Optimal Power Allocation and User Scheduling in Multicell Networks: Base Station Cooperation Using a Game-Theoretic Approach

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***Abstract*—This paper proposes a novel base station (BS) coordination approach for intercell interference mitigation in the orthogonal frequency-division multiple access based cellular networks. Specifically, we first propose a new performance metric for evaluating end user's quality of experience (QoE), which jointly considers spectrum efficiency, user fairness, and service satisfaction. Interference graph is applied here to capture and analyze the interactions between BSs. Then, a QoE-oriented resource allocation problem is formulated among BSs as a local cooperation game, where BSs are encouraged to cooperate with their peer nodes in the adjacent cells in user scheduling and power allocation. The existence of the joint-strategy Nash equilibrium (NE) has been proved, in which no BS player would unilaterally change its own strategy in user scheduling or power allocation. Furthermore, the NE in the formulated game is proved to lead to the global optimality of the network utility. Accordingly, we design an iterative searching algorithm to obtain the global optimum (i.e., the best NE) with an arbitrarily high probability in a decentralized manner, in which only local information exchange is needed. Theoretical analysis and simulation results both validate the convergence and optimality of the proposed algorithm with fairness improvement.**

***Index Terms*—OFDMA, inter-cell interference mitigation, QoE, BS cooperation, potential game, Nash equilibrium, decentralized algorithm, global optimality.**

I. Introduction

INTER-CELL interference is a fundamental problem which limits the performance improvement in the orthogonal frequency division multiple access (OFDMA)-based cellular networks with reuse of the spectral resource. Traditionally this problem is majorly addressed by carefully planning the spectral resource [1], including conventional frequency planning (Reuse-1 and Reuse-3), fractional frequency reuse, partial frequency reuse, and soft frequency reuse. However, these approaches reduce inter-cell interference at the cost of decreasing the spectral efficiency. Future network evolutions are envisioned to employ a full (or an aggressive) frequency reuse to meet the rapidly growing demand of broadband mobile access. Therefore, efficient interference mitigation techniques are urgently required.

Recently, BS cooperation has emerged as a promising approach to mitigate inter-cell interference. Since any change of resource allocation in a single cell will affect the performance of the nearby cells, joint resource allocation over a cluster of neighboring cells via BS coordination proves to be effective [2]–[5]. These solutions usually require neighboring BSs coordinate their resource allocation for the joint network utility optimization, which usually result in high cost in backhaul communications with huge control overhead. This paper treats the coordination problem in an alternative way where user transmission strategies and resource allocation schemes, rather than data flows, are coordinated across the BSs [5], [6]; hence, much less backhaul coordination bandwidth is needed. Most state-of-the-art work concentrates on the (weighted) sum-rate maximization [2], [4], [7], while the achievable solutions are generally far from global optimum. Moreover, the existing solutions introduce unfairness to edge users [2], [7], because edge users usually experience more path loss while the network manager tends to privilege the users closer to the BS with better channel conditions in the resource allocation. Most existing work addresses fairness issue only by using network-level criteria like max-min but neglects the specific requirements of individual users.

In this paper, we take spectrum efficiency, fairness and user's requirements into consideration jointly to improve QoE in the formulated optimization problem. QoE-driven techniques adaptively allocate the limited resources to enhance end user experience so that they reduce the waste of radio resources compared with other techniques adopting the objective metrics, e.g., sum-rate, which neglect individual users' satisfaction of services. For example, if the users with better channel conditions have been allocated with adequate resources, QoE-driven optimizer would then privilege users with poor channel conditions who could experience substantial improvement of satisfaction. Therefore, QoE-driven techniques will bring fairness while increasing efficiency. This paper adopts the mean

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opinion score (MOS) [9] to be the utility metric, which is widely used to provide a generic measure of the user's QoE [10]–[12], [33].

A. Challenges and Contributions

In this paper, we employ BS cooperation to solve the QoE-oriented resource allocation problem in the multicell OFDMA networks, which consists of user scheduling and power allocation as a joint optimization decision by BSs. Furthermore, in the aggressive frequency reuse deployment, the co-channel interference makes the resource allocation among cells coupled and correlated. Moreover, the non-convexity of the utility metric (i.e., MOS) makes the problem more complicated. In this case, centralized algorithms cannot guarantee the global optimality over the network given that the demand on backhaul signaling and computational resources grows rapidly with the number of cells, subchannels and end users. In practical systems, the interference sources to individual users usually come from a small number of neighboring cells (which makes it possible to limit the backhaul signaling and complexity) [3]. Therefore, how to design an efficient distributed algorithm to find the globally optimal solution with only local information exchange throws a great challenge.

We study this problem by applying game theory to analyze the distributed decisions made at individual BSs considering the mutual interference and coupling among their strategies [13]–[16]. The main contributions of our work are summarized below:

- An interference graph is generated to capture and analyze the interaction between BSs. Then, based on the interference graph, the network sum-utility maximization problem is formulated as a local cooperation game, where each BS acts as a rational player. Furthermore, we prove it to be an exact potential game, whose best NE point coincides with the optimal solution with the sum-utility maximization.
- We design a decentralized iterative algorithm to obtain the best NE (i.e., the global optimum) with an arbitrarily high probability, where only local information exchange is needed between neighboring BSs. The convergence, optimality and computational complexity are investigated. Moreover, the fairness improvement by adopting QoE as the optimization goal is theoretically analyzed.

B. Related Work

In recent years, resource allocation for cellular networks has stepped into the focus of extensive studies, because *i)* coordinated resource allocation brings significant performance improvement by effectively mitigating the inter-cell interference, *ii)* coordination across multiple cells poses a great challenge not only in implementation, but also in finding the optimal solutions, since the inter-cell interference leads to inherent non-convexity in the problem structure [6].

One promising way is to use heuristic-based algorithms to obtain satisfactory solutions [17]–[20]. Another way is to decompose the original problem into multiple subproblems and solve them iteratively [6], [21]–[24]. Besides, there are some discussions [25]–[29] concentrating on respective studies (e.g., subchannel allocation, power control) due to the intractability of joint optimization.

Furthermore, many researchers have referred to game theory to seek for a satisfactory solution. In [27]–[29], potential game based subchannel allocation algorithms for interference minimization are proposed. In [26], [30], taking the inter-cell interference into account, the authors study the transmit power control in multicell OFDMA systems by using non-cooperative game. However, almost all consider a simplified system model and just concentrate on only one aspect (either power control or subchannel allocation). In [18], joint subchannel and power allocation is investigated by using game theory. The existence and uniqueness of equilibrium are theoretically proved. However, this work is decomposed into two subgames, in which the subchannel assignment and power control are performed iteratively. Therefore, the obtained solution is suboptimal. Buzzi *et al.* [31] use potential game to make a comprehensive analysis on the joint subchannel and power allocation in a very general system model, but only suboptimal solution is obtained as well. Moreover, the existing game theoretic approaches mainly make an investigation on the existence and uniqueness of the NE point, but pay less attention to the relationship between the NE and the global optimum.

In addition, it should be noted that the coordinated resource allocation in the literature mainly concentrates on QoS optimization, which does not consider the user's satisfaction of services. QoE has recently been under the spotlight in wireless networks. General wireless multimedia transmission schemes have been well studied in [12], [32], [33], in which resource allocation and multimedia scheduling are the focus. Hassan *et al.* [34] investigate the QoE-driven resource allocation from the perspective of the interaction between the provider and the VoIP user, which is naturally formulated as a non-cooperative game. In [10], [11], the authors study the QoE-oriented multiuser resource allocation in the OFDMA systems. To our knowledge, most QoE-driven resource allocation work is limited in single-cell optimization. Sheen *et al.* [35] discuss the performance evaluation and optimization of a general relay-assisted multicell network and a genetic algorithm is proposed to solve the problem. However, this work aims at the joint optimization of the system parameters, including relay's position, reuse pattern, path selection, etc., which is out of the scope of our work.

