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Resource Allocation for Cognitive Small Cell Networks: A Cooperative Bargaining Game Theoretic Approach

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Abstract—Cognitive small cell networks have been envisioned as a promising technique to meet the exponentially increasing mobile traffic demand. Recently, many technological issues pertaining to cognitive small cell networks have been studied, including resource allocation and interference mitigation, but most studies assume non-cooperative schemes or perfect channel state information (CSI). Different from the existing works, we investigate the joint uplink subchannel and power allocation problem in cognitive small cells using cooperative Nash bargaining game theory, where the cross-tier interference mitigation, minimum outage probability requirement, imperfect CSI and fairness in terms of minimum rate requirement are considered. A unified analytical framework is proposed for the optimization problem, where the near optimal cooperative bargaining resource allocation strategy is derived based on Lagrangian dual decomposition by introducing time-sharing variables and recalling the Lambert-W function. The existence, uniqueness, and fairness of the solution to this game model are proved. A cooperative Nash bargaining resource allocation algorithm is developed, and is shown to converge to a Pareto-optimal equilibrium for the cooperative game. Simulation results are provided to verify the effectiveness of the proposed cooperative game algorithm for efficient and fair resource allocation in cognitive small cell networks.

Index Terms—Cognitive small cell, cooperative game, fairness, Nash bargaining, OFDMA, power control, resource allocation.

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I. INTRODUCTION

Driven by the rapid development of wireless terminal equipments and wide usage of bandwidth-hungry applications of mobile Internet, wireless data traffic is increasing in an exponential manner. Traditional deployment of macrocell base stations (MBS) suffers from poor quality of service (QoS) and coverage for indoor and cell edge users, especially for potential use of high carrier frequency in 5G [1]. Therefore, off-loading the traffic from primary macrocells, improving the capacity and enhancing the coverage of indoor and cell edge scenarios are critically needed. In this context, deployment of low-power, low-cost small access points (e.g., microcell, picocell and femtocell) becomes a promising technique [2]. Small cells can significantly improve the efficiency of frequency reuse and spectrum sharing. Heterogeneous networks, comprised of small base stations (SBS) and MBSs, is also an important candidate technique for 5G mobile communications. Compared with the orthogonal deployment, spectrum sharing between macrocells and small cells is more attractive due to easy implementation and more efficient utilization of spectrum. In spectrum sharing, the macrocells can be considered as the primary network and small cells can be regarded as the secondary cognitive network [3]. However, cross-tier interference could be severe in spectrum sharing cognitive heterogeneous small cell networks. Therefore, the benefits of cognitive small cell deployments come with a number of fundamental challenges, which include resource management and cross-tier interference mitigation.

Game theory based resource allocation and interference mitigation in small cells have been widely investigated in existing works [4]–[11]. In [4], non-cooperative power allocation with signal-to-interference-plus-noise ratio (SINR) adaptation is used to alleviate the interference from femtocells to macrocells, while in [5] Stackelberg game based power control is formulated to maximize femtocells' capacity under a cross-tier interference constraint. In [6], a non-cooperative power and subchannel allocation scheme for co-channel deployed femtocells is proposed, together with macrocell user transmission protection. In [7], the authors consider a capacity maximizing power allocation based on a Stackelberg game, where the MBS is the leader and the FBSs are assumed as followers. Subchannel allocation in femtocells is formulated into a correlated equilibrium game-theoretic approach to minimize their interference to the primary MBS in [8].

A unique Nash equilibrium (NE) is achieved and a hybrid access protocol is designed for the Stackelberg game in [10]. A non-cooperative game based power control algorithm is proposed in [11] together with a base station association scheme for heterogeneous networks. In our previous work [12] [13], resource scheduling (based on uniform pricing and differential pricing game) and power control were proposed for small cell networks.

Moreover, game theory based energy efficient resource allocation has also been investigated for small cells. In [9], the energy efficiency aspect of spectrum sharing and power allocation was studied using a Stackelberg game in heterogeneous cognitive radio networks with femtocells. While in [14], NE of a power adaptation game was derived to reduce power consumption and an admission control algorithm was proposed. However, most of the aforementioned resource allocation algorithms are based on non-cooperative game, where the NEs are not always efficient, while cooperative bargaining game modeling [15]–[18] is more suitable for resource allocation in small cell networks. Moreover, most of the existing works do not consider the fairness for users in small cells.

Although some works have been done for fair resource allocation in cognitive radio [20] and femtocell networks [19], these papers mainly focus on the resource allocation with the assumption of perfect channel state information (CSI). However, in practice, it is difficult for cognitive small cell users to have perfect knowledge of a dynamic radio environment due to hardware limitations, short sensing durations and network connectivity issues in cognitive small cell networks. To the best of our knowledge, interference-aware resource allocation for small cell networks considering fairness, imperfect CSI and outage limitations has not been studied in previous works.

In this paper, we investigate the joint subchannel scheduling and power allocation problem for orthogonal frequency division multiple access (OFDMA) cognitive small cell networks based on a cooperative bargaining game model with consideration of fairness for users in each small cell, cross-tier interference limitation, QoS in terms of outage constraint, imperfect CSI and maximum power constraints. The main contributions of this paper are summarized as follows.

- We formulate the uplink subchannel and power allocation problem in cognitive small cells as a cooperative Nash bargaining game, where a cross-tier interference temperature limit is imposed to protect the primary macrocell, a minimum outage probability requirement is employed to provide reliable transmission for cognitive small cell users, a minimum rate requirement is considered to guarantee fairness for users in each small cell, and imperfect CSI is considered.
- We present a unified analytical framework for the optimization problem in cognitive small cell networks, where the near optimal cooperative bargaining resource allocation strategy is derived by introducing time-sharing variables and the Lambert-W function. The existence, uniqueness, and fairness of the solution to this game are proved analytically. Accordingly, a cooperative Nash bargaining resource allocation algorithm is developed,

and is shown to converge to a Pareto-optimal equilibrium for the cooperative game.

- Small cells are enabled with cognitive capabilities, thus the spectrum sharing primary macrocell can be protected by cross-tier interference temperature. Moreover, imperfect CSI results in outage in the small cells. In our proposed joint power and subchannel allocation scheme, the achievable sum rate is maximized subject to not only the minimum data rate but also an acceptable outage probability in the cognitive small cells.
- The proposed algorithm is evaluated by extensive simulations, which show that the proposed cooperative bargaining resource allocation algorithm outperforms the existing centralized maximal rate (MR) approach, and round-robin (RR) fairness, giving a good trade-off between throughput and fairness.

The rest of the paper is organized as follows. Section II presents the system model and the problem formulation. Section III provides basics for the Nash bargaining solution (NBS) of cooperative game theory and the utility design of the cooperative game. Section IV provides the solutions and algorithm implementation of the cooperative bargaining game in small cell networks, while in Section V, performance of the proposed algorithms is evaluated by simulations. Finally, Section VI concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

As shown in Fig. 1, we consider an OFDMA cognitive small cell network where K co-channel cognitive small base stations (CSBSs) are overlaid on a primary macrocell. We focus on resource allocation in the uplink of cognitive small cells. Let M denotes the numbers of active primary macro users in the macrocell. Each small cell contains the **same** F number of users. The OFDMA system has a bandwidth of B , which is divided into N subchannels. The channel fading of each subcarrier is assumed the same within a subchannel, but may vary across different subchannels. We denote $g_{k,i,n}^{MS}$ and $g_{k,i,n}^S$ as the channel power gains on subchannel n from cognitive small cell user i in cognitive small cell k to the primary MBS and CSBS k , respectively, where $k \in \{1, 2, \dots, K\}$, $i \in \{1, 2, \dots, F\}$, $n \in \{1, 2, \dots, N\}$; denote $g_{k,j,n}^{MS}$ as the channel power gain on subchannel n from user j ($j \in \{1, 2, \dots, M\}$) in the macrocell to CSBS k ; denote $p_{k,i,n}^S$ and $p_{j,n}^M$ as cognitive user i 's transmit power on subchannel n in cognitive small cell k and primary macro user j 's power on subchannel n , and $\mathbf{P} = [p_{k,i,n}^S]_{K \times F \times N}$ is the power allocation matrix of the K cognitive small cells. Denote $\mathbf{A} = [a_{k,i,n}]_{K \times F \times N}$ as the subchannel allocation matrix, where $a_{k,i,n} = 1$ means that subchannel n is assigned to cognitive user i in cognitive cell k , and $a_{k,i,n} = 0$ otherwise.

Then, the received SINR at the k^{th} CSBS for cognitive small cell user i occupying the n^{th} subchannel is given by,

$$\gamma_{k,i,n}^S = \frac{p_{k,i,n}^S g_{k,i,n}^S}{p_{j,n}^M g_{k,j,n}^{MS} + \sigma^2} \quad (1)$$

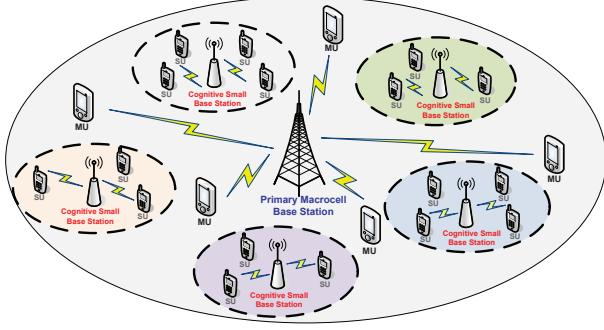


Fig. 1. System model of cognitive heterogeneous small cell networks.

where $p_{j,n}^M g_{k,j,n}^{MS}$ is the cross-tier interference caused by the primary macrocell, and σ^2 is the additive white Gaussian noise (AWGN) power. Note that in (1), co-channel interference between small cells is assumed as part of the thermal noise because of the severe wall penetration loss and low power of CSBSs [21]. This is particularly the case for sparse deployment of small cells in suburban environments [5], where co-tier inter-small cell interference is negligible as compared with cross-tier interference [22], [23].

