}^{B_i}, P_{i,2}^{B_i}, \dots, P_{i,K}^{B_i}]$. The payoff of SU i is the utility function $U_i^{B_i}$, which depends on the strategies of all players. The solution of the game is the NE.

3.1 Utility Function

In this game, the utility function of SU i can be defined as the reward received by this SU from the network. This reward should depend on this SU's action $\mathbf{P}_i^{B_i}$ and the set of all other SUs' action $\mathbf{P}_{-i}^{B_{-i}}$, where $\mathbf{P}_{-i}^{B_{-i}} \square [P_1^{B_1}, \dots, P_{i-1}^{B_{i-1}}, P_{i+1}^{B_{i+1}}, \dots, P_N^{B_N}]^T$. The basic principle of defining a utility function is to characterize and resolve practical problems. A natural selection of the utility function of an SU i is its transmission rate, which is taken as the channel capacity. SUs select their transmission powers to maximize their own utility functions, and under certain conditions, they eventually reach an NE after several iterations. Because of the non-cooperative nature of the game, each SU behaves selfishly. Thus the resulting NE may be far from the Pareto optimum [17]. To drive the NE towards the Pareto optimum boundary, we exploit a pricing function to coerce SUs into working in a cooperative manner. The utility function is shown as follows:

$$u_i^{B_i}(P_{i,k}^{B_i}) = \log_2 \left(1 + \frac{P_{i,k}^{B_i} H_{i,k}^{B_i}}{\sum_{B_j \in \mathcal{B}, j \in B_j} P_{j,k}^{B_j} H_{j,k}^{B_j} + \eta I_k^{PR} + N_{i,k}} \right) - P_{i,k}^{B_i} \mathcal{P}_{i,k}^{B_i} \tag{1}$$

Where $H_{i,k}^{B_i}$ denotes the channel gain between SU i and BS B_i over channel k , $N_{i,k}$ is the background noise over channel k , I_k^{PR} denotes the PU-to-SU interference, while η is a protection factor, given as:

$$\eta = \begin{cases} 1 & B_j \notin B_i^{Adjacent} \\ \eta \geq 1 & else \end{cases} \quad (2)$$

It has the implication that the PU-to-SU interference and SU-to-PU interference are relevant (e.g., in a Time Division Duplex (TDD) system, they can be considered the same), η gives the PU priority to avoid being severely interfered with by SUs, where $B_i^{Adjacent}$ is B_i 's adjacent BSs. $\mathcal{P}_{i,k}^{B_i}$ denotes the pricing factor of an SU i on channel k . In this paper, we define user-dependent pricing corresponding to different interference degrees and driving SUs to converge to efficient NE. In addition, this utility function is specialized for the uplink, When used in the downlink the interfering SUs' channel gain $H_{j,k}^{B_i}$ should be transformed to $H_{i,k}^{B_j}$, which denotes the channel gain between interference BS to SU i . The same is with other terms in the discussion.

Considering the priority of different SUs may be different, we define a weighted sum of all utilities for all SUs, shown as follows:

$$\max \sum_{i=1}^N \omega_i U_i^{B_i}(\mathbf{P}_i^{B_i}, \mathbf{P}_{-i}^{B_i}) = \max \sum_{i=1}^N \omega_i \sum_{k=1}^K u_i^{B_i}(P_{i,k}^{B_i}) \quad (3)$$

s.t.

$$\begin{aligned} P_{i,k}^{B_i} &\geq 0, \forall i \in \mathbf{N} \text{ and } k \in \mathbf{K} \\ \sum_{k \in \mathbb{F}_i} P_{i,k}^{B_i} &\leq P_{\max}, \forall i \in \mathbf{N} \text{ and } k \in \mathbf{K} \\ P_{i,k}^{B_i} &\leq P_{\max}^k, \forall i \in \mathbf{N} \text{ and } k \in \mathbf{K} \end{aligned}$$

where ω_i denotes the weight assigned to SU i , which can be explained in different ways (e.g., priority of SU i). Based on the above utility definition and optimization objectives with corresponding constraints, the QoS of SUs will be guaranteed.