To sum up, QoE-oriented resource allocation in multicell networks has not been well studied, and the existing solutions are generally far from global optimum. Therefore, in this paper, we employ BS cooperation to improve the efficiency of the solution from a game theoretic perspective. Accordingly, a decentralized iterative algorithm is designed to achieve the global optimum with an arbitrarily high probability.

C. Paper Organization

The remainder of the paper is organized as follows. In Section II, we present the system model followed by the problem formulation for the QoE-driven resource allocation. In Section III, we formulate the local BS cooperation game and investigate the properties of its NE points. In Section IV, a QoE-driven joint user scheduling and power allocation algorithm is proposed to find the global optimum of our problem. Section V presents simulation results and discussion. Conclusions are drawn in Section VI.

II. System Model and Problem Formulation

A. System Model

We consider an OFDMA-based cellular network which consists of a set of L BSs, denoted by $\mathcal{L} = \{1, 2, \ldots, l, \ldots L\}$. We assume each cell is served by a BS and BSs communicate with the users in a single-hop fashion. We also assume BSs are temporally synchronized. BSs and users are equipped with one transmit and one receive antenna, respectively. $\mathcal{N} = \{1, 2, \ldots, n, \ldots N\}$ is the network user set. The set of users served by BS $l \in \mathcal{L}$ is denoted by $\mathcal{N}_l$, $\mathcal{N}_l \subseteq \mathcal{N}$, and $\bigcup_l \mathcal{N}_l = \mathcal{N}$. Each user is connected to only one base station that is selected based on long-term channel quality measurement. Thus, $\mathcal{N}_l \cap \mathcal{N}_{l'} = \emptyset$, for $l \neq l'$. We consider the universal frequency reuse deployment in which every cell shares the whole bandwidth. The available spectrum is divided into K subchannels[1] and the index set of all subchannels is denoted by $\mathcal{K} = \{1, 2, \ldots, k, \ldots K\}$. $N = |\mathcal{N}|$ and $K = |\mathcal{K}|$ are the cardinalities of $\mathcal{N}$ and $\mathcal{K}$, respectively. In this paper we focus on the study of downlink communications from BSs to the users. Our analysis can be easily extended to the uplink discussion.

1) MAC and Physical Layer: In the network, the spectral resource slots are shared by all cells, leading to an interference and noise impaired system. Let $s_l^k \in \mathcal{N}_l$ denote the user connected to base station l in spectral slot k. When perfect synchronization is assumed, the discrete-time baseband signal received by user s_l^k in slot k is given by

$$r_{s_l^k} = \underbrace{H_{l,s_l^k} x_{s_l^k}}_{\text{useful data}} + \underbrace{\sum_{i=1, i\neq l}^{L} H_{l,s_i^k} x_{s_i^k}}_{\text{intercell interference}} + \underbrace{Z_{s_l^k}}_{\text{noise}}, \tag{1}$$

where $x_{s_l^k}$ and H_{l,s_l^k} are the transmitted complex symbol and the complex channel response from BS l to user s_l^k, respectively. $Z_{s_l^k}$ is the additional noise, which is modeled as a white Gaussian variable with power $\mathbb{E}|Z_{s_l^k}|^2 = \sigma^2$.

Suppose user n is connected with BS l, i.e., $n \in \mathcal{N}_l$. Let $\delta_{l,n}^k$ be the spectral slot allocation indicator to denote whether slot k is allocated to the user n in cell l: $\delta_{l,n}^k = 1$ if the slot is allocated to the user; otherwise, $\delta_{l,n}^k = 0$. Then, the signal-to-interference-plus-noise ratio (SINR) of user n within cell l in slot k, is written as

$$\gamma_{l,n}^k = \frac{\delta_{l,n}^k p_l^k G_{l,n}^k}{\sum_{i=1, i\neq l}^{L} \delta_{l,n}^k p_i^k G_{i,n}^k + \sigma^2}, \tag{2}$$

where p_l^k is the transmit power of BS l in slot k, $G_{l,n}^k = |H_{l,n}^k|^2$ is the channel power gain from BS l to user n in slot k.

[1] We will use spectral slot and subchannel interchangeably in this paper.

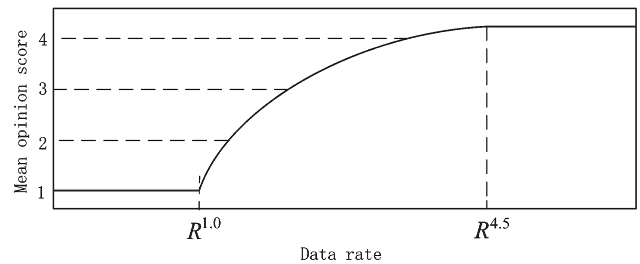

Fig. 1. Generic application model (The subscription of data rate denoting the specific user is omitted).

Without loss of generality, we assume that the bandwidth of each subchannel is less than the coherence bandwidth of the channel so that flat fading is considered in each subchannel.

The corresponding achievable information rate is given by the following Shannon's formula:

$$R_{l,n}^k = \frac{B}{K} \log_2 \left(1 + \frac{\gamma_{l,n}^k}{\Gamma}\right), \tag{3}$$

where $\Gamma = -\ln(5\text{BER})/1.5$ is BER gap. Then, the aggregate rate of user n is $R_{l,n} = \sum_{k\in\mathcal{K}_n} R_{l,n}^k$, where $\mathcal{K}_n$ is the set of slots occupied by user n.

2) Application Layer: MOS is used as a measure of the user's QoE for the services like video streaming, file download, and web browsing. The value of MOS is distributed between 1 and 4.5. MOS $= 1$ reflects an unacceptable application quality, and MOS $= 4.5$ corresponds to an excellent quality experienced by the user.

The considered generic application characteristic [10] resembles a bounded logarithmic relationship between perceived quality and data rate as illustrated in Fig. 1, described by the MOS as a function of the data rate,

$$\text{MOS}_{l,n}(R_{l,n}) = \begin{cases} 4.5, & R_{l,n} \geq R_{l,n}^{4.5}, \\ a \log \frac{R_{l,n}}{b}, & R_{l,n}^{1.0} < R_{l,n} < R_{l,n}^{4.5}, \\ 1, & R_{l,n} \leq R_{l,n}^{1.0}, \end{cases} \tag{4a}$$

with

$$a = \frac{3.5}{\log\left(R_{l,n}^{4.5}/R_{l,n}^{1.0}\right)}, \tag{4b}$$

$$b = R_{l,n}^{1.0} \left(\frac{R_{l,n}^{1.0}}{R_{l,n}^{4.5}}\right)^{1/3.5}, \tag{4c}$$

$$0 \leq R_{l,n}^{1.0} < R_{l,n}^{4.5}, \qquad \forall n \in \mathcal{N}_l. \tag{4d}$$

The semilogarithmic plot of Fig. 1 visualizes the related parameters: the parameter a determines the slope of $\text{MOS}_{l,n}(R_{l,n})$ while b shifts the curve along the X-axis. Each user's application characteristic can be parameterized by only two parameters, $\{R_{l,n}^{1.0}, R_{l,n}^{4.5}\}$, or alternatively $\{a, b\}$.

B. Problem Formulation

Since the system is based on OFDMA, intra-cell multi-user access is orthogonal, while inter-cell multi-user access is simply superposed due to full reuse of spectrum. It is the superposition of the slots that results in severe co-channel interference, which majorly limits the system performance. Therefore, it is intuitive to decouple the optimization of resources in various spectral resource slots (i.e., frequency bands, or sub-channels), and we may study the user scheduling and power allocation which maximize the system performance in a particular slot [8]. We will suppress the slot index hereafter, concentrating in one arbitrary slot. In any given spectral resource slot shared by all cells, we denote the user that is granted access to the slot (i.e., scheduled) in cell l by $s_l \in \mathcal{N}_l$.