Based on Shannon's capacity formula, the achievable capacity of small cell user i on subchannel n in small cell k is given by:

$$C_{k,i,n}^S = \log_2 (1 + \gamma_{k,i,n}^S) \text{ (bps/Hz).} \quad (2)$$

The channel-to-interference-plus-noise ratio (CINR) is

$$h_{k,i,n}^S = \frac{g_{k,i,n}^S}{I_{k,i,n} + \sigma^2} \quad (3)$$

where $I_{k,i,n} = p_{j,n}^M g_{k,j,n}^{MS}$. Therefore, eq. (2) can be rewritten as

$$C_{k,i,n}^S = \log_2 (1 + p_{k,i,n}^S h_{k,i,n}^S) \text{ (bps/Hz).} \quad (4)$$

The k^{th} small cell allocates the radio resources based on an imperfect estimation of the CINR $\hat{h}_{k,i,n}^S$, where

$$h_{k,i,n}^S = \hat{h}_{k,i,n}^S + \Delta_{k,i,n} \quad (5)$$

and where $\Delta_{k,i,n}$ is the channel estimation error, which is modeled as a zero-mean complex Gaussian random variable with variance $\delta_{k,i,n}$. $\Delta_{k,i,n}$ are independent and identically distributed (i.i.d.) for different subchannels, different users and different cognitive small cells. Assuming a minimum mean square error (MMSE) estimator, the CSI estimation error and the actual CSI are mutually uncorrelated [25] [24].

The achievable rate of user i on subchannel n in small cell k can be defined as [32]

$$r_{k,i,n}^S = \log_2 (1 + p_{k,i,n}^S \hat{h}_{k,i,n}^S) \text{ (bps/Hz).} \quad (6)$$

The outage probability [26] imposed by imperfect CSI for user i on subchannel n is defined as

$$P_{outage_{k,i,n}} = \Pr\{r_{k,i,n}^S \geq C_{k,i,n}^S\}. \quad (7)$$

Due to the fundamental role of primary macrocells in providing blanket cellular coverage, a macrocell users QoS

should not be affected by small cell deployments. Therefore, to implement cross-tier interference protection, we impose an interference temperature limit to constrain the cross-tier interference suffered by primary MBS. Let I_n^{th} denote the maximum tolerable interference level on subchannel n for the primary macrocell, we have,

$$\sum_{k=1}^K \sum_{i=1}^F a_{k,i,n} p_{k,i,n}^S g_{k,i,n}^{MS} \leq I_n^{th}, \forall n. \quad (8)$$

B. Problem Formulation

In this paper, our target is to maximize the cognitive small cells' utilities while protecting primary macrocell users' QoS. We assume that the cross-tier interference temperature limit is sent by a primary MBS periodically, which requires little overhead in the primary macrocell. In this case, the subchannel assignment and power control in primary macrocells are not part of the optimization. Thus, the corresponding joint subchannel scheduling and power allocation problem for uplink CSBS can be mathematically formulated as,

$$\max_{\mathbf{A}, \mathbf{P}} \sum_{k=1}^K U_k \quad (9)$$

$$\begin{aligned} \text{s.t. } C1: & \sum_{n=1}^N a_{k,i,n} p_{k,i,n}^S \leq P_{max}, \forall k, i \\ C2: & p_{k,i,n}^S \geq 0, \forall k, i, n \\ C3: & \sum_{k=1}^K \sum_{i=1}^F a_{k,i,n} p_{k,i,n}^S g_{k,i,n}^{MS} \leq I_n^{th}, \forall n \\ C4: & \sum_{i=1}^F a_{k,i,n} \leq 1, \forall k, n \\ C5: & a_{k,i,n} \in \{0, 1\}, \forall k, i, n \\ C6: & P_{outage_{k,i,n}} \leq \varepsilon, \forall k, i, n \end{aligned} \quad (10)$$

where U_k is the objective function, which will be designed in Section III.B. Constraint C1 limits the transmit power of each cognitive small cell user to be below P_{max} ; C2 represents the non-negative power constraint of the transmit power on each subchannel; C3 sets the tolerable interference temperature level on each subchannel of a primary macrocell; C4 and C5 are imposed to guarantee that each subchannel can only be assigned to at most one user in each cognitive small cell. C6 expresses the outage probability constraint of each cognitive user in cognitive small cells, where ε is the outage probability limit for user i on subchannel n in small cell k .

III. GAME THEORETIC RESOURCE ALLOCATION IN SMALL CELL NETWORKS

In this section, we briefly review the basic definition and concepts of cooperative bargaining games and their application in resource allocation problems. Then, the utility function is designed based on the bargaining games.

A. Basics of Bargaining Games

Let $\mathcal{K} = \{1, \dots, k, \dots, K\}$ be the set of players, which are the small cells in this paper. Let \mathbf{S} be the resource allocation strategy of the players, with \mathbf{A}_n and \mathbf{P}_n being the subchannel assignment space and the power allocation strategy space, respectively; Let \mathbf{S}_k be the resource allocation strategy of the player k ; Let U_k be the utility/payoff function of player k , and U_k^{min} is the minimum payoff that player k expects, where U_k^{min} is defined as a minimum QoS requirement in terms of data rate. In a cooperative game, if the minimal payoff U_k^{min} is not achieved, player k would not cooperate.

In non-cooperative games, players do not collaborate with one another. The stable solution for a non-cooperative game is the NE, if the NE exists and it is unique. A NE in a non-cooperative game is defined as,

$$U_k(\mathbf{S}_k^{NE}, \mathbf{S}_{-k}^{NE}) \geq U_k(\mathbf{S}_k, \mathbf{S}_{-k}^{NE}), \quad \forall \mathbf{S}_k \quad (11)$$

where \mathbf{S}_k^{NE} is the resource allocation strategy of player k in NE, and \mathbf{S}_{-k}^{NE} is the strategy of the other $K-1$ players under Nash Equilibrium except for player k . Nash Equilibrium is defined as the fixed points where no player can improve its utility by changing its strategy unilaterally [27].

1) *Nash Bargaining Solutions*: It is known that the NE in a non-cooperative game is not always efficient, that is, the strategy under NE may not be efficient. Therefore, we resort to cooperative bargaining games [29]. Let \mathcal{U} be a closed and convex subset of \mathcal{R}^N that represents the set of feasible payoff allocations that the players can get if they all cooperate. Suppose $\{U_k \in \mathcal{U} | U_k \geq U_k^{min}, \forall k \in \mathcal{K}\}$ is a nonempty bounded set. Define $\mathbf{U}^{min} = (U_1^{min}, \dots, U_K^{min})$, then the pair of $(\mathcal{U}, \mathbf{U}^{min})$ constructs a K -player bargaining game. Here, we define the Pareto efficient point [27], where a player can not find another point that improves the utility of all the players at the same time.

Definition 1: (Pareto Optimality) A point is said to be Pareto optimal if and only if there is no other allocation U'_k such that $U'_k \geq U_k, \forall k \in \mathcal{K}$, and $U'_k > U_k, \exists k \in \mathcal{K}$, i.e., there exists no other allocation that leads to superior performance for some players without causing inferior performance for some other players [27].

There may be an infinite number of Pareto optimal points in a game of multi-players. Thus, we must address how to select a Pareto point for a cooperative bargaining game. We need a criterion to select the best Pareto point of the system. A possible criterion is the fairness of resource allocation. Specially, the fairness of bargaining games is NBS, which can provide a unique and fair Pareto optimal point under the following axioms.

Definition 2: $\bar{\mathbf{u}}$ is an NBS in \mathcal{U} for \mathbf{U}^{min} , that is, $\bar{\mathbf{u}} = f(\mathcal{U}, \mathbf{U}^{min})$, if the following axioms are satisfied [27].

- 1) *Individual Rationality*: $\bar{U}_k \geq U_k^{min}$, where $\bar{U}_k \in \bar{\mathbf{u}}, \forall k \in \mathcal{K}$.
- 2) *Feasibility*: $\bar{\mathbf{u}} \in \mathcal{U}$.
- 3) *Pareto Optimality*: $\bar{\mathbf{u}}$ is Pareto optimal.
- 4) *Independence of Irrelevant Alternatives*: If $\bar{\mathbf{u}} \in \mathcal{U}' \subset \mathcal{U}$, $\bar{\mathbf{u}} = f(\mathcal{U}, \mathbf{U}^{min})$, then $\bar{\mathbf{u}} = f(\mathcal{U}', \mathbf{U}^{min})$.

- 5) *Independence of Linear Transformations*: For any linear scale transformation ψ , $\psi(f(\mathcal{U}, \mathbf{U}^{min})) = f(\psi(\mathcal{U}), \psi(\mathbf{U}^{min}))$.
- 6) *Symmetry*: If \mathcal{U} is invariant under all exchanges of players (small cells), $f_i(\mathcal{U}, \mathbf{U}^{min}) = f_j(\mathcal{U}, \mathbf{U}^{min}), \forall i, j$.

Axioms 1), 2) and 3) define the bargaining set \mathbf{B} . Hence, the NBS locates in the bargaining set. Axioms 4), 5), and 6) are called axioms of fairness. Axiom 5) ensures that the bargaining solution is scale invariant. The symmetry axiom 6) ensures that if the feasible ranges for all players are completely symmetric, then all users have the same solution. Axiom 6) implies that if players have the same QoS requirements and utility functions, they will have the same utility regardless of their indices. This represents an important fairness criterion for our cooperative game that gives incentives to players to collaborate, as they can rely on the network to treat them fairly when their utility-resource trade-offs vary over time.