3.2 Pricing function

Pricing is an idea originating from economic, and always used to improve the efficiency of a NE [18] as well as mitigate interference [19]. Although an "optimal" pricing function may exist that allows the NE to converge to a Pareto-optimum solution, the search for such a pricing function generally requires global information and is difficult to implement. In this paper, we propose a user-dependent pricing function, which requires neighborhood interference information. Through pricing calculation and interaction, it can improve the NE and suppress interference among SUs.

We derive a linear pricing function by introducing the Lagrangian function for (3) satisfying Karush-Kuhn-Tucker (KKT) necessary conditions [6][19]. The pricing factor of SU i is shown as follows:

$$\mathcal{P}_{i,k}^{B_i} = \frac{1}{\omega_i} \sum_{B_j \in B_i^{\text{Adjacent}}, j \in B_j} \omega_j \frac{P_{j,k}^{B_j} H_{j,k}^{B_j} H_{i,k}^{B_j}}{I_{j,k}^{\text{Total}} (I_{j,k}^{\text{Total}} + P_{j,k}^{B_j} H_{j,k}^{B_j})} \quad (4)$$

From the above pricing function, we can conclude that a higher pricing factor $\mathcal{P}_{i,k}^{B_i}$ will prevent an SU i from using a large transmission power on channel k . In order to get an optimal pricing function, an SU i should obtain the transmission power $P_{j,k}^{B_j}$, the measured interference plus noise $I_{j,k}^{\text{Total}}$ and the channel gain $H_{j,k}^{B_j}$ of its neighbor j on channel k , so cooperation is required between SUs. The information can be exchanged through control signaling in a broadcast.

3.3 Game analysis and algorithm

From the aforementioned propositions, the players, strategy and payoffs are all specifically defined. By definition, the NE of a game is a strategy profile with the property that no player can increase his payoff by choosing a different action, given other players' actions. In this case, the NE is obtained by using the best response function which is the most advantageous strategy of player given others' strategies. The best response function of SU i is given as:

$$B_i(\mathbf{P}_{-i}) = \arg \max_{P_i^{B_i}} U_i^{B_i}(\mathbf{P}_i^{B_i}, \mathbf{P}_{-i}^{B_{-i}}) \quad (5)$$

The set $\mathbf{P}^* = [P_1^*, P_2^*, \dots, P_N^*]$ denotes the NE of this game on power if and only if $\mathbf{P}_i^* = \mathcal{B}_i(\mathbf{P}_{-i}^*)$, where \mathbf{P}_{-i}^* denotes the set of the best response of player j for $j \neq i$.

In view of the above, it is indicative that this is a strictly convex optimization problem with bounds on individual variables. The optimal solution $\mathbf{P}^* = [P_1^*, P_2^*, \dots, P_N^*]$ can be derived by the method of Lagrange multipliers, for solving the problem of conditional extreme values. Specifically, without considering the priority of different SUs, this sequential algorithm is described as follows:

$$\text{maximize } \{P_{1,k}^{B_i}, P_{2,k}^{B_i}, \dots, P_{N,k}^{B_i}\}$$

$$u_i^{B_i}(P_{i,k}^{B_i}) = \log_2 \left(1 + \frac{P_{i,k}^{B_i} H_{i,k}^{B_i}}{\sum_{B_j \in \mathcal{B}, j \in B_j} P_{j,k}^{B_j} H_{j,k}^{B_j} + \eta I_k^{\text{PR}} + N_{i,k}} \right) - P_{i,k}^{B_i} \mathcal{P}_{i,k}^{B_i}$$

s.t.

$$P_{i,k}^{B_i} \geq 0, \forall i \in \mathcal{N} \text{ and } k \in \mathcal{K}$$

$$\begin{aligned} \sum_{k \in \mathbb{F}_i} P_{i,k}^{B_i} &\leq P_{\max}, \forall i \in \mathbb{N} \text{ and } k \in \mathbb{K} \\ P_{i,k}^{B_i} &\leq P_{mask}^k, \forall i \in \mathbb{N} \text{ and } k \in \mathbb{K} \end{aligned} \quad (6)$$

If there's a solution to the game, it would be one that will achieve the NE. The following proposition shows that an NE solution always exists for the above game.

Proposition: For any given and values, there is at least one NE solution for (6).

Proof: The game in our setup can be shown to be a concave game if the following two properties are satisfied:

- 1) the action space is a closed and bounded convex set;
- 2) the utility function is concave over its strategy set.