Definition 1: A ***scheduling vector*** characterizes the set of users simultaneously scheduled across all cells in the same slot: $\mathbf{s} = (s_1, s_2, \ldots, s_l, \ldots, s_L)$, where $[\mathbf{s}]_l = s_l$. Noting that $s_l \in \mathcal{N}_l$, the constraint set of scheduling vectors (i.e. the scheduling strategy space) is given by $\mathbb{S} = \mathcal{N}_1 \otimes \mathcal{N}_2 \otimes \cdots \otimes \mathcal{N}_L$, where $\otimes$ denotes the Cartesian product.

Definition 2: A ***transmit power vector*** characterizes the transmit power values used by each BS to communicate with its respective scheduled user: $\mathbf{p} = (p_1, p_2, \ldots, p_l, \ldots, p_L)$, where $[\mathbf{p}]_l = p_l$. Note that in real practice, the cellular standards like the 3GPP LTE standard only support discrete power control[2] in the downlink. We assume each BS can use $M \geq 2$ different power levels for transmission, namely $\{\lambda_1 P_{l,\max}, \lambda_2 P_{l,\max}, \ldots, \lambda_M P_{l,\max}\}$, where $0 = \lambda_1 < \lambda_2 < \ldots < \lambda_M = 1$. Then, the constraint set of transmit power vectors is given by $\mathbb{P} = \{\mathbf{p} | p_l \in \{\lambda_1 P_{l,\max}, \lambda_2 P_{l,\max}, \ldots, \lambda_M P_{l,\max}\}, \forall l = 1, \ldots, L\}$.

Base stations are coordinated to jointly determine the optimal scheduling vector and transmit power vector which maximize the system utility (i.e., MOS). From the system optimization point of view, the sum-utility optimal resource allocation problem can now be formalized simply as

$$(\mathbf{s}^{\text{opt}}, \mathbf{p}^{\text{opt}}) = \arg\max_{\mathbf{s} \in \mathbb{S}, \mathbf{p} \in \mathbb{P}} U_0, \tag{5}$$

where $U_0 = \sum_{l \in \mathcal{L}} \text{MOS}_l = \sum_{l \in \mathcal{L}} \sum_{n \in \mathcal{N}_l} \omega_{l,n} \text{MOS}_{l,n}$ is the network utility function, $\omega_{l,n}$ is the weight of the scheduled user in the lth cell.

Remark 1: The sum-MOS optimal joint user scheduling and power allocation problem for a multicell wireless network belongs to a class of combinatorial optimization problems; finding the globally optimal solution $(\mathbf{s}^{\text{opt}}, \mathbf{p}^{\text{opt}})$ is NP-hard. Hence, standard optimization techniques cannot be applied directly and even centralized algorithms cannot guarantee the globally optimal solution.

III. Interference Game for QoE-Oriented BS Coordination

In this section, we discuss on the distributed solution of the above problem (5) by using game theory. The ability to model individual, independent decision makers, whose strategies are interactional, makes game theory particularly attractive to analyze the performance of decentralized network/framework.

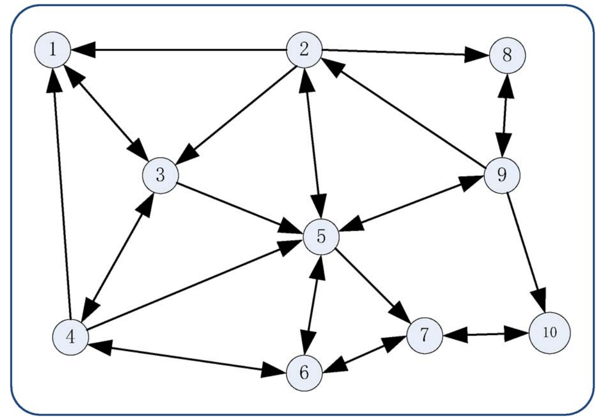

Fig. 2. A unilateral interference graph with 10 BSs (Each node represents a BS, and each directional edge represents an interference link from one end to another end).

A. Interference Graph

In order to quantify the inter-cell interference, we employ the interference metric (IM) in [2], which is defined by

$$\text{IM}_l^i = \frac{1}{|\mathcal{N}_l|} \sum_{n \in \mathcal{N}_l} \frac{G_{i,n}}{G_{l,n}}, \tag{6}$$

where $G_{i,n}$ is the channel gain from BS i to user $n \in \mathcal{N}_l$, and $|\mathcal{N}_l|$ is the number of elements in $\mathcal{N}_l$. Notice that the ratio $G_{i,n}/G_{l,n}$ indicates the amount of interference caused by BS i to user n, and IM_l^i is simply calculated by averaging the ratio $G_{i,n}/G_{l,n}$ over all users served by BS l.

The interference relationship is now characterized by a directional graph $\mathbf{G}_d = (\mathcal{L}, \varepsilon)$. The graph $\mathbf{G}_d$ consists of the BS set $\mathcal{L}$, and a set of edges $\varepsilon \in \mathcal{L}^2$. Denote each edge as an ordered pair (i, l), obviously, $(i, l) \in \varepsilon$. In cellular networks, the transmission is severely interfered with only by BSs located in a few surrounding cells, and the interference from the remote BSs is trivial. To capture the near-far effect, deciding the edge of the interference graph is based on (6). Only if the value of IM_l^i is larger than a predefined threshold IM_l^0, there is an edge from BS i to l, which means BS i causes non-ignorable interference to cell l. Moreover, since the mutual interference is not symmetrical $(\text{IM}_l^i \neq \text{IM}_i^l)$ in the cellular system, the produced interference graph is unilateral with directional edges, as shown in Fig. 2. Then for each BS l, the following two neighbor sets can be defined:

- the in-neighbor set $\mathcal{B}_l^{\text{in}} : \mathcal{B}_l^{\text{in}} = \{i \in \mathcal{L} : (i, l) \in \varepsilon\}$.
- the out-neighbor set $\mathcal{B}_l^{\text{out}} : \mathcal{B}_l^{\text{out}} = \{j \in \mathcal{L} : (l, j) \in \varepsilon\}$.

We use $\mathbf{p}_{\mathcal{B}_l^{\text{in}}}$ and $\mathbf{s}_{\mathcal{B}_l^{\text{in}}}$ to denote the power allocation and user scheduling strategy profile of BS l's in-neighbors, respectively. Then, cell l's performance is denoted by $\text{MOS}_l(p_l, \mathbf{p}_{\mathcal{B}_l^{\text{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\text{in}}})$, since it is affected by the cochannel interference from the neighboring BSs.

It is worth noting that other metrics can also be used to decide the interference graph (e.g., simply based on the geographic location of BSs and users [36], or further considering the

[2]It is worth noting in [2] that discrete power control which offers two main benefits over continuous power control: *i)* the transmitter design is simplified, *ii)* the overhead of information exchange among network nodes is significantly reduced.

traffic load, etc.). However, there would be little variation in the following game model and the main conclusions. Since the optimal construction of the interference graph is not the focus of this work, we adopt the metric in [2] in order to perform convictive algorithm comparison.