B. Utility Design and Resource Allocation Game Formulation

The following theorem shows the existence and uniqueness of the NBS that satisfies the axioms 1)-6).

Theorem 1: There is a unique and fair solution function $f(\mathcal{U}, \mathbf{U}^{min})$ that satisfies all the axioms in Definition 2, and the solution can be obtained by

$$f(\mathcal{U}, \mathbf{U}^{min}) \in \arg \max_{\mathbf{U} \in \mathcal{U}, \mathbf{U} \geq \mathbf{U}^{min}} \prod_{k=1}^K (U_k - U_k^{min}). \quad (12)$$

Proof: The proof of the theorem is omitted due to space limitations. A similar detailed proof can be found in [28]. ■

Here, we relax $a_{k,i,n}$ to be a continuous real variable in the range [0,1]. In this case, $a_{k,i,n}$ can be interpreted as the fraction of time that subchannel n is assigned to user i in small cell k during one transmission frame. We first introduce the following Lemma,

$$\begin{aligned} \text{Lemma} \quad I: \quad \text{Define} \quad U_k &= \sum_{i=1}^F \ln(V_{k,i}(S_{k,i})) = \sum_{i=1}^F \ln(R_{k,i} - R_{k,i}^{min}) = \\ &\sum_{i=1}^F \ln\left(\left(\sum_{n=1}^N a_{k,i,n} r_{k,i,n}^S(p_{k,i,n}^S)\right) - R_{k,i}^{min}\right), \quad \text{where} \\ &V_{k,i}(S_{k,i}) = R_{k,i} - R_{k,i}^{min} \text{ is the difference between user } i \text{'s data rate and it's required minimum data rate, and } R_{k,i}^{min} \\ &\text{is user } i \text{'s minimum data rate in small cell } k. S_{k,i} \text{ is the resource allocation strategy of user } i \text{ in small cell } k. \text{ If the} \\ &\text{expression of } R_{k,i} \text{ is concave over } S_{k,i}, U_k \text{ will satisfy the Nash axioms required in Theorem 1.} \end{aligned}$$

Proof: As can be seen as a given condition, $R_{k,i}$ is concave over $S_{k,i}$, then $\ln(V_{k,i}(S_{k,i}))$ is concave, and thus U_k is also concave in \mathbf{S}_k . Therefore, U_k defined here can satisfy all the axioms in Definition 2 and Theorem 1. ■

Fig. 2 shows a simple example of a two-small-cell case, where U_1 and U_2 are the with different utilities of the two small cells [29]. Area \mathbf{S} is the feasible region for U_1 and U_2 . When $\mathbf{U}^{min} = 0$, the objective function in (12) is reduced to $\prod_{k=1}^K (U_k - U_k^{min})|_{U_k^{min}=0, K=2} = U_1 U_2 = \tilde{C}$, where \tilde{C} is a constant. The optimal point of the NBS is B at $(\tilde{U}_1, \tilde{U}_2)$. The physical meaning of this is that “after the small cells are

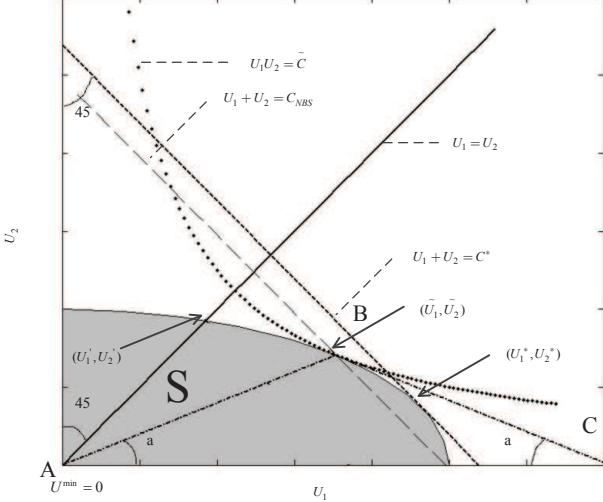


Fig. 2. An NBS example of the two small cells with two different utilities [29].

assigned with the minimal rate, the remaining resources are divided between the two small cells in a ratio equal to the rate at which the utility can be transferred.” [29]. The optimal point for the Max-Rate approach is at (U_1^*, U_2^*) , which is the tangent of line $U_1 + U_2 = C^*$ and the feasible region S . As it can be seen from Fig. 2, the sum rate of NBS solution, $\tilde{U}_1 + \tilde{U}_2 = C_{NBS}$, is smaller than the Max-Rate approach, because of the tradeoff of sum rate and fairness in NBS. Moreover, C_{NBS} is much larger at (U'_1, U'_2) , which induces the most fair solution of $U_1 = U_2$. That is, the NBS solution can well balance throughput and fairness.

According to Lemma 1 and Theorem 1, the unique Nash bargaining equilibrium with fairness can be found over the strategy space. By adopting the objective utility function in Lemma 1, the optimization problem in (9) under the constraints (10) can be rewritten as,

$$\max_{\mathbf{A}, \mathbf{P}} \sum_{k=1}^K \left(\sum_{i=1}^F \ln \left(\left(\sum_{n=1}^N a_{k,i,n} r_{k,i,n}^S(p_{k,i,n}^S) \right) - R_{k,i}^{min} \right) \right) \quad (13)$$

s.t. $C1, C2, C3, C4, C5, C6$ (14)

It can be seen that the problem defined in (13) under the constraints of (14) is a non-convex mixed integer programming problem because of the discrete characteristics of the subchannel constraints in $C4$ and $C5$. The optimal solution can be obtained by exhaustive search, which has a high complexity. To reduce the complexity and meet the requirements in Definition 2, the optimization problem above should be transformed into a convex problem.

Before Lemma 1, we relax $a_{k,i,n}$ to be a continuous real variable in the range $[0,1]$. This time-sharing relaxation was first proposed in [30]. After introducing the time-sharing method, the transformed optimization problem is regarded as a low bound of the original problem [30]. Time-sharing method has been widely used to transform non-convex combinatorial optimization problems into convex optimization problems

for multiuser subchannel allocation in multichannel OFDMA systems [32]. According to [31], it is shown that the duality gap for a nonconvex optimization problem approaches zero in multichannel systems when the number of subchannels is large enough. In the real systems, it’s a typical configuration of 50 resource blocks (RBs) for LTE/LTE-Advanced. Similarly, in this paper, we assume there are 50 subchannels ($N = 50$) in our considered system. It’s large enough for the dual problem to have a near-zero-gap. For notational brevity, denote the actual power allocated to user i in cognitive small cell k on subchannel n as $q_{k,i,n} = a_{k,i,n} p_{k,i,n}^S$. Similarly, denote $I_{k,i,n} = p_{j,n}^M g_{k,j,n}^{MS} + \sigma^2$ and $\tilde{r}_{k,i,n}^S = \log_2 \left(1 + \frac{q_{k,i,n} g_{k,i,n}^S}{a_{k,i,n} I_{k,i,n}} \right)$ the received interference power and capacity of user i on subchannel n in small cell k , respectively. Now, the problem (13) subject to the constraints in (14) can be converted into

$$\max_{\mathbf{A}, \mathbf{Q}} \sum_{k=1}^K \left(\sum_{i=1}^F \ln \left(\left(\sum_{n=1}^N a_{k,i,n} r_{k,i,n}^S(q_{k,i,n}) \right) - R_{k,i}^{min} \right) \right) \quad (15)$$

$$\begin{aligned} \text{s.t. } & C1 : \sum_{n=1}^N q_{k,i,n} \leq P_{max}, \forall k, i \\ & C2 : p_{k,i,n}^S \geq 0, \forall k, i, n \\ & C3 : \sum_{k=1}^K \sum_{i=1}^F q_{k,i,n} g_{k,i,n}^{MS} \leq I_n^{th}, \forall n \\ & C4 : \sum_{i=1}^F a_{k,i,n} \leq 1, \forall k, n \\ & C5 : 0 \leq a_{k,i,n} \leq 1, \forall k, i, n \\ & C6 : P_{outage_{k,i,n}} \leq \varepsilon, \forall k, i, n \end{aligned} \quad (16)$$

where $\mathbf{Q} = [q_{k,i,n}]_{K \times F \times N}$.

Theorem 2: The problem in (15) under the constraints (16) is a convex optimization problem.

Proof: It can easily be proved that the Hessian matrix of (15) over $a_{k,i,n}$ and $q_{k,i,n}$ is negative semidefinite, thus, the objective function of (15) is concave. Moreover, the feasible set of the objective function in (15) is convex, and the corresponding optimization problem is a convex optimization problem. ■

Therefore, there is a unique optimal solution of problem (15) under the constraints (16), because the problem and its feasible set are convex.

Theorem 3: The utility function in (15) meets the Nash bargaining axioms defined in Definition 2, and the NBS is reduced into proportional fairness, when $R_{k,i}^{min} = 0$ in the utility function of (15).

Proof: Since the objective function in (15) is concave and injective, it meets all the Nash Bargaining axioms defined in Definition 2. When $R_{k,i}^{min} = 0$, the utility function in (15) can be written as $\prod_{k=1}^K \ln(R_{k,i} - R_{k,i}^{min})|_{R_{k,i}^{min}=0} = \prod_{k=1}^K \ln(R_{k,i})$. When $R_{k,i}^{min} = 0$, the NBS is the same as proportional fairness, which requires that $\prod_{k=1}^K \frac{(R_{k,i} - R_{k,i}^{min})}{R_{k,i}} \geq 0$ for the interested

utility $R_{k,i}, \forall i$.