It is straightforward to show that the two properties are satisfied by the game. Because a concave game always admits at least one NE [20], the proposition follows immediately.

Thus, (6) is a convex problem and it can be solved by the way of Lagrange multipliers. Then the Lagrangian of (6) is given by

$$L(\vec{x}, \vec{y}, z, \vec{\gamma}) = u_i^{B_i}(x_i) - \sum y_i x_i + z(P_{\max} - \sum_{k \in \mathbb{F}_i} x_i) + \sum \gamma_i (P_{mask}^k - x_i) \quad (7)$$

where $x_i = P_{i,k}^{B_i}$. Accordingly, $\vec{y} = (y_1, \dots, y_N)$, z and $\vec{\gamma} = (\gamma_1, \dots, \gamma_N)$ are the Lagrange multipliers, y_i and γ_i are non-negative real numbers, and z is real number.

In order to solve the optimization problem and obtain the NE, we have to solve the following set of equations $\partial L / \partial x_i$ for all SUs mathematically. This is depicted as follows:

$$\frac{\partial L}{\partial x_i} = 0, \quad x_i = P_{i,k}^{B_i}, i = 1, 2, \dots, N \quad (8)$$

Substituting Eq. (7) into (8), we get

$$\begin{aligned} \frac{\partial L}{\partial x_i} &= \frac{\partial u_i^{B_i}(x_i)}{\partial x_i} - \frac{\partial(\sum y_i x_i)}{\partial x_i} + \frac{\partial(z(P_{\max} - \sum_{k \in \mathbb{F}_i} x_i))}{\partial x_i} \\ &\quad + \frac{\partial \sum \gamma_i (P_{mask}^k - x_i)}{\partial x_i} \\ &= \frac{\partial u_i^{B_i}(x_i)}{\partial x_i} - y_i - z - \gamma_i \\ &= 0 \end{aligned} \quad (9)$$

In addition, for the optimum solution of $u_i^{B_i}(x_i)$, we have to determine the value of those Lagrange multipliers. They are depicted as follows:

$$\frac{\partial L}{\partial y_i} = 0, \quad y_i = y_1, \dots, y_N \quad (10)$$

$$\frac{\partial L}{\partial \beta_i} = 0, \quad \beta_i = \beta_1, \dots, \beta_N \quad (11)$$

$$\frac{\partial L}{\partial z} = 0 \quad (12)$$

Using Eqs. (7), (10), (11) and (12), we get the value of $\bar{x} = (x_1, \dots, x_N)$, $\bar{y} = (y_1, \dots, y_N)$ and z . Substituting Eq. (1) and these values into Eq. (9), then

$$x_i^* = \frac{H_{i,k}^{B_i}}{\ln 2(\mathcal{P}_{i,k}^{B_i} + y_i + z + \gamma_i)} - \left(\sum_{B_j \in \mathcal{B}, j \in B_j} P_{j,k}^{B_j} H_{j,k}^{B_j} + \eta I_k^{PR} + N_{i,k} \right) \quad (13)$$

where $x_i = P_{i,k}^{B_i}$, and x_i^* is just the NE of the game.

Furthermore, substituting Eq. (13) into (1), we get the maximum value of $u_i^{B_i}(P_{i,k}^{B_i})$ for SU i on the channel k , which is the optimum solution of the problem. That is,

$$\max u_i^{B_i}(P_{i,k}^{B_i}) = \log_2 \left(1 + \frac{x_i^* H_{i,k}^{B_i}}{\sum_{B_j \in \mathcal{B}, j \in B_j} P_{j,k}^{B_j} H_{j,k}^{B_j} + \eta I_k^{PR} + N_{i,k}} \right) - \mathcal{P}_{i,k}^{B_i} x_i^* \quad (14)$$

Finally, substituting Eq. (14) into (5), we arrive at the best response function of SU i on the channel k , referring to Eq. (15).

$$B_i(\mathbf{P}_{-i}) = \arg \max_{P_{i,k}^{B_i}} u_i^{B_i}(P_{i,k}^{B_i}) = \arg \left\{ \log_2 \left(1 + \frac{x_i^* H_{i,k}^{B_i}}{\sum_{B_j \in \mathcal{B}, j \in B_j} P_{j,k}^{B_j} H_{j,k}^{B_j} + \eta I_k^{PR} + N_{i,k}} \right) - \mathcal{P}_{i,k}^{B_i} x_i^* \right\} \quad (15)$$