B. Game Model With Local BS Cooperation

Based on the interference graph, the game is formally denoted by $\mathcal{G} = [\mathcal{L}, \{\mathcal{S}_l \otimes \mathcal{P}_l\}_{l\in\mathcal{L}}, \mathbf{G}_d, \{U_l\}_{l\in\mathcal{L}}]$, where $\mathcal{L} = \{1, 2, \ldots, L\}$ is the set of players (i.e., BSs), $\mathcal{S}_l \otimes \mathcal{P}_l$ is the set of available joint power and channel allocation strategy for player l, and U_l is the utility function of player l. To improve the efficiency of the game and obtain the globally optimal solution, the utility function of each player l is defined as

$$U_l\left(p_l, \mathbf{p}_{\mathcal{D}_l}, s_l, \mathbf{s}_{\mathcal{D}_l}\right) = \mathrm{MOS}_l\left(p_l, \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right) + \sum_{i\in\mathcal{B}_l^{\mathrm{out}}} \mathrm{MOS}_i\left(p_i, \mathbf{p}_{\mathcal{B}_i^{\mathrm{in}}}, s_i, \mathbf{s}_{\mathcal{B}_i^{\mathrm{in}}}\right), \quad (7)$$

where $\mathcal{D}_l$ represents the interacting neighbor set of player l, $\mathbf{p}_{\mathcal{D}_l} \in \mathcal{P}_{\mathcal{D}_l}$ and $\mathbf{s}_{\mathcal{D}_l} \in \mathcal{S}_{\mathcal{D}_l}$ denote the power allocation and user scheduling strategy profile of player l's interacting neighbors (excluding l), respectively. $\mathcal{P}_{\mathcal{D}_l} \equiv \otimes\mathcal{P}_i$, $\mathcal{S}_{\mathcal{D}_l} \equiv \otimes\mathcal{S}_i$, $\forall i \in \mathcal{D}_l$, are the sets of action profiles. According to (7), we can get

$$\mathcal{D}_l = \bigcup_{i\in\mathcal{B}_l^{\mathrm{out}}} \mathcal{B}_i^{\mathrm{in}} \cup \mathcal{B}_l^{\mathrm{in}} \cup \mathcal{B}_l^{\mathrm{out}}. \quad (8)$$

Then, referring to the definitions of $\mathcal{B}_l^{\mathrm{in}}$ and $\mathcal{B}_l^{\mathrm{out}}$, the interacting neighbor set $\mathcal{D}_l$ is further decided by

$$\mathcal{D}_l = \mathcal{B}_l^{\mathrm{in}} \cup \mathcal{B}_l^{\mathrm{out}} \cup \left\{j : j \neq l, \mathcal{B}_j^{\mathrm{out}} \cap \mathcal{B}_l^{\mathrm{out}} \neq \emptyset\right\}. \quad (9)$$

If $i_1 \in \mathcal{D}_{i_2}$, we say that two BSs i_1 and i_2 are interacting neighbors. Obviously, $i_1 \in \mathcal{D}_{i_2} \Leftrightarrow i_2 \in \mathcal{D}_{i_1}$.

Note that the above defined utility function is comprised of two parts: the individual utility of player l and the aggregate utility of its interfered neighbors. In other words, when a player makes a decision, it not only considers itself but also considers its interfered neighbors. Then, the local cooperation game is expressed as follows:

$$(\mathcal{G}): \max_{p_l\in\mathcal{P}_l, s_l\in\mathcal{S}_l} U_l\left(p_l, \mathbf{p}_{\mathcal{D}_l}, s_l, \mathbf{s}_{\mathcal{D}_l}\right), \ \forall l \in \mathcal{L}. \quad (10)$$

*Definition 3 (**Nash Equilibrium**):* A resource allocation profile $(\mathbf{p}^*, \mathbf{s}^*) = (p_1^*, p_2^*, \ldots, p_L^*, s_1^*, s_2^*, \ldots, s_L^*)$ is a pure strategy NE point of $\mathcal{G}$ if and only if no player can improve its utility by deviating unilaterally, i.e.,

$$U_l\left(p_l^*, \mathbf{p}_{\mathcal{D}_l}^*, s_l^*, \mathbf{s}_{\mathcal{D}_l}^*\right) \geq U_l\left(p_l, \mathbf{p}_{\mathcal{D}_l}^*, s_l, \mathbf{s}_{\mathcal{D}_l}^*\right), \quad \forall l \in \mathcal{L},\ \forall p_l \in \mathcal{P}_l \setminus \{p_l^*\},\ \forall s_l \in \mathcal{S}_l \setminus \{s_l^*\}, \quad (11)$$

where $A_1 \setminus A_2$ means that A_2 is excluded from A_1.

C. Analysis of NE

Theorem 1: The QoE-oriented resource allocation game $\mathcal{G}$ is an exact potential game which has at least one pure strategy NE.

Proof: The following proof follows the idea of proof given in [27]–[29].

First we construct a potential function as

$$\Phi(p_l, \mathbf{p}_{-l}, s_l, \mathbf{s}_{-l}) = \sum_{l\in\mathcal{L}} \mathrm{MOS}_l(p_l, \mathbf{p}_{-l}, s_l, \mathbf{s}_{-l}), \quad (12)$$

where $\mathbf{p}_{-l}$ and $\mathbf{s}_{-l}$ represents the power allocation and user scheduling strategy profile of all the BSs excluding BS l, respectively. Since $\mathrm{MOS}_l(p_l, \mathbf{p}_{-l}, s_l, \mathbf{s}_{-l}) = \mathrm{MOS}_l(p_l, \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}})$ based on the interference graph, we have

$$\begin{aligned}\Phi\left(p_l, \mathbf{p}_{-l}, s_l, \mathbf{s}_{-l}\right) &= \sum_{l\in\mathcal{L}} \mathrm{MOS}_l\left(p_l, \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right)\\ &= \mathrm{MOS}_l\left(p_l, \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right) + \sum_{i\in\mathcal{B}_l^{\mathrm{out}}} \mathrm{MOS}_i\left(p_i, \mathbf{p}_{\mathcal{B}_i^{\mathrm{in}}}, s_i, \mathbf{s}_{\mathcal{B}_i^{\mathrm{in}}}\right)\\ &\quad + \sum_{i\in\left\{\mathcal{N}\setminus\mathcal{B}_l^{\mathrm{out}}\right\}, i\neq l} \mathrm{MOS}_i\left(p_i, \mathbf{p}_{\mathcal{B}_i^{\mathrm{in}}}, s_i, \mathbf{s}_{\mathcal{B}_i^{\mathrm{in}}}\right). \end{aligned} \quad (13)$$

1) Suppose that an arbitrary player, say l, unilaterally changes its transmit power from p_l to p_l', then the change in potential function is given by (14), shown at the bottom of the page. For $i \in \mathcal{B}_l^{\mathrm{out}}$, we have $l \in \mathcal{B}_i^{\mathrm{in}}$; thus, when l changes its transmit power from p_l to p_l', $\mathbf{p}'_{\mathcal{B}_i^{\mathrm{in}}} \neq \mathbf{p}_{\mathcal{B}_i^{\mathrm{in}}}$. However, if $i \in \{\mathcal{N} \setminus \mathcal{B}_l^{\mathrm{out}} \setminus \{l\}\}$, $\mathbf{p}'_{\mathcal{B}_i^{\mathrm{in}}} = \mathbf{p}_{\mathcal{B}_i^{\mathrm{in}}}$ when l changes its transmit power. Thus, the following equation holds:

$$\mathrm{MOS}_i\left(p_i, \mathbf{p}'_{\mathcal{B}_i^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right) = \mathrm{MOS}_i\left(p_i, \mathbf{p}_{\mathcal{B}_i^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right), \quad \forall i \in \left\{\mathcal{N} \setminus \mathcal{B}_l^{\mathrm{out}}\right\},\ i \neq l \quad (15)$$

$$\begin{aligned}&\Phi\left(p_l', \mathbf{p}_{-l}, s_l, \mathbf{s}_{-l}\right) - \Phi(p_l, \mathbf{p}_{-l}, s_l, \mathbf{s}_{-l})\\ &= \sum_{l\in\mathcal{L}} \mathrm{MOS}_l\left(p_l', \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right) - \sum_{l\in\mathcal{L}} \mathrm{MOS}_l\left(p_l, \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right)\\ &= \mathrm{MOS}_l\left(p_l', \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right) - \mathrm{MOS}_l\left(p_l, \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right) + \sum_{i\in\mathcal{B}_l^{\mathrm{out}}}\left(\mathrm{MOS}_i\left(p_i, \mathbf{p}'_{\mathcal{B}_i^{\mathrm{in}}}, s_i, \mathbf{s}_{\mathcal{B}_i^{\mathrm{in}}}\right) - \mathrm{MOS}_i\left(p_i, \mathbf{p}_{\mathcal{B}_i^{\mathrm{in}}}, s_i, \mathbf{s}_{\mathcal{B}_i^{\mathrm{in}}}\right)\right)\\ &\quad + \sum_{i\in\left\{\mathcal{N}\setminus\mathcal{B}_l^{\mathrm{out}}\right\}, i\neq l}\left(\mathrm{MOS}_i\left(p_i, \mathbf{p}'_{\mathcal{B}_i^{\mathrm{in}}}, s_i, \mathbf{s}_{\mathcal{B}_i^{\mathrm{in}}}\right) - \mathrm{MOS}_i\left(p_i, \mathbf{p}_{\mathcal{B}_i^{\mathrm{in}}}, s_i, \mathbf{s}_{\mathcal{B}_i^{\mathrm{in}}}\right)\right). \end{aligned} \quad (14)$$