IV. BARGAINING RESOURCE ALLOCATION SOLUTIONS FOR SMALL CELL NETWORKS

We first substitute (4) and (7) into $C6$ and have,

$$\Pr\{r_{k,i,n}^S \geq \log_2 (1 + p_{k,i,n}^S h_{k,i,n}^S)\} \leq \varepsilon \quad (17)$$

and (17) can be rewritten as

$$\Pr\left\{h_{k,i,n}^S \leq \frac{2^{r_{k,i,n}^S} - 1}{p_{k,i,n}^S}\right\} \leq \varepsilon. \quad (18)$$

Here, we assume that $h_{k,i,n}^S$ is a non-central chi-squared distributed random variable [33]; Following the simplification used in many previous works on the effects of imperfect CSI [25], we only consider the case of $P_{outage} = \varepsilon$, and have

$$F_{h_{k,i,n}^S}\left(\frac{2^{r_{k,i,n}^S} - 1}{p_{k,i,n}^S}\right) = \varepsilon. \quad (19)$$

where $F_{h_{k,i,n}^S}$ is the CDF of $h_{k,i,n}^S$. Therefore, the data rate that satisfies the outage probability requirement can be given as

$$r_{k,i,n}^S = \log_2 \left(1 + p_{k,i,n}^S F_{h_{k,i,n}^S}^{-1}(\varepsilon)\right). \quad (20)$$

Substituting (20) into (15), we transform the optimization problem in (15)-(16) into

$$\begin{aligned} \max_{\mathbf{A}, \mathbf{Q}} & \sum_{k=1}^K \left(\sum_{i=1}^F \left(\sum_{n=1}^N a_{k,i,n} \log_2 \left(1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}^S}^{-1}(\varepsilon) \right) \right) - R_{k,i}^{\min} \right) \\ \text{s.t. } & C1, C2, C3, C4, C5 \end{aligned} \quad (21)$$

Since the optimization problem in (15)-(16) is convex, the transformed problem in (21) and (22) is also convex.

A. Solution of the Cooperative Resource Allocation Game

The solution gap between the primal problem and its dual problem can be considered zero for most engineering problems. Since the duality gap is zero, we can solve the problem in the dual domain. Moreover, the system considered here is a multi-subchannel network; therefore, dual decomposition can be an effective method. The Lagrangian function of the primal problem in (21)-(22) is given by (23) at the top of next page. Where $\boldsymbol{\lambda} = [\lambda_{k,i}]_{K \times F}$ is the Lagrange multipliers corresponding to the joint power constraint, and $\boldsymbol{\mu} = [\mu_n]_{N \times 1}$ and $\boldsymbol{\eta} = [\eta_{k,n}]_{K \times N}$ are Lagrange multipliers vectors associated with the cross-tier interference limit and subchannel usage constraints, respectively.

Thus, the dual problem is given by

$$\min_{\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\eta} \geq 0} \Xi(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\eta}) \quad (24)$$

■ where the dual function $\Xi(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\eta})$ can be given as

$$\begin{aligned} \Xi(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\eta}) &= \max_{\mathbf{A}, \mathbf{Q}} \mathcal{L}(\mathbf{A}, \mathbf{Q}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\eta}) \\ &= P_{\max} \sum_{k=1}^K \sum_{i=1}^F \lambda_{k,i} + \sum_{k=1}^K \sum_{n=1}^N \eta_{k,n} \\ &\quad + \sum_{n=1}^N \mu_n I_n^{th} + \Psi(\mathbf{A}, \mathbf{Q}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\eta}) \end{aligned} \quad (25)$$

where $\Psi(\mathbf{A}, \mathbf{Q}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\eta})$ for a fixed set of Lagrange multipliers $\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\eta}$ is given by (26) at the top of next page.

Based on standard optimization techniques and the Karush-Kuhn-Tucker (KKT) conditions [34], the power allocation for user i in small cell k on subchannel n is obtained by taking the first derivative of (26) with respect to $q_{k,i,n}$, which can be given as

$$\frac{\partial \Psi(\mathbf{Q}, \boldsymbol{\lambda}, \boldsymbol{\mu})}{\partial q_{k,i,n}} = \frac{\frac{F_{h_{k,i,n}^S}^{-1}(\varepsilon)}{\ln 2(1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}^S}^{-1}(\varepsilon))}}{\log_2 \left(1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}^S}^{-1}(\varepsilon) \right) - R_{k,i}^{\min} - \lambda_{k,i} - \mu_n g_{k,i,n}^{MS}} \quad (27)$$

According to the KKT conditions,

$$\begin{aligned} & \frac{F_{h_{k,i,n}^S}^{-1}(\varepsilon)}{\ln 2(\lambda_{k,i} + \mu_n g_{k,i,n}^{MS})} \\ &= (1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}^S}^{-1}(\varepsilon))(\log_2 \left(1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}^S}^{-1}(\varepsilon) \right) - R_{k,i}^{\min}). \end{aligned} \quad (28)$$

Note that (28) is a transcendental algebraic equation over $q_{k,i,n}$, which can be solved by recursive numerical methods. The solution of (28) can be obtained as follows. Let

$$\Lambda_{k,i,n} = 1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}^S}^{-1}(\varepsilon), \quad (29)$$

and

$$\Gamma_{k,i,n} = \frac{F_{h_{k,i,n}^S}^{-1}(\varepsilon)}{\ln 2(\lambda_{k,i} + \mu_n g_{k,i,n}^{MS})}. \quad (30)$$

Substituting (29) and (30) into (28), we get,

$$\Lambda_{k,i,n}(\log_2(\Lambda_{k,i,n}) - R_{k,i}^{\min}) = \frac{\Gamma_{k,i,n}}{a_{k,i,n}}. \quad (31)$$

Letting $\Upsilon = 2^{R_{k,i}^{\min}}$, we have

$$\Lambda_{k,i,n} \log_2 \left(\frac{\Lambda_{k,i,n}}{\Upsilon} \right) = \frac{\Gamma_{k,i,n}}{a_{k,i,n}}. \quad (32)$$

Multiplying both sides of (32) with $\frac{1}{\Upsilon}$, we have

$$\log_2 \left(\frac{\Lambda_{k,i,n}}{\Upsilon} \right)^{\frac{\Lambda_{k,i,n}}{\Upsilon}} = \frac{\Gamma_{k,i,n}}{a_{k,i,n} \Upsilon}. \quad (33)$$

Letting $\varphi = \frac{\Lambda_{k,i,n}}{\Upsilon}$, we can get

$$\varphi^\varphi = 2^{\frac{\Gamma_{k,i,n}}{a_{k,i,n} \Upsilon}}. \quad (34)$$

Using the Lambert-W function properties, φ can be given as

$$\varphi = \exp \left(W \left(\ln \left(2^{\frac{\Gamma_{k,i,n}}{a_{k,i,n} \Upsilon}} \right) \right) \right) \quad (35)$$

$$\begin{aligned}
& \mathcal{L}(\mathbf{A}, \mathbf{Q}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\eta}) \\
&= \sum_{k=1}^K \sum_{i=1}^F \ln \left(\left(\sum_{n=1}^N a_{k,i,n} r_{k,i,n}^S (q_{k,i,n}) \log_2 \left(1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}^S}^{-1} (\varepsilon) \right) \right) - R_{k,i}^{min} \right) + \\
& \sum_{k=1}^K \sum_{i=1}^F \lambda_{k,i} \left(P_{max} - \sum_{n=1}^N q_{k,i,n} \right) + \sum_{n=1}^N \mu_n \left(I_n^{th} - \sum_{k=1}^K \sum_{i=1}^F q_{k,i,n} g_{k,i,n}^{MS} \right) + \sum_{k=1}^K \sum_{n=1}^N \eta_{k,n} \left(1 - \sum_{i=1}^F a_{k,i,n} \right)
\end{aligned} \tag{23}$$

$$\begin{aligned}
\Psi(\mathbf{A}, \mathbf{Q}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\eta}) &= \max_{\mathbf{A}, \mathbf{Q}} \left\{ \begin{array}{l} \sum_{k=1}^K \sum_{i=1}^F \ln \left(\left(\sum_{n=1}^N a_{k,i,n} \log_2 \left(1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}^S}^{-1} (\varepsilon) \right) \right) - R_{k,i}^{min} \right) \\ - \sum_{k=1}^K \sum_{i=1}^F \lambda_{k,i} \left(\sum_{n=1}^N q_{k,i,n} \right) - \sum_{n=1}^N \mu_n \left(\sum_{k=1}^K \sum_{i=1}^F q_{k,i,n} g_{k,i,n}^{MS} \right) \\ - \sum_{k=1}^K \sum_{n=1}^N \eta_{k,n} \left(\sum_{i=1}^F a_{k,i,n} \right) \end{array} \right\} \\
&= \max_{\mathbf{A}, \mathbf{Q}} \left\{ \begin{array}{l} \sum_{k=1}^K \sum_{i=1}^F \ln \left(\left(\sum_{n=1}^N a_{k,i,n} \log_2 \left(1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}^S}^{-1} (\varepsilon) \right) \right) - R_{k,i}^{min} \right) \\ - \sum_{k=1}^K \sum_{i=1}^F \sum_{n=1}^N \lambda_{k,i} q_{k,i,n} - \sum_{n=1}^N \sum_{k=1}^K \sum_{i=1}^F \mu_n q_{k,i,n} g_{k,i,n}^{MS} \\ - \sum_{k=1}^K \sum_{n=1}^N \sum_{i=1}^F \eta_{k,n} a_{k,i,n} \end{array} \right\} \\
&= \max_{\mathbf{A}, \mathbf{Q}} \sum_{k=1}^K \sum_{i=1}^F \left\{ \begin{array}{l} \ln \left(\left(\sum_{n=1}^N a_{k,i,n} \log_2 \left(1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}^S}^{-1} (\varepsilon) \right) \right) - R_{k,i}^{min} \right) \\ - \sum_{n=1}^N \lambda_{k,i} q_{k,i,n} - \sum_{n=1}^N \mu_n q_{k,i,n} g_{k,i,n}^{MS} \\ - \sum_{n=1}^N \eta_{k,n} a_{k,i,n} \end{array} \right\}.
\end{aligned} \tag{26}$$

where $W(\cdot)$ is the Lambert's W function given by $W(\cdot) = \sum_{i=1}^{+\infty} ((-i)^{i-1} / i!) (\cdot)^i$. Substituting $\varphi = \frac{\Lambda_{k,i,n}}{\Upsilon}$ and (29) into (35), we can obtain

$$1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}^S}^{-1} (\varepsilon) = \Upsilon \exp \left(W \left(\ln \left(2^{\frac{\Lambda_{k,i,n}}{\Upsilon}} \right) \right) \right). \tag{36}$$