According to real scenarios, by treating other SUs' transmission as interference, the best response of SU i on channel k is given as follows:

$$B_i(\mathbf{P}_{-i,k}) = \left[\frac{1}{\lambda + P_{i,k}^{B_i}} - \frac{I_{i,k}^{Total}}{H_{i,k}^{B_i}} \right]_0^{P_{i,k}^{mask}} \quad (16)$$

where $[x]_a^b$, with $b > a$, denotes the Euclidean projection of x in the interval $[a, b]$, i.e., $[x]_a^b = a$ if $x < a$, $[x]_a^b = x$ if $a < x < b$, and $[x]_a^b = b$ if $x > b$. λ denotes the fixed water level, which is constrained by the total transmission power. $\mathcal{P}_{i,k}^{B_i}$ contributes a user-dependent water

level, which is ultimately determined by the interference SU i and its neighbors measured together. This user-dependent variable water level improves the efficiency of power allocation and spectrum utilization.

We exploit a classical iterative algorithm to reach the NE. It can be generalized as follows:

Algorithm

- 0: Initialize $P_{i,k}^{B_i} = 0$, for all SUs on all channels.
 - Initialize iterative count $j = 1$
 - 1: Repeat
 - 2: for $i = 1$ to N SUs do
 - 3: for $k = 1$ to K channels do
 - 4: Estimate the total interference plus noise level $I_{i,k}^{Total}$ and channel gain $H_{i,k}^{B_i}$
 - 5: Calculate pricing factor $\mathcal{P}_{i,k}^{B_i}$
 - 6: end for
 - 7: $\mathbf{P}_i^{B_i(j)} = \mathcal{S}_i(\mathbf{P}_1^{B_1(j)}, \dots, \mathbf{P}_{i-1}^{B_{i-1}(j)}, \mathbf{P}_{i+1}^{B_{i+1}(j-1)}, \dots, \mathbf{P}_N^{B_N(j-1)})$
 - 8: Transmission on selected channels
 - 9: end for
 - 10: $j = j + 1$
 - 11: if $j > Loop_{max}$ or $(|\mathbf{P}_i^{B_i(j)} - \mathbf{P}_i^{B_i(j-1)}| / \mathbf{P}_i^{B_i(j-1)}) \leq \varepsilon$
 - 12: end repeat
-

The convergence condition can be predefined as the maximum circle time $Loop_{max}$ or the terminating criteria $(|\mathbf{P}_i^{B_i(j)} - \mathbf{P}_i^{B_i(j-1)}| / \mathbf{P}_i^{B_i(j-1)}) \leq \varepsilon$, where ε is a small value (e.g., 5%).

4. Performance Evaluation

4.1 Parameter Setting

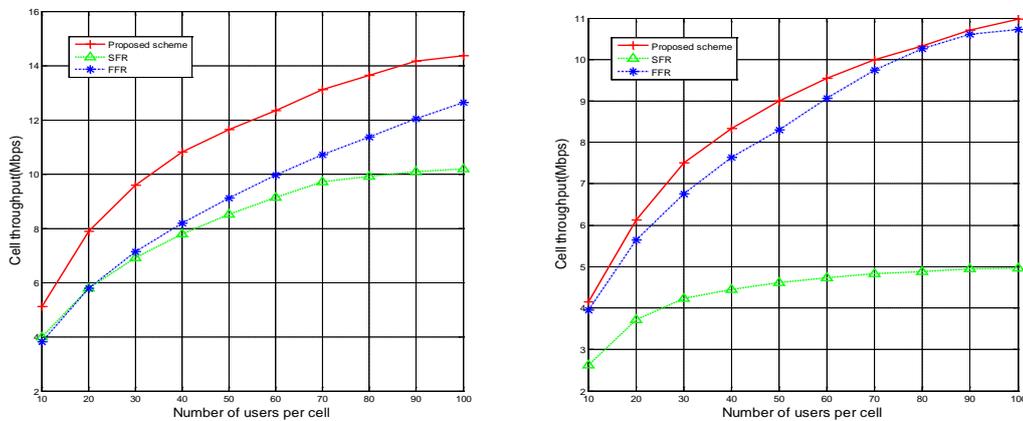
In this section, we evaluate the performance of the proposed DSA scheme. We simulate this scheme in a multi-user cellular network with the specific parameter settings list as **Table 1**. There are 27 cells depolyed with Hexagonal grid. The parameters are in line with LTE requirement. Path loss and shadowing are both taken into account. Because the time scale of resource allocation is longer than that of fast fading, so it is reasonable to average the effect of fast fading. The interference model is mainly based on the LTE multi-cell scenario with homogeneous network deployment. The schemes compared are the SFR and FFR schemes introduced in the introduction and related works.