On the other hand, the change of individual utility function caused by this unilaterally change is given by

$$U_l\left(p_l', \mathbf{p}_{\mathcal{D}_l}, s_l, \mathbf{s}_{\mathcal{D}_l}\right) - U_l\left(p_l, \mathbf{p}_{\mathcal{D}_l}, s_l, \mathbf{s}_{\mathcal{D}_l}\right)$$
$$= \mathrm{MOS}_l\left(p_l', \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right) - \mathrm{MOS}_l\left(p_l, \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right)$$
$$+ \sum_{i\in\mathcal{B}_l^{\mathrm{out}}}\left(\mathrm{MOS}_i\left(p_i, \mathbf{p}'_{\mathcal{B}_i^{\mathrm{in}}}, s_i, \mathbf{s}_{\mathcal{B}_i^{\mathrm{in}}}\right) - \mathrm{MOS}_i\left(p_i, \mathbf{p}_{\mathcal{B}_i^{\mathrm{in}}}, s_i, \mathbf{s}_{\mathcal{B}_i^{\mathrm{in}}}\right)\right). \tag{16}$$

Then, based on (14)–(16), we can get

$$\Phi\left(p_l', \mathbf{p}_{-l}, s_l, \mathbf{s}_{-l}\right) - \Phi\left(p_l, \mathbf{p}_{-l}, s_l, \mathbf{s}_{-l}\right)$$
$$= U_l\left(p_l', \mathbf{p}_{\mathcal{D}_l}, s_l, \mathbf{s}_{\mathcal{D}_l}\right) - U_l\left(p_l, \mathbf{p}_{\mathcal{D}_l}, s_l, \mathbf{s}_{\mathcal{D}_l}\right). \tag{17}$$

2) Given transmit power vector $\mathbf{p} = (p_1, p_2, \ldots, p_L)$, the user selection problem decouples across BSs. It is a particular property of the downlink in the cellular network, since the received interference as well as the MOS value does not change with the variation of user selection strategies of other cells when the transmit power vector given. In other words, each BS's MOS value is independent of the user scheduling strategies of other BSs, but only depends on its own user scheduling strategy, i.e.,

$$\mathrm{MOS}_i\left(p_i, \mathbf{p}_{\mathcal{B}_i^{\mathrm{in}}}, s_i, \mathbf{s}_{\mathcal{B}_i^{\mathrm{in}}}\right) = \mathrm{MOS}_i\left(p_i, \mathbf{p}_{\mathcal{B}_i^{\mathrm{in}}}, s_i\right), \forall i \in \mathcal{L}. \tag{18}$$

Therefore, when player l unilaterally changes its user selection strategy from s_l to s_l', $\forall i \neq l$, MOS_i keeps unchanged. Then, it is easy to get

$$\Phi\left(p_l, \mathbf{p}_{-l}, s_l', \mathbf{s}_{-l}\right) - \Phi\left(p_l, \mathbf{p}_{-l}, s_l, \mathbf{s}_{-l}\right)$$
$$= \mathrm{MOS}_l\left(p_l, \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l', \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right) - \mathrm{MOS}_l\left(p_l, \mathbf{p}_{\mathcal{B}_l^{\mathrm{in}}}, s_l, \mathbf{s}_{\mathcal{B}_l^{\mathrm{in}}}\right)$$
$$= U_l\left(p_l, \mathbf{p}_{\mathcal{D}_l}, s_l', \mathbf{s}_{\mathcal{D}_l}\right) - U_l\left(p_l, \mathbf{p}_{\mathcal{D}_l}, s_l, \mathbf{s}_{\mathcal{D}_l}\right). \tag{19}$$

It is shown from (17) and (19) that the change in individual utility function caused by any player's unilateral deviation equals to the change in the potential function. Thus, according to the definition given in [37], $\mathcal{G}$ is an exact potential game with network utility U_0 serving as the potential function. Exact potential game is a special kind of game since it admits several promising properties, among which the most important one is that every exact potential game has at least one pure strategy NE point. Therefore, Theorem 1 is proved. ■

The players in the game focus on maximizing their individual utility functions, as specified by (10). This may result in inefficiency and dilemma, which is known as tragedy of commons [38]. Although Theorem 1 demonstrates that this game has at least one pure NE point, analyzing the achievable performance of NE points of a general exact potential game is interesting and important.

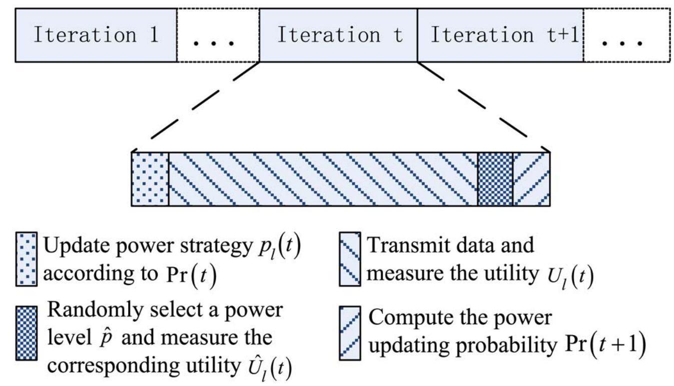

Fig. 3. The schematic diagram of the proposed decentralized iterative algorithm (Once the power strategy is updated, the user scheduling updating based on Eq. (20) follows, which is omitted for brevity in this figure).

Theorem 2: The globally optimal solution of the network sum-MOS maximization problem constitutes a pure strategy NE of $\mathcal{G}$.

Proof: It is proved by D. Monderer and L. S. Shapley [37] that all Nash equilibria are the maximizers of the potential function Φ, either locally or globally. Furthermore, according to (12) and the definition of network utility U_0, we know that the potential function coincides with the network utility U_0. Therefore, all Nash equilibria maximize the network utility U_0 either locally or globally, and the best NE serves as the global optimum of the network utility. Hence, Theorem 2 is proved. ■

According to Theorem 2, in order to achieve the global optimum, we only need to develop an effective algorithm to obtain the best NE.

IV. Decentralized Iterative Algorithm for Achieving Globally Optimal Solution

With the joint power allocation and user scheduling problem now formulated as an exact potential game, there are several learning algorithms available in the literature to achieve the pure strategy NE, e.g., best response dynamic [37], fictitious play [39], [40], and no-regret learning [41]. However, all of them aim at achieving an equilibrium solution, and are easily trapped in an undesirable equilibrium. Recently, a γ-logit approach has attracted significant attention in potential game theory, e.g., [13], [27], [42], [43], due to its favorable property of equilibrium selection and exploring global optimum. In this section, we propose a γ-logit based decentralized iterative algorithm to obtain the optimal solution to the problem in (5) with an arbitrarily high probability. The algorithm runs at the beginning of each scheduling interval and has multiple iterations in which the user scheduling and the transmit power are updated.

A. Algorithm Description

Let $p_l(t)$, $s_l(t)$ be the transmit power level and the user assignment of BS l at iteration t, respectively, for $l = 1, \ldots, L$ and $t \geq 0$. The proposed procedure is described in Algorithm 1 and the schematic diagram is shown in Fig. 3.

γ-logit based decentralized iterative algorithm

Initialization: Set the iteration $t = 0$, and let each BS l, $\forall l \in \mathcal{L}$, select the maximum power level $P_{l,\max}$. Then, each BS randomly selects a user for its communication.