Therefore, given the optimal subchannel allocation $\hat{a}_{k,i,n}$, the optimal power allocation $\hat{p}_{k,i,n}^S$ can be obtained as

$$\begin{aligned}
\hat{p}_{k,i,n}^S &= \frac{\hat{q}_{k,i,n}}{\hat{a}_{k,i,n}} \\
&= \frac{1}{F_{h_{k,i,n}^S}^{-1} (\varepsilon)} \left(\Upsilon \exp \left(W \left(\ln \left(2^{\frac{\Lambda_{k,i,n}}{\Upsilon}} \right) \right) \right) - 1 \right)^+
\end{aligned} \tag{37}$$

where $(x)^+ = \max(0, x)$.

Given the optimal power allocation, the first derivative of (26) with respect to $a_{k,i,n}$ is given as

$$\frac{\partial \Psi(\mathbf{A}, \boldsymbol{\lambda}, \boldsymbol{\mu})}{\partial a_{k,i,n}} = H_{k,i,n} - \eta_{k,i,n} \tag{38}$$

where

$$\begin{aligned}
H_{k,i,n} &= \frac{\log_2 \left(1 + \hat{p}_{k,i,n}^S F_{h_{k,i,n}^S}^{-1} (\varepsilon) \right)}{\log_2 \left(1 + \hat{p}_{k,i,n}^S F_{h_{k,i,n}^S}^{-1} (\varepsilon) \right) - R_{k,i}^{min}} - \lambda_{k,i} \hat{p}_{k,i,n}^S \\
&\quad - \mu_n \hat{p}_{k,i,n}^S g_{k,i,n}^{MS}.
\end{aligned} \tag{39}$$

Subchannel n is assigned to the user with the largest $H_{k,i,n}$ in small cell k [30] [32]; that is,

$$\hat{a}_{k,i^*,n} = 1 |_{i^* = \arg \max_i H_{k,i,n}}, \forall k, n. \tag{40}$$

B. Update of the Dual Variables

Both the ellipsoid and subgradient method can be adopted in the update of dual variables [34]. Here, we choose the subgradient method to update the dual variables, as formulated in Lemma 2

Lemma 2: The subgradient of $\lambda_{k,i}$ and μ_n are respectively given by

$$P_{max} - \sum_{n=1}^N \hat{p}_{k,i,n}^S \tag{41}$$

$$I_n^{th} - \sum_{k=1}^K \sum_{i=1}^F \hat{p}_{k,i,n}^S g_{k,i,n}^{MS}. \tag{42}$$

Proof: The proof is provided in Appendix A. \blacksquare

According to Lemma 2, the dual variables can be updated as

$$\lambda_{k,i}^{(l+1)} = \left[\lambda_{k,i}^{(l)} - \beta_1^{(l)} \left(P_{max} - \sum_{n=1}^N \hat{p}_{k,i,n}^S \right) \right]^+, \forall k, i \tag{43}$$

$$\mu_n^{(l+1)} = \left[\mu_n^{(l)} - \beta_2^{(l)} \left(I_n^{th} - \sum_{k=1}^K \sum_{i=1}^F \hat{p}_{k,i,n}^S g_{k,i,n}^{MS} \right) \right]^+, \forall n \tag{44}$$

where $\beta_1^{(l)}$ and $\beta_2^{(l)}$ are the step sizes of iteration l ($l \in \{1, 2, \dots, L_{\max}\}$), L_{\max} is the maximum number of iterations, and the step sizes should satisfy the condition,

$$\sum_{l=1}^{\infty} \beta_l^{(l)} = \infty, \lim_{l \rightarrow \infty} \beta_l^{(l)} = 0, \forall l \in \{1, 2\}. \quad (45)$$

C. Cooperative Bargaining Resource Scheduling Algorithm

Although (37), (40), (43)-(44) give a solution to the joint subchannel scheduling and power allocation problem of (13)-(14), it still remains to design an algorithm to provide the execution structure and the executing entity for the equations. Therefore, we propose Algorithm 1 as an implementation of our cooperative bargaining resource scheduling solution. The proposed iterative Algorithm 1 will guarantee convergence by using the subgradient method.

Algorithm 1 Cooperative Bargaining Resource Scheduling Algorithm

```

1: Initialize  $I_{\max}$  and Lagrangian variables vectors  $\lambda, \mu$ , set
    $i = 0$ 
2: Initialize  $p_{k,i,n}$  with an uniform power distribution among
   all subchannels
3: Initialize  $a_{k,i,n}$  with subchannel allocation method in [38],
    $\forall k, i, n$ 
4: repeat
5:   for  $k = 1$  to  $K$  do
6:     for  $n = 1$  to  $N$  do
7:       for  $i = 1$  to  $F$  do
8:         a) Cognitive users update  $\hat{p}_{k,i,n}^S$  according to
            (37);
9:         b) Calculate  $H_{k,i,n}$  according to (39);
10:        c) CSBS updates  $\hat{a}_{k,i^*,n}$  according to (40);
11:        d) CSBS updates  $\lambda$  according to (43);
12:       end for
13:     end for
14:   end for
15:   MBS updates  $\mu$  according to (44), and broadcasts those
      values to all CSBSs via backhaul link,  $l = l + 1$ .
16: until Convergence or  $l = L_{\max}$ 

```

Note that $g_{k,i,n}^{MS}$ required in Algorithm 1 can be estimated at cognitive user i in small cell k by measuring the downlink channel power gain of subchannel n from the macrocell and utilizing the symmetry between uplink and downlink channels, or by using site specific knowledge [35]. Furthermore, it can be assumed that there is a direct wire connection between a CSBS and the MBS for the CSBS to coordinate with the central MBS [5], [36], according to a candidate scheme proposed for 3GPP small cell mobility enhancement [37].

Algorithm 1 can be implemented by each CSBS utilizing only local information and limited interaction with the MBS; therefore, Algorithm 1 is distributed and the practicality is ensured.

V. SIMULATION RESULTS AND DISCUSSION

In this section, simulation results are given to evaluate the performance of the proposed algorithms. In the simulations,

spectrum-sharing CSBSs and primary users are randomly distributed in the range of MBS, and cognitive small cell users are uniformly distributed in the coverage area of their serving small cell; the carrier frequency is 2 GHz, $B = 10$ MHz, $N = 50$, $M = 50$, and $\sigma^2 = \frac{B}{N}N_0$, where $N_0 = -174$ dBm/Hz is the AWGN power spectral density. The CINR $h_{k,i,n}^S$ is assumed as a non-central chi-squared distributed random variable. The primary macro users' maximum transmit powers are set at 30 dBm. The coverage radius of the MBS is 500 m, and that of a small cell is 10 m. We assume that all small cell users have the same QoS requirement.

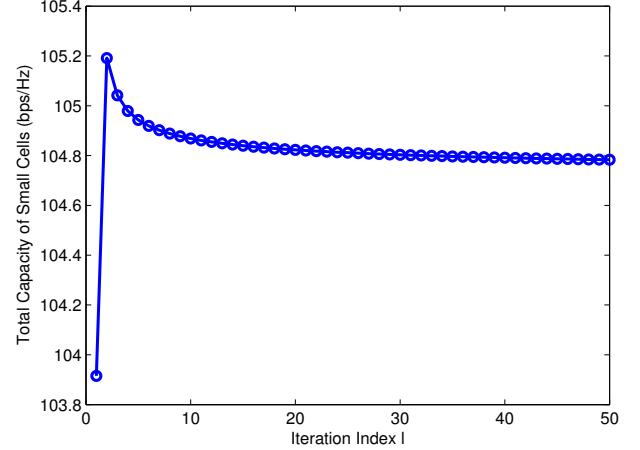


Fig. 3. Convergence of the proposed Algorithm 1.

In Fig. 3, the convergence of Algorithm 1 is evaluated with the outage probability constraint $\varepsilon = 0.01$, the cross-tier interference limit $I_n^{th} = 7.5 \times 10^{-14}$ W, minimum data rate requirement $R_{k,i}^{min} = 0.5$ bps/Hz, the variance of channel estimate error $\delta_{k,i,n} = 0.05$, number of users per small cell $F = 4$ and maximal transmit power of small cell user $P_{max} = 20$ dBm. As can be seen from Fig. 3, the total capacity of the small cells converges after 30 iterations. This result, together with the previous analysis, indicates that the proposed Algorithm 1 converges in heterogeneous networks.