Table 1. Simulation Parameters and Setting

Parameter	Value
Carrier frequency	2GHz
System bandwidth	10MHz
Cellular Layout	Hexagonal grid, 27 cells
Cell radius	1000m
Distance-dependent path loss	$L=128.1 + 37.6\log_{10}(R)$, R in km
Lognormal Shadowing	0 mean, 8dB standard deviation
BS transmit power	46dBm
Link Adaptation	Perfect
Target BER	10^{-6}
Total sub-carriers	600
Sub-carrier spacing	15 kHz
White noise power density	-174 dBm/Hz

4.2 Simulation Results

The simulation results are shown with the Fig. 2 to Fig. 5. Fig. 2 shows that the cell throughput of the DSA scheme is always larger than SFR and FFR schemes with different Frequency Reuse Factor (FRF). That is because the full frequency reuse leads to a more accessible frequency in cell edge under interference and total power constraints. Fig. 2 also shows that the improvement of a DSA scheme is relatively large when the user number is moderate, while it is relatively small when the user number is very small or large. The reason is that the cell-edge accessible frequency is sufficient with a small user number in SFR and FFR schemes, producing slight interference and leading to a high transmission rate. While, when the user number is large, the interference is severe, limiting the performance of the DSA scheme. This takes into account the mutual interference of SUs as pricings. Comparing these following simulation results, it's obviously that the cell throughput decreases along with FRF. It results from the higher FRF, and means more available frequency in the cell center, which has a better channel quality and can produce higher throughput.



(a) FRF=8/9

(b) FRF=1/2

Fig. 2. Cell Throughput with different FRF

Fig. 3 shows that the cell-edge average transmission rate of a DSA scheme is always better than SFR and FFR schemes with different FRF, because of the full frequency reuse and the interference information interactions of SUs in cell edge. **Fig. 3** also shows that the improvement decreases as the user number increases, due to the interference worsening with more access users. Obviously, the average data bits increase as FRF decreases. Because smaller FRF leads to more available frequency in the cell edge.

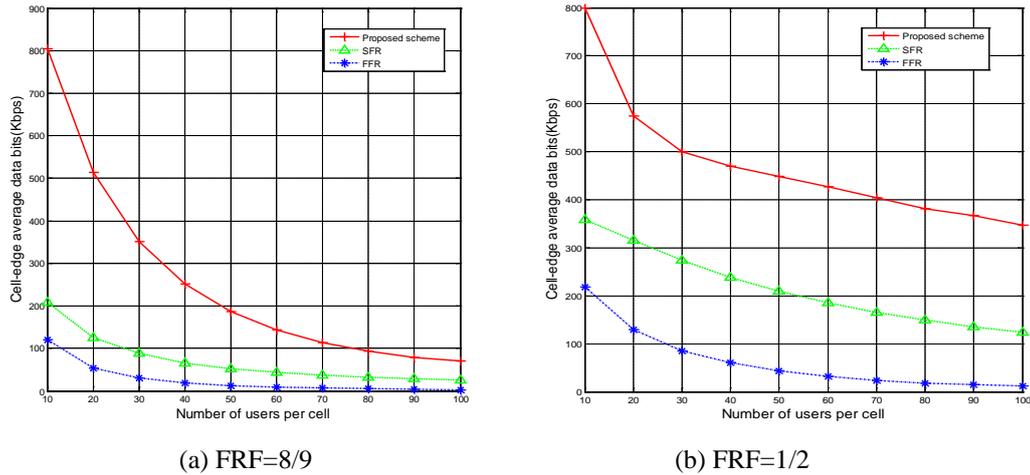


Fig. 3. Cell-edge Average transmission rate with different FRF

Fig. 4 shows the CDF curves of users' throughput of the three schemes with FRF=8/9. We can see that the DSA scheme is always better than SFR and FFR schemes, because the object of the proposed DSA scheme is to maximize the throughput of each SU in a cell edge. With the enhancement of the performance of the edge users, the whole network is encouraged.