Loop for $t = 0, 1, 2, \ldots$

1) **Player selection**: A set of non-interacting BSs, say $\mathcal{C}(t)$, is randomly selected in an autonomous and distributed manner. $\forall i_1, i_2 \in \mathcal{C}(t), i_1 \notin \mathcal{D}_{i_2}$. Then, each selected BS computes its current utility value $U_l(t)$ by (7) through the communication[3] with neighboring BSs.
2) **Exploration**: Each selected BS $l \in \mathcal{C}(t)$ randomly chooses a power level $\hat{p} \in \{\lambda_1 P_{l,\max}, \lambda_2 P_{l,\max}, \ldots, \lambda_M P_{l,\max}\}$ with equal probability $1/M$. Then, based on the new transmit power levels, BS l as well as its neighbors independently decides its best user assignment $\hat{s}_i(t)$ as[4]

$$\hat{s}_i(t) = \arg\max_{n \in \mathcal{N}_i} \omega_{i,n} \mathrm{MOS}_{i,n}, \forall i \in \left\{\mathcal{B}_l^{\mathrm{out}} \cup \{l\}\right\}, \quad (20)$$

The BSs adhere to their selections in an estimation period and calculate their respective MOS value. Then, the selected BS $l \in \mathcal{C}(t)$ computes its exploring utility value $\hat{U}_l(t)$ by (7) through the communication with its neighboring BSs.
3) **Strategy Updating**: Each selected BS l updates its power level according to the following rule:

$$\begin{cases} \Pr\left(p_l(t+1) = \hat{p}\right) = \frac{\exp\left\{\beta \hat{U}_l(t)\right\}}{\Psi} \\ \Pr\left(p_l(t+1) = p_l(t)\right) = \frac{\exp\{\beta U_l(t)\}}{\Psi}, \end{cases} \quad (21)$$

where $\Psi = \exp\{\beta \hat{U}_l(t)\} + \exp\{\beta U_l(t)\}$ and β is a positive parameter. Meanwhile, all the other BSs keep their selections unchanged, i.e., $p_i(t+1) = p_i(t)$, $\forall i \in \mathcal{L} \setminus \mathcal{C}(t)$. Then, based on the updated power levels, each BS recomputes the best user assignment $s_i(t+1)$ by (20).

End loop until the stopping criterion is met.

In order to find the globally optimal solution, *i)* neighboring BSs cooperate to exchange information directly[5] and only local information is involved, *ii)* interacting neighbors are not allowed to simultaneously change the transmit power level in the proposed algorithm. In the player selection step of Algorithm 1, the selection of the non-interacting BSs set can be implemented through contention mechanisms over a common control channel or a priority-based method in [2]. The stop criterion can be one of the following: *i*) the maximum number of iterations is reached, *ii*) the variation of the network utility during a period is less than a predefined threshold.

[3]Necessary communication is used to obtain its neighbors' MOS.

[4]In the downlink of the cellular network, each BS's MOS value is independent of the user scheduling strategies of other BSs, but only depends on its own user scheduling strategy, as shown in (18). Therefore, the optimal user assignment problem decouples across BSs when the power vector $\mathbf{p}$ is given.

[5]Neighboring BSs are connected though high-speed wireline, thus their information exchange is very easy.

The γ-logit based decentralized algorithm is inspired by the work in [13], [42], [43], where the idea of probabilistic decision making is proposed and developed. The probabilistic decision making rule in step 3 is referred to as Boltzmann exploration strategy [13], [45], [46], and the parameter β is analogous to the concept of temperature in simulated annealing. We introduce such a probabilistic strategy selection into our algorithm for the coordinated resource allocation problem in order to escape from local optimal points and finally converge to the optimal NE (i.e., global optimum). In addition, the same resource allocation problem is also addressed in [2], while the designed algorithm there is essentially the best response (BR) in which each player explores its whole strategy space and selects the best strategy. It should be noted that the best response may easily get trapped at an undesirable NE [43].

The basic requirement for the convergence of the existing logit algorithm is that only one player updates its action at one time [27], [42], [43]. However, in a large-scale multi-cell network, the scheme of only one player's strategy updating would slow the convergence of the algorithm. To accelerate the convergence, we improve the algorithm by allowing multiple (non-neighboring) players to update their respective actions simultaneously. Secondly, in the typical logit algorithm, each active player's strategy updating is based on the exploration in the whole strategy space. Our problem is joint power allocation and user scheduling. Thus, the strategy space is two-dimensional, and each active player should explore the action from the two-dimensional strategy space. In this case, the complexity is high, and the convergence speed slows down. To decrease the complexity and also accelerate the convergence, we modify the algorithm by decomposing the joint problem into two steps (i.e., reducing the scale of the explored strategy space) while keeping the optimality of the solution. The convergence of the proposed modified algorithm needs to be revisited, which will be proved in Subsection C.

B. Convergence and Optimality Analysis

Theorem 3: If all players adhere to the proposed decentralized iterative algorithm, the unique stationary distribution $\pi(\mathbf{p}, \mathbf{s})$ of any joint user scheduling and power allocation strategy profile $(\mathbf{p}, \mathbf{s})$, is given by:

$$\pi(\mathbf{p}, \mathbf{s}) = \frac{\exp\left\{\beta \Phi(\mathbf{p}, \mathbf{s})\right\}}{\sum_{\mathbf{p} \in \mathbb{P}} \exp\left\{\beta \Phi(\mathbf{p}, \mathbf{s})\right\}}, \quad (22)$$

where $\mathbb{P}$ is the space of transmit power profile for all BSs, Φ is the potential function given in (12) and $\mathbf{s}$ is the user scheduling vector which is uniquely determined by $\mathbf{p}$, i.e., $\mathbf{s} = g(\mathbf{p})$.

Proof: Given transmit power vector $\mathbf{p}$, the user selection problem decouples across BSs, thus each BS can decide its own user scheduling strategy independently in our proposed algorithm. Hence, the user scheduling vector $\mathbf{s}$ is uniquely determined by $\mathbf{p}$, and we use function $g(\cdot)$ to denote this relationship.

Following similar proof given in [27], [42], [47], we denote the power allocation state in the t-th iteration by $\mathbf{p}(t) = (p_1(t), p_2(t), \ldots, p_L(t))$. Notably, $\mathbf{p}(t)$ is a discrete time

Markov process, which is irreducible and aperiodic. Therefore, it has an unique stationary distribution. Denote any two arbitrary network states by X and Y, $X, Y \in \mathbb{P}$, and the transition probability from X to Y by $\Pr(Y|X)$.

In the following part, we will show that the unique distribution must be (22) by verifying that the distribution (22) satisfies the following balanced equation:

$$\pi(X)\Pr(Y|X) = \pi(Y)\Pr(X|Y). \tag{23}$$

If $X = Y$, (23) obviously holds. Then, we focus on the case of $X \neq Y$. Note that only non-neighbor BSs are allowed to update their strategies simultaneously in each iteration, which results in the change of corresponding elements in X. For clear presentation, we denote X by $(p_1, p_2, \ldots, p_L)$, where the iteration index t and the subchannel superscript k are omitted. Without loss of generality, suppose that the set of non-interacting BSs who simultaneously update their strategies is $\mathcal{C} = \{1, 2, \ldots, |\mathcal{C}|\}$, where $|\mathcal{C}|$ denotes the number of $\mathcal{C}$'s elements. Therefore, $Y = (p'_1, p'_2, \ldots, p'_{|\mathcal{C}|}, p_{|\mathcal{C}|+1}, p_{|\mathcal{C}|+2}, \ldots, p_L)$. Additionally, we assume the probability of $\mathcal{C}$ to be chosen as the set of updating players is η. Since any power level has probability $1/M$ of being chosen in the proposed algorithm, we can get (24), shown at the bottom of the page.