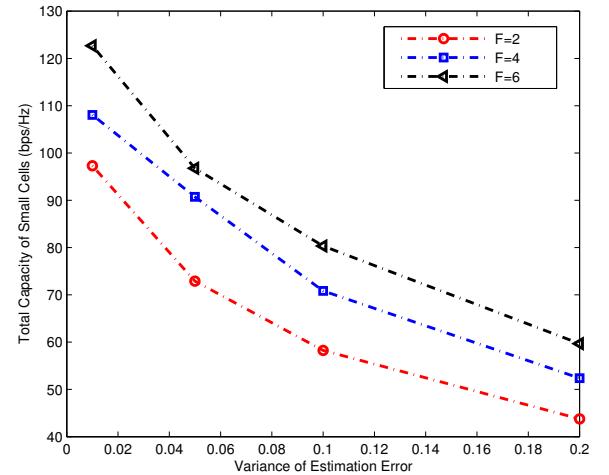


Fig. 4. Total capacity of small cells vs variance of estimation error.

Fig. 4 shows the total uplink capacity of K small cells

when the variance of estimation error $\delta_{k,i,n}$ increases from 0.01 to 0.2 for all k, i, n with the user number per small cell $F = 2, 4, 6$. The simulation parameters are set as $K = 10$, $R_{k,i}^{min} = 0.5 \text{ bps/Hz}$ for all k, i , $\varepsilon = 0.01$, $P_{max} = 20 \text{ dBm}$ and $I_n^{th} = 7.5 \times 10^{-14} \text{ W}$ (-101.2 dBm) for all n . The capacity of all small cells decreases with the increase of the variance of estimation error, because of the imperfect estimation of CSI. We also observe that a higher capacity is obtained with a larger number of F because of the multi-user diversity.

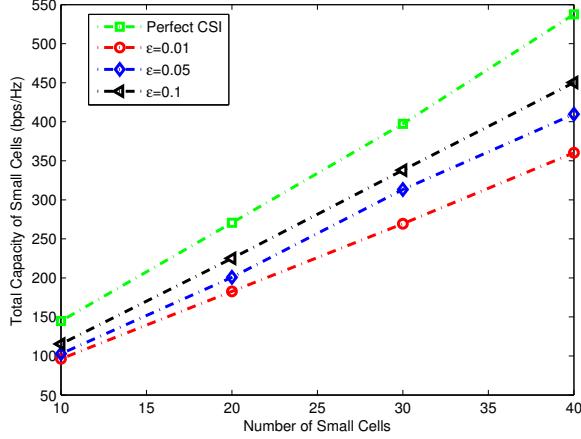


Fig. 5. Total capacity of small cells vs number of small cells.

Fig. 5 shows the total uplink capacity of K small cells when the number of small cells K increases from 10 to 40, for the outage probability constraint $\varepsilon = 0.01, 0.05, 0.1$. The simulation parameters are set as $F = 4$, $R_{k,i}^{min} = 0.5 \text{ bps/Hz}$ for all k, i , $\delta_{k,i,n} = 0.05$ for all k, i, n , $P_{max} = 20 \text{ dBm}$ and $I_n^{th} = 7.5 \times 10^{-14} \text{ W}$ (-101.2 dBm) for all n . The total capacity of small cells increases with the increase of the number of small cells. It also can be seen from Fig. 5 that a higher outage probability limit ε induces a higher total capacity of small cells, because a larger value of ε enlarges the feasible region of the variables in the original problem defined in (13)-(14), etc.

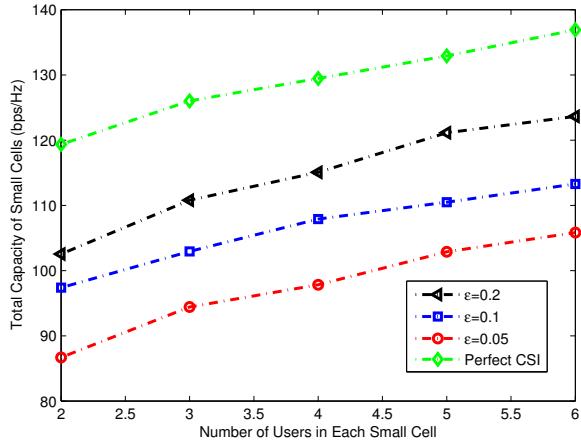


Fig. 6. Total capacity of small cells vs number of users in each small cell.

Fig. 6 shows the total uplink capacity of K small cells when the number of users per small cells F increases from 2 to 6,

for the outage probability limit $\varepsilon = 0.05, 0.1, 0.2$. The other simulation parameters are set as $K = 10$, $R_{k,i}^{min} = 0.5 \text{ bps/Hz}$ for all k, i , $\delta_{k,i,n} = 0.05$ for all k, i, n , $P_{max} = 20 \text{ dBm}$ and $I_n^{th} = 7.5 \times 10^{-14} \text{ W}$ (-101.2 dBm) for all n . The capacity of all small cells increases with the increase of F because of the multi-user diversity. Similar to the results in Fig. 5, a higher outage probability limit ε induces a higher total capacity of small cells.

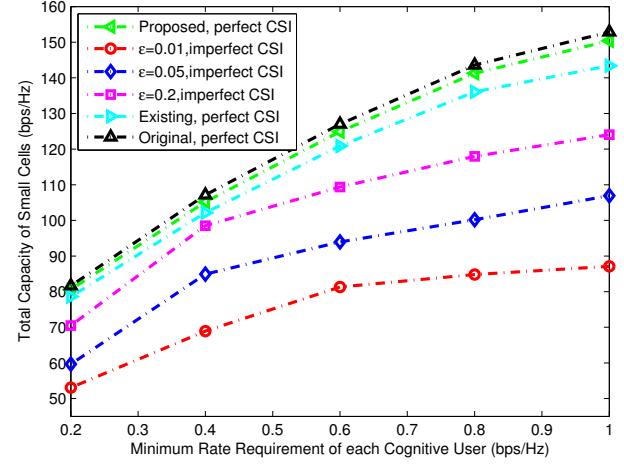


Fig. 7. Total capacity of small cells vs minimum rate requirement of each cognitive user.

Fig. 7 shows the total uplink capacity of K small cells when the minimum rate requirement of each cognitive user $R_{k,i}^{min}$ increases from 0.2 bps/Hz to 1 bps/Hz , for the outage probability limit $\varepsilon = 0.01, 0.05, 0.2$. The other simulation parameters are set as $K = 10$, $\delta_{k,i,n} = 0.05$ for all k, i, n , $P_{max} = 20 \text{ dBm}$ and $I_n^{th} = 7.5 \times 10^{-14} \text{ W}$ (-101.2 dBm) for all n . The capacity of all small cells increases with increasing $R_{k,i}^{min}$, because larger $R_{k,i}^{min}$ enlarges the feasible region of the optimizing variable. Similar to the results in Fig. 5 and Fig. 6, a higher outage probability limit ε induces a higher total capacity of small cells. In this figure, we also compare the proposed Algorithm 1 with existing cooperative resource allocation methods when the CSI is perfectly known. The existing scheme is composed of cooperative power allocation in [39] and subchannel allocation in [38]. As can be seen from Fig. 7, proposed Algorithm 1 has better performance in terms of capacity than the existing schemes with the assumption of perfect CSI. With the assumption of perfect CSI, Fig. 7 also showed about 1% 2% performance loss from the original solution of (13) to the convex optimization solution of (15), where the original solution is solved by exhaustive method with high complexity.

Fig. 8 shows the total uplink capacity of K small cells when the maximum transmit power per cognitive small cell user P_{max} increases from 25 dBm to 40 dBm , for the interference temperature limit $I_n^{th} = 7.5 \times 10^{-13} \text{ W}$, $7.5 \times 10^{-14} \text{ W}$, $7.5 \times 10^{-15} \text{ W}$. The other simulation parameters are set as $K = 10$, $R_{k,i}^{min} = 0.5 \text{ bps/Hz}$ for all k, i , $\varepsilon = 0.01$, $\delta_{k,i,n} = 0.05$ for all k, i, n , and $P_{max} = 20 \text{ dBm}$. The total capacity of the small cells increases with the increase of P_{max} , because higher P_{max} enlarges the feasible region S . It also can be seen

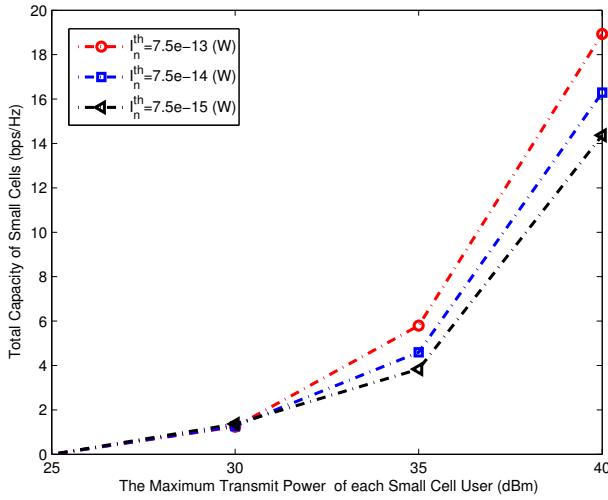


Fig. 8. Total capacity of small cells vs maximum transmit power of each user.

from the figure that higher interference temperature limit I_n^{th} induces higher total capacity of the small cells.

In order to evaluate the fairness of users in small cells, we use the fairness index (FI) [40], which is defined as

$$\left(\sum_{k=1}^K \sum_{i=1}^F \left(\frac{R_{k,i}}{R_{k,i}^{min}} \right) \right)^2 \Big/ \left(KF \left(\sum_{k=1}^K \sum_{i=1}^F \left(\frac{R_{k,i}}{R_{k,i}^{min}} \right)^2 \right) \right). \quad (46)$$

This fairness index is widely applied in the literature to evaluate the level of fairness achieved by resource allocation algorithms.