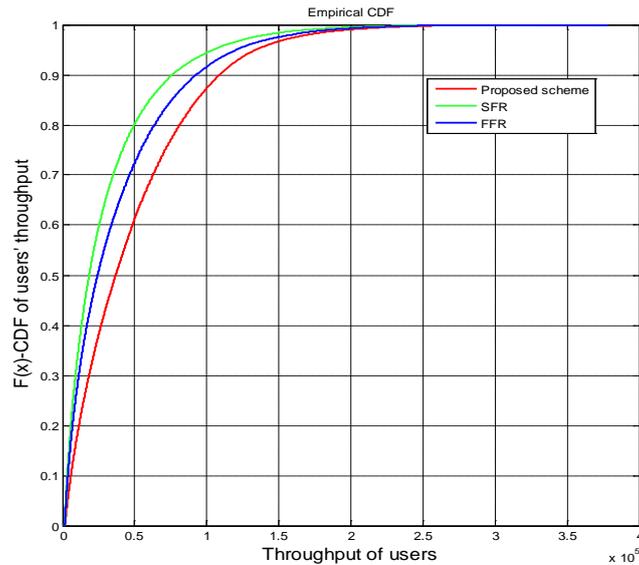


Fig. 4. CDF of users' throughput with FRF=8/9

Fig. 5 shows the outage of users of a DSA scheme is always larger than SFR and FFR schemes with $FRF=8/9$, because the object of the DSA scheme is to maximize the utility of SUs. By the way of user-dependent water filling, users with better performance will be allocated higher power. As a result, the outage is higher than SFR and FFR schemes. **Fig. 5** also shows that the outage of a DSA scheme increases at first but then decreases. This is consequent to the feature of the water filling algorithm, which is stated above.

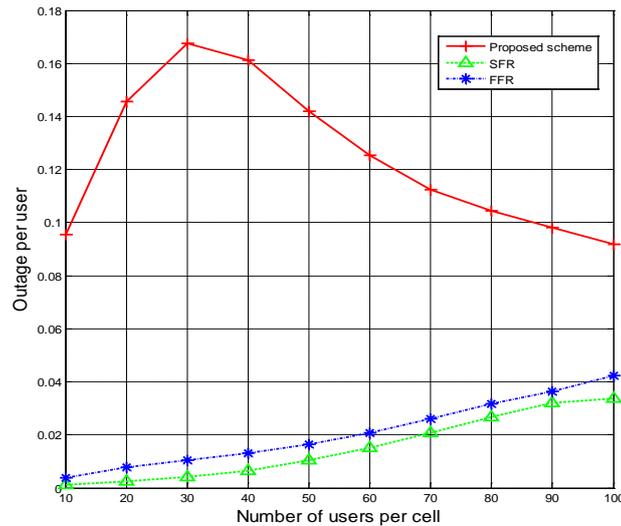


Fig. 5. Outage of users with $FRF=8/9$

5. Conclusion

In this paper, a game theory based DSA scheme specialized for cellular network cell edge SUs is proposed, in which full frequency reuse is realized and inter-cell interference is mitigated according to SUs' sensing, measurement and interaction. We define a utility function to maximize the transmission rate under the interference and total power constraints. A user-dependent pricing function is designed. We also propose a joint power/channel allocation algorithm that improves cell-edge user experience and network performance through setting user-dependent water filling levels relevant to user-dependent pricings. We compare it with SFR and FFR schemes. Simulation results show that the proposed scheme outperforms existing SFR and FFR schemes on cell throughput and cell-edge average data bits. The DSA scheme obviously improves cell-edge performance, spectrum utilization and spectrum efficiency.

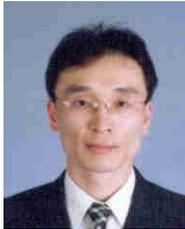
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