By defining α as (25), shown at the bottom of the page, we have

$$\begin{aligned}\pi(X)&\Pr(Y|X)\\ &= \alpha\exp\{\beta\Phi(X, g(X))\}\prod_{i\in\mathcal{C}}\exp\{\beta U_i(p'_i, \mathbf{p}_{\mathcal{D}_i}, g(p'_i, \mathbf{p}_{\mathcal{D}_i}))\}\\ &= \alpha\exp\left\{\beta\Phi(X, g(X)) + \beta\sum_{i\in\mathcal{C}} U_i(p'_i, \mathbf{p}_{\mathcal{D}_i}, g(p'_i, \mathbf{p}_{\mathcal{D}_i}))\right\}.\end{aligned} \tag{26}$$

Due to the symmetry property, we also have

$$\begin{aligned}\pi(Y)&\Pr(X|Y)\\ &= \alpha\exp\left\{\beta\Phi(Y, g(Y)) + \beta\sum_{i\in\mathcal{C}} U_i(p_i, \mathbf{p}_{\mathcal{D}_i}, g(p_i, \mathbf{p}_{\mathcal{D}_i}))\right\}.\end{aligned} \tag{27}$$

Construct a sequence as $X_0, X_1, X_2, \ldots, X_{|\mathcal{C}|}$, where $X_0 = X$ and $X_i = (p'_1, p'_2, \ldots, p'_i, p_{i+1}, p_{i+2}, \ldots, p_L)$, $\forall i \in \mathcal{C}$. Obviously, $Y = X_{|\mathcal{C}|}$. We obtain

$$\begin{aligned}\Phi(Y, g(Y)) &- \Phi(X, g(X))\\ &= \Phi\left(X_{|\mathcal{C}|}, g\left(X_{|\mathcal{C}|}\right)\right) - \Phi(X_0, g(X_0))\\ &= \sum_{i\in\mathcal{C}}\left(\Phi(X_i, g(X_i)) - \Phi(X_{i-1}, g(X_{i-1}))\right)\\ &= \sum_{i\in\mathcal{C}}\left(U_i(X_i, g(X_i)) - U_i(X_{i-1}, g(X_{i-1}))\right).\end{aligned} \tag{28}$$

Because all players in $\mathcal{C}$ are not mutually interacting neighbors, i.e., $\forall i_1, i_2 \in \mathcal{C}$, $i_1 \notin \mathcal{D}_{i_2}$. Therefore,

$$\begin{aligned}U_i&(X_i, g(X_i)) - U_i(X_{i-1}, g(X_{i-1}))\\ &= U_i(p'_i, \mathbf{p}_{\mathcal{D}_i}, g(p'_i, \mathbf{p}_{\mathcal{D}_i})) - U_i(p_i, \mathbf{p}_{\mathcal{D}_i}, g(p_i, \mathbf{p}_{\mathcal{D}_i})).\end{aligned} \tag{29}$$

According to (28) and (29), we can get

$$\begin{aligned}\Phi&(Y, g(Y)) - \Phi(X, g(X))\\ &= \sum_{i\in\mathcal{C}}\left(U_i(p'_i, \mathbf{p}_{\mathcal{D}_i}, g(p'_i, \mathbf{p}_{\mathcal{D}_i})) - U_i(p_i, \mathbf{p}_{\mathcal{D}_i}, g(p_i, \mathbf{p}_{\mathcal{D}_i}))\right).\end{aligned} \tag{30}$$

Then, (26) and (27) immediately yield the balanced (23). Thus, we have

$$\begin{aligned}\sum_{X\in\mathbb{P}}\pi(X)\Pr(Y|X) &= \sum_{X\in\mathbb{P}}\pi(Y)\Pr(X|Y)\\ &= \pi(Y)\sum_{X\in\mathbb{P}}\Pr(X|Y) = \pi(Y),\end{aligned} \tag{31}$$

which is exactly the balanced stationary equation of the Markov process $\mathbf{p}(t)$.

Since the proposed algorithm has an unique stationary distribution and the distribution given by (22) satisfies the balanced equations of its Markov process, we can conclude that its stationary distribution must be (22). Therefore, Theorem 2 is proved. ■

Theorem 4: With a sufficiently large β, the proposed algorithm achieves the globally optimal solution to the sum-MOS maximization problem with an arbitrarily high probability.

Proof: Let $\mathbf{p}^{\text{opt}}$ and $\mathbf{s}^{\text{opt}} = g(\mathbf{p}^{\text{opt}})$ be the globally optimal power allocation vector and user scheduling vector, respectively. Furthermore, Theorem 2 has demonstrated that the global optimum is exactly the best pure strategy NE of $\mathcal{G}$, which maximizes the potential function globally. Thus, we have

$$(\mathbf{p}^{\text{opt}}, \mathbf{s}^{\text{opt}}) = \arg\max_{\mathbf{p}\in\mathbb{P}, \mathbf{s}\in\mathbf{S}} \Phi(\mathbf{p}, \mathbf{s}). \tag{32}$$

$$\pi(X)\Pr(Y|X) = \frac{\exp\{\beta\Phi(X, g(X))\}}{\sum_{X\in\mathbb{P}^k}\exp\{\beta\Phi(X, g(X))\}}\cdot\frac{\eta}{M}\cdot\prod_{i\in\mathcal{C}}\frac{\exp\{\beta U_i(p'_i, \mathbf{p}_{\mathcal{D}_i}, g(p'_i, \mathbf{p}_{\mathcal{D}_i}))\}}{\exp\{\beta U_i(p_i, \mathbf{p}_{\mathcal{D}_i}, g(p_i, \mathbf{p}_{\mathcal{D}_i}))\} + \exp\{\beta U_i(p'_i, \mathbf{p}_{\mathcal{D}_i}, g(p'_i, \mathbf{p}_{\mathcal{D}_i}))\}} \tag{24}$$

$$\alpha = \frac{\eta}{M\sum_{X\in\mathbb{P}^k}\exp\{\beta\Phi(X, g(X))\}}\cdot\prod_{i\in\mathcal{C}}\frac{1}{\exp\{\beta U_i(p_i, \mathbf{p}_{\mathcal{D}_i}, g(p_i, \mathbf{p}_{\mathcal{D}_i}))\} + \exp\{\beta U_i(p'_i, \mathbf{p}_{\mathcal{D}_i}, g(p'_i, \mathbf{p}_{\mathcal{D}_i}))\}} \tag{25}$$

In addition, we have proved in Theorem 3 that the algorithm converges to a unique stationary distribution $\pi(\mathbf{p}, \mathbf{s})$ given by (22), which relies on the parameter β. When the parameter β is sufficiently large (i.e., $\beta \to \infty$), $\exp\{\beta\Phi(\mathbf{p}^{\rm opt}, \mathbf{s}^{\rm opt})\} \gg \exp\{\beta\Phi(\mathbf{p}', \mathbf{s}')\}$, $\forall(\mathbf{p}', \mathbf{s}') \in \mathcal{A} \setminus (\mathbf{p}^{\rm opt}, \mathbf{s}^{\rm opt})$, where $\mathcal{A}$ is the joint strategy space. In this case, according to (22), the unique stationary distribution will be $(0, \ldots, 0, 1, 0, \ldots, 0)$. The probability 1 is given to the globally optimal solution $(\mathbf{p}^{\rm opt}, \mathbf{s}^{\rm opt})$ which maximizes the potential function, while other solutions $(\mathbf{p}', \mathbf{s}') \in \mathcal{A} \setminus (\mathbf{p}^{\rm opt}, \mathbf{s}^{\rm opt})$ are in probability 0. That is,

$$\lim_{\beta \to \infty} \pi(\mathbf{p}^{\rm opt}, \mathbf{s}^{\rm opt}) = 1, \tag{33}$$

which substantiates that the proposed algorithm converges to the global optimum with an arbitrarily high probability. Thus, the proof is completed. ■

Remark 2: The proposed approach leads to optimal network sum-utility with an arbitrarily high probability no matter which metric (e.g., MOS, information rate) is defined as the utility function. For instance, if the information rate is designed as the utility function, the proposed algorithm can achieve the sum-rate optimal solution. Overall, the proposed approach is generic to solve this class of NP-hard problems.