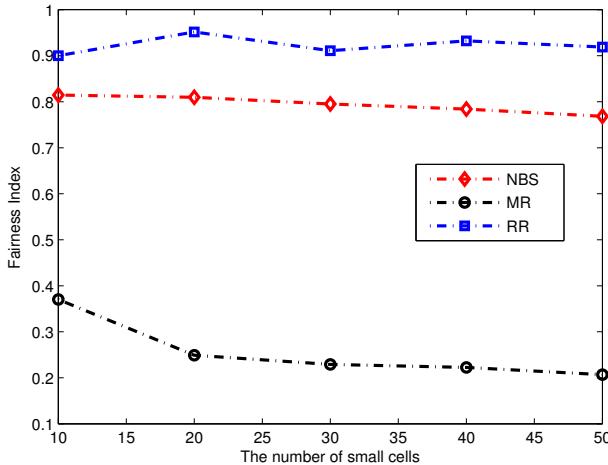


Fig. 9. Fairness index vs number of small cells.

Fig. 9 shows the fairness among all the users in K small cells when the number of small cells increases from 10 to 50, with the outage probability limit $\varepsilon = 0.01$, $I_n^{th} = 7.5 \times 10^{-13}$ W, $R_{k,i}^{min} = 1 \text{ bps/Hz}$, $F = 4$, $\delta_{k,i,n} = 0.05$ for all k, i, n , and $P_{max} = 30 \text{ dBm}$. As can be seen from the figure, Algorithm 1 achieves a higher fairness index than the centralized MR approach, while round-robin(RR) method has the highest fairness index among the three schemes. Here, the centralized MR approach is composed by exhaustive method of subchannel

allocation and waterfilling power allocation. RR method is composed of round-robin subchannel and the proposed power allocation proposed in this paper. Therefore, it's verified that the cooperative bargaining resource scheduling algorithm can achieve higher fairness index with the cost of small reduction in throughput, compared with the centralized MR approach.

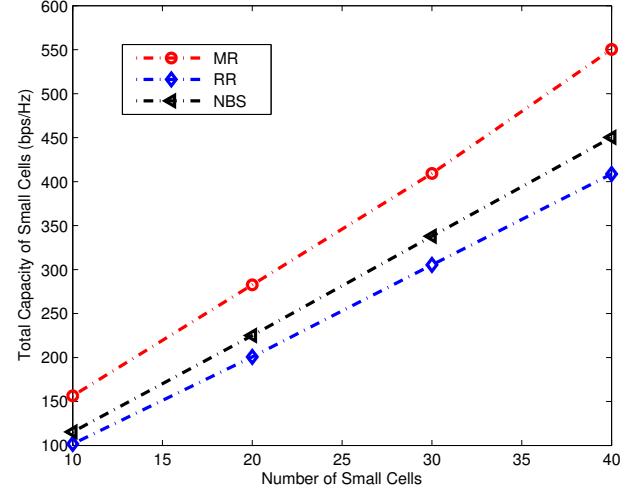


Fig. 10. Capacity vs number of small cells.

Fig. 10 shows the capacity of K small cells when the number of small cells increases from 10 to 40, with the outage probability limit $\varepsilon = 0.1$, $I_n^{th} = 7.5 \times 10^{-13}$ W, $R_{k,i}^{min} = 1 \text{ bps/Hz}$, $F = 4$, $\delta_{k,i,n} = 0.05$ for all k, i, n , and $P_{max} = 30 \text{ dBm}$. As can be seen from the figure, the Algorithm 1 achieves a lower capacity compared with the centralized MR approach, and higher capacity than the RR scheme. As one can conclude from Fig. 9 and Fig. 10, the proposed Algorithm 1 achieves a better trade-off between capacity and fairness than existing known algorithms. The complexity of proposed Algorithm 1 is compared with the existing MR and RR schemes. In Algorithm 1, the calculation of (39) for every small cell user on each subchannel in every small cell entails KFN operations, and a worst-case complexity of solving (40) needs KFN operations in each iteration. Suppose the subgradient method used in Algorithm 1 needs Δ iterations to converge, updating λ and ν needs $O(KF)$ operations each [31] [34], and the computation of μ calls $O(N)$ operations, therefore, Δ is a polynomial function of K^2F^2N . The total complexity of Algorithm 1 is thus $O(K^2F^2N^2\Delta)$. The complexity of RR is $O(N\Delta)$. MR approach use exhaustive search of subchannel allocation and waterfilling power allocation with subgradient update [32]. Therefore, the complexity of central MR approach is extremely high of $O(KFN\Delta)$. Compared with the exhaustive search for subchannel allocation, which has a worst-case complexity of $O(KFN)$, the proposed Algorithm 1 has a much lower complexity than MR approach and higher complexity than RR approach. In other words, the proposed Algorithm 1 (NBS approach) can also achieve a tradeoff between capacity and complexity.

$$\Xi(\lambda', \mu') = \max_{\mathbf{A}, \mathbf{Q}} \left\{ \begin{array}{l} \sum_{k=1}^K \sum_{i=1}^F \ln \left(\left(\sum_{n=1}^N a_{k,i,n} \log_2 \left(1 + \frac{q_{k,i,n}}{a_{k,i,n}} F_{h_{k,i,n}}^{-1}(\varepsilon) \right) \right) - R_{k,i}^{min} \right) \\ - \sum_{k=1}^K \sum_{i=1}^F \lambda_{k,i}' \left(\sum_{n=1}^N q_{k,i,n} \right) - \sum_{n=1}^N \mu_n' \left(\sum_{k=1}^K \sum_{i=1}^F q_{k,i,n} g_{k,i,n}^{MS} \right) + \\ \sum_{k=1}^K \sum_{i=1}^F \lambda_{k,i}' P_{max} + \sum_{n=1}^N \mu_n' I_n^{th} \end{array} \right\}. \quad (47)$$

$$\Xi(\lambda', \mu') \geq \left\{ \begin{array}{l} \sum_{k=1}^K \sum_{i=1}^F \ln \left(\left(\sum_{n=1}^N \hat{a}_{k,i,n} \log_2 \left(1 + \frac{\hat{q}_{k,i,n}}{\hat{a}_{k,i,n}} F_{h_{k,i,n}}^{-1}(\varepsilon) \right) \right) - R_{k,i}^{min} \right) \\ - \sum_{k=1}^K \sum_{i=1}^F \lambda_{k,i}' \left(\sum_{n=1}^N \hat{q}_{k,i,n} \right) - \sum_{n=1}^N \mu_n' \left(\sum_{k=1}^K \sum_{i=1}^F \hat{q}_{k,i,n} g_{k,i,n}^{MS} \right) + \\ \sum_{k=1}^K \sum_{i=1}^F \lambda_{k,i}' P_{max} + \sum_{n=1}^N \mu_n' I_n^{th} \end{array} \right\}. \quad (48)$$

VI. CONCLUSION

In this paper, we have investigated the joint subchannel and power allocation problem in cognitive small cell networks. The resource allocation problem was formulated as a cooperative Nash bargaining game, where a cross-tier interference temperature limit is imposed to protect the primary macrocell, a minimum outage probability requirement is employed to provide reliable transmission for cognitive small cell users, a minimum rate requirement is considered to guarantee intra-small cell fairness, and imperfect CSI is considered in the analysis and algorithm design. The near optimal cooperative bargaining resource allocation solutions are derived by relaxing subchannel allocation variables and using the Lambert-W function. The existence, uniqueness, and fairness of the solution to this game model were proved analytically. Accordingly, a cooperative Nash bargaining resource allocation algorithm was developed, and was shown to converge to a Pareto-optimal equilibrium for the cooperative game. Simulation results showed that the proposed algorithms not only converge within a few iterations, but also achieve a better trade-off between capacity and fairness than the existing algorithms.

APPENDIX A PROOF OF LEMMA 2

Based on (25), we can get (47) on the top of this page.

From (29), we get (48) on the top of this page.

Therefore, we have

$$\begin{aligned} \Xi(\lambda', \mu') &\geq \sum_{k=1}^K \sum_{i=1}^F (\lambda_{k,i}' - \lambda_{k,i}) \left(P_{max} - \sum_{n=1}^N \hat{q}_{k,i,n} \right) \\ &+ \sum_{n=1}^N (\mu_n' - \mu_n) \left(I_n^{th} - \sum_{k=1}^K \sum_{i=1}^F \hat{q}_{k,i,n} g_{k,i,n}^{MS} \right) \\ &+ \Xi(\lambda, \mu). \end{aligned} \quad (49)$$

Eq. (49) verifies the definition of subgradient and completes the proof. \blacksquare

REFERENCES

- [1] H. Zhang, C. Jiang, N. Beaulieu, X. Chu, X. Wen, and M. Tao, "Resource allocation in spectrum-sharing OFDMA femtocells with heterogeneous services," *IEEE Trans. Commun.*, vol. 62, no. 7, pp. 2366–2377, July 2014.
- [2] H. Zhang, C. Jiang, Q. Hu, and Y. Qian, "Self-Organization in Disaster Resilient Heterogeneous Small Cell Networks," *IEEE Network*, 2015.
- [3] H. Zhang, X. Chu, W. Guo, and S. Wang, "Coexistence of Wi-Fi and Heterogeneous Small Cell Networks Sharing Unlicensed Spectrum," *IEEE Commun. Mag.*, 2015.
- [4] V. Chandrasekhar, J. G. Andrews, T. Muharemovic, Z. Shen, and A. Gatherer, "Power control in two-tier femtocell networks," *IEEE Trans. Wireless Commun.*, vol. 8, no. 8, pp. 4316–4328, Aug. 2009.
- [5] X. Kang, R. Zhang, and M. Motani, "Price-based resource allocation for spectrum-sharing femtocell networks: a Stackelberg game approach," *IEEE J. Sel. Areas in Commun.*, vol. 30, no. 3, pp. 538–549, Apr. 2012.
- [6] J.-H. Yun and K. G. Shin, "Adaptive interference management of ofdma femtocells for co-channel deployment," *IEEE J. Sel. Areas in Commun.*, vol. 29, no. 6, pp. 1225–1241, June 2011.
- [7] S. Gurucharya, D. Niyato, Dong In Kim, and E. Hossain, "Hierarchical Competition for Downlink Power Allocation in OFDMA Femtocell Networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 4, pp. 1543–1553, Apr. 2013.
- [8] J. W. Huang and V. Krishnamurthy, "Cognitive base stations in lte/3gpp femtocells: A correlated equilibrium game-theoretic approach," *IEEE Trans. Wireless Commun.*, vol. 59, no. 12, pp. 3485–3493, Dec. 2011.
- [9] R. Xie, F.R. Yu, H. Ji, and Y. Li, "Energy-Efficient Resource Allocation for Heterogeneous Cognitive Radio Networks with Femtocells," *IEEE Trans. Wireless Commun.*, vol. 11, no. 11, pp. 3910–3920, Nov. 2012.
- [10] Y. Chen, J. Zhang, and Q. Zhang, "Utility-Aware Refunding Framework for Hybrid Access Femtocell Network," *IEEE Trans. Wireless Commun.*, vol. 11, no. 5, pp. 1688–1697, May 2012.
- [11] V. Ha, and L. Le, "Distributed Base Station Association and Power Control for Heterogeneous Cellular Networks," *IEEE Trans. Veh. Technol.*, vol. 63, no. 1, pp. 282–296, Jan. 2014.
- [12] H. Zhang, X. Chu, W. Ma, et al. "Resource allocation with interference mitigation in OFDMA femtocells for co-channel deployment," *Eurasip Journal on Wireless Communications and Networking*, vol. 12, no. 9, pp. 1–9, Sep. 2012.
- [13] W. Ma, H. Zhang, W. Zheng, and X. Wen, "Differentiated-pricing based power allocation in dense femtocell networks," Pro. of WPMC 2012, pp. 599–603, Sep. 2012.
- [14] Long Bao Le, D. Niyato, and E. Hossain, Dong In Kim and Dinh Thai Hoang, "QoS-Aware and Energy-Efficient Resource Management in OFDMA Femtocells," *IEEE Trans. Wireless Commun.*, vol. 12, no. 1, pp. 180–194, Jan. 2013.
- [15] Y. Liu and L. Dong, "Spectrum sharing in MIMO cognitive radio networks based on cooperative game theory", *IEEE Trans. Wireless Commun.*, vol. 13, no. 9, pp. 4807–4820, Sep. 2014.
- [16] J. Chen, and A. L. Swindlehurst, "Applying bargaining solutions to resource allocation in multiuser MIMO OFDMA broadcast systems," *IEEE J. Sel. Top. Sign. Proces.*, vol. 6, no. 2, pp. 127–139, Apr. 2012.
- [17] Q. Ni, and C. C. Zarakovitis, "Nash bargaining game theoretic scheduling for joint channel and power allocation in cognitive radio systems," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 1, pp. 70–81, Jan. 2012.
- [18] N. Prasad, K. Li, and X. Wang, "Fair rate allocation in multiuser OFDM SDMA networks," *IEEE Trans. Signal Process.*, vol. 57, no. 7, pp. 2797–2808, July 2009.
- [19] V. Ha, and L. Le, "Fair Resource Allocation for OFDMA Femtocell

Networks with Macrocell Protection,” *IEEE Trans. Veh. Technol.*, vol. 63, no. 3, pp. 1388–1401, Mar. 2014.

[20] S. Haykin, “Cognitive radio: brain-empowered wireless communications,” *IEEE J. Sel. Areas in Commun.*, vol. 23, no. 2, pp. 201–220, Feb. 2005.

[21] V. Chandrasekhar and J. G. Andrews, “Femtocell networks: A survey,” *IEEE Commun. Mag.*, vol. 46, no. 9, pp. 59–67, Sep. 2008.

[22] H. Zhang, W. Zheng, X. Chu, X. Wen, M. Tao, A. Nallanathan, and D. Lopez-Perez, “Joint subchannel and power allocation in interference-limited OFDMA femtocells with heterogeneous QoS guarantee,” *IEEE Global Communications Conference (GLOBECOM)*, 2012, pp.4572–4577, Dec. 2012.

[23] H.-S. Jo, C. Mun, J. Moon, and J.-G. Yook, “Interference mitigation using uplink power control for two-tier femtocell networks,” *IEEE Trans. Wireless Commun.*, vol. 8, no. 10, pp. 4906–4910, Oct. 2009.

[24] H. Zhang, C. Jiang, X. Mao, and H. Chen, “Interference-Limit Resource Allocation in Cognitive Femtocells with Fairness and Imperfect Spectrum Sensing”, *IEEE Trans. Veh. Technol.*, 2015.

[25] N. Mokari, K. Navaie, and M.G. Khoshkhohlg, “Downlink Radio Resource Allocation in OFDMA Spectrum Sharing Environment with Partial Channel State Information,” *IEEE Trans. Wireless Commun.*, vol.10, no.10, pp.3482–3495, Oct. 2011.

[26] D. W. K. Ng and R. Schober, “Cross-layer scheduling for OFDMA amplify-and-forward relay networks,” *IEEE Trans. Veh. Technol.*, vol. 59, no. 3, pp. 1443–1458, Mar. 2010.

[27] D. Fudenberg, J. Tirole: *Game Theory*. MIT Press 1993.

[28] J. Nash, “The bargaining problem,” *Econometrica: Journal of the Econometric Society*, 1950: 155–162.

[29] Z. Han, Z. Ji, and K. J. R. Liu, “Fair multiuser channel allocation for OFDMA networks using Nash bargaining solutions and coalitions,” *IEEE Trans. Commun.*, vol.53, no.8, pp.1366–1376, Aug. 2005.

[30] C. Y. Wong, R. Cheng, K. Lataief, and R. Murch, “Multiuser ofdm with adaptive subcarrier, bit, and power allocation,” *IEEE J. Sel. Areas in Commun.*, vol. 17, no. 10, pp. 1747–1758, Oct. 1999.

[31] W. Yu and R. Lui, “Dual methods for nonconvex spectrum optimization of multicarrier systems,” *IEEE Trans. Commun.*, vol. 54, no. 7, pp. 1310–1322, July 2006.

[32] M. Tao, Y.-C. Liang, and F. Zhang, “Resource allocation for delay differentiated traffic in multiuser ofdm systems,” *IEEE Trans. Wireless Commun.*, vol. 7, no. 6, pp. 2190–2201, June 2008.

[33] J. G. Proakis, *Digital Communications*. McGraw-Hill, 2001.

[34] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.

[35] J. K. Chen, G. de Veciana, and T. S. Rappaport, “Site-specific knowledge and interference measurement for improving frequency allocations in wireless networks,” *IEEE Trans. Veh. Technol.*, vol. 58, no. 5, pp. 2366–2377, June 2009.

[36] K. Son, S. Lee, Y. Yi, and S. Chong, “Refim: A practical interference management in heterogeneous wireless access networks,” *IEEE J. Sel. Areas in Commun.*, vol. 29, no. 6, pp. 1260–1272, June 2011.

[37] *Way forward proposal for (H)eNB to HeNB mobility*, 3GPP Std. R3-101849, 2010.

[38] Z. Shen, J. G. Andrews, and B. L. Evans, “Adaptive resource allocation in multiuser ofdm systems with proportional rate constraints,” *IEEE Trans. Wireless Commun.*, vol. 4, no. 6, pp. 2726–2737, Nov. 2005.

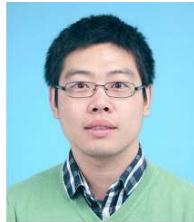
[39] C. Yang, J. Li, and Z. Tian, “Optimal Power Control for Cognitive Radio Networks Under Coupled Interference Constraints: A Cooperative Game-Theoretic Perspective,” *IEEE Trans. Veh. Technol.*, vol. 59, no. 4, pp. 1696–1706, May 2010.

[40] R. Jain, D. M. Chiu, and W. R. Hawe, “A quantitative measure of fairness and discrimination for resource allocation in shared computer system,” Eastern Research Laboratory, Digital Equipment Corporation, 1984.



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Simulation and Deployment, Cambridge University Press (May 2013) and the book *4G Femtocells: Resource Allocation and Interference Management*, Springer US (Nov. 2013). She is Guest Editor of the Special Section on Green Mobile Multimedia Communications for IEEE Transactions on Vehicular Technology (Jun. 2014) and the Special Issue on Cooperative Femtocell Networks for ACM/Springer Journal of Mobile Networks & Applications (Oct. 2012). She is Co-Chair of Wireless Communications Symposium for the IEEE International Conference on Communications 2015 (ICC'15), was Workshop Co-Chair for the IEEE International Conference on Green Computing and Communications 2013 (GreenCom'13), and has been Technical Program Committee Co-Chair of several workshops on heterogeneous networks for IEEE GLOBECOM, WCNC, PIMRC, etc. She received the UK EPSRC Cooperative Awards in Science and Engineering for New Academics in 2008, the UK EPSRC First Grant in 2009, and the RCUK UK-China Science Bridges Fellowship in 2011.



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