C. Computational Complexity Analysis

In each iteration, each selected BS needs a random number to choose a power level with a computational complexity of $O(1)$, and then decides the best user assignment with a complexity of $O(|\mathcal{N}_l|)$. As for the computation of the MOS value, it needs $|\mathcal{B}_l^{\rm in}| + 1$ additions and $|\mathcal{B}_l^{\rm in}| + 5$ multiplications (divisions) to first compute the information rate, and then two comparisons and no more than 2 multiplications and one logarithmic operation to calculate the MOS value. Then, it needs $|\mathcal{B}_l^{\rm out}| - 1$ additions to compute the utility U_l according to (22). Thus, the total complexity for computing the utility is $O(|\mathcal{B}_l^{\rm in}| \cdot |\mathcal{B}_l^{\rm out}|)$. In addition, the procedure of strategy updating involves the operations of 2 exponents, 1 additions and 4 multiplications, and hence the complexity is $O(1)$. Therefore, in total, the computational complexity for each selected BS[6] is $O(|\mathcal{B}_l^{\rm in}| \cdot |\mathcal{B}_l^{\rm out}| + |\mathcal{N}_l|)$.

The complexity depends on the number of served users as well as the scale of the neighbor set. The scale of the neighbor set then relies on the predefined threshold IM_l^0 for the interference metric (IM). If the threshold IM_l^0 is set to be low, the interference graph will capture more interference links (even weak interference links), which is closer to the real interference environment. In this case, the scale of the neighbor set will be larger, and more interfering BSs will be incorporated into the coordination to further improve the performance. However, it introduces higher computational complexity. In the extreme case ($\mathrm{IM}_l^0 = 0$), BS l's neighbor set will include all the other BSs, i.e., $|\mathcal{B}_l^{\rm in}| = |\mathcal{B}_l^{\rm out}| = |\mathcal{L}| - 1$, thus, the computational complexity is $O(|\mathcal{L}|^2 + |\mathcal{N}_l|)$.

[6]Since the non-selected BSs do not have any operation, the computational complexity is 0.

The above analysis provides the computational complexity for each iteration of the proposed algorithm. Furthermore, the whole computational complexity also relies on the number of iterations needed for convergence (i.e., convergence speed). However, there is a tradeoff between the performance and convergence speed of the proposed algorithm. On one hand, we have proved in Theorem 4 that the probability of achieving the global optimum by our proposed algorithm would be close to 1 when β is sufficiently large, however, it cannot be obtained in finite number of iterations [44]. On the other hand, if β is not sufficiently large for practical application, there may exist performance loss which will be shown in the simulation part.

D. Fairness Analysis

Note that sum-rate optimal resource allocation schemes [2], [7] tend to privilege users with good channel conditions, while the good users may not need such a lot of spectral bands, which results in the waste of resources. In contrast, if a user cannot contribute enough capacity gain to the system to outweigh the generated interference, it may not be scheduled in the spectral slots. Thus, a user may be allocated a number of spectral slots over its need or none at all. To solve this problem, we employ sum-MOS as the optimization goal which not only depends on the user's channel condition, but also considers the user's requirement. In the following, we will prove that our proposed algorithm aiming at sum-MOS maximization will solve the fairness issue effectively.

A single typical cell l is considered. Suppose that there are N identical video-stream users in cell l, and the number of subchannels (i.e., spectral slots) is K and $K = N$. For simplicity, we assume the K subchannels are all identical, which bring the same rate gain for the same user. That is, $R_n^1 = R_n^2 = \cdots = R_n^K = R_n^0$, $\forall n$. Moreover, we assume $R_1^0 > R_2^0 > \cdots > R_N^0$. In the following, we analyze the fairness by using Jain's fairness index (JFI) [48], which translates a resource allocation vector $\{R_1, R_2, \ldots, R_N\}$ into a score in the interval of $[1/N, 1]$ and higher JFI means the resource allocation is fairer. The following theorem characterizes the achieved fairness for different optimization goal.

Theorem 5: Suppose $R^{4.5} > R_1^0 > R_2^0 > \cdots > R_N^0 > R^{1.0}$ and $R_N^0 > 2b$, the JFI achieved by sum-rate maximizing algorithm is $1/N$, while that achieved by sum-MOS maximizing algorithm is lower bounded by $1 + 2\lambda(N-1)/N$, where λ is constrained by

$$\begin{cases} R_1^0 \leq \frac{1+\sqrt{1-4\lambda^2}}{2\lambda} R_N^0 \\ 0 \leq \lambda \leq \frac{1}{2} \end{cases} \tag{34}$$

Proof: Since $R_1^k > R_2^k > \cdots > R_N^k$, $\forall k$, all subchannels will be allocated to user 1 by sum-rate maximizing algorithm. Thus, $R_1 = \sum_{k \in \mathcal{K}} R_1^k = K R_1^0$, while $R_2 = \cdots = R_N = 0$. In this case, JFI is obviously $1/N$.

As for the sum-MOS optimal scheme, $a\log(R_1^k/b) > a\log(R_2^k/b) > \cdots > a\log(R_N^k/b)$ due to the monotony property of the logarithmic function. Therefore, the first subchannel will be scheduled to the first user. When it comes to the scheduling of the second subchannel, the increment of the first user's MOS, say ΔMOS_1, is $(a\log(R_1^1 + R_1^2/b) - a\log(R_1^1/b))$. Note that $R_n^1 = R_n^2 = \ldots = R_n^K = R_n^0,\ \forall n$, we have $\Delta\text{MOS}_1 = a\log 2$. When $R_2^2 > 2b$, $a\log(R_2^2/b) > \Delta\text{MOS}_1$. Therefore, the second subchannel will be assigned to user 2. Following this line of analysis, each user will be allocated exact one subchannel to. In this case, each user's rate can be expressed as $R_n = R_n^0, \forall n$.

Note that

$$\left(\sum_{n=1}^{N} R_n\right)^2 = \sum_{n=1}^{N}(R_n)^2 + 2\sum_{i<j\le N} R_i R_j, \tag{35}$$

we aim to achieve the JFI bound by proving the following inequality:

$$R_i R_j \ge \lambda\left((R_i)^2 + (R_j)^2\right),\ \forall i \le j. \tag{36}$$

For analysis, we rewrite the above inequality as

$$\lambda(R_i)^2 + \lambda(R_j)^2 - R_i R_j \le 0. \tag{37}$$

Now, it is easy to get the constrained condition for the above inequality being right as $\lambda = 0$, or

$$\begin{cases} \lambda > 0 \\ 1 - 4\lambda^2 \ge 0 \\ R_j \frac{1-\sqrt{1-4\lambda^2}}{2\lambda} \le R_i \le R_j \frac{1+\sqrt{1-4\lambda^2}}{2\lambda}. \end{cases} \tag{38}$$

Since $R_n = R_n^0, \forall n$ and $R_1^0 > R_2^0 > \ldots > R_N^0$, we can get the requirement as (34). In this case, the bound of the JFI fairness is given by

$$\begin{aligned} J &= \frac{\left(\sum_{n=1}^{N} R_n\right)^2}{N\sum_{n=1}^{N}(R_n)^2} = \frac{\sum_{n=1}^{N}(R_n)^2 + 2\sum_{i<j\le N} R_i R_j}{N\sum_{n=1}^{N}(R_n)^2} \\ &\ge \frac{\sum_{n=1}^{N}(R_n)^2 + 2\lambda\sum_{i<j\le N}\left((R_i)^2 + (R_j)^2\right)}{N\sum_{n=1}^{N}(R_n)^2} \\ &= \frac{\sum_{n=1}^{N}(R_n)^2 + 2\lambda(N-1)\sum_{i=1}^{N}(R_i)^2}{N\sum_{n=1}^{N}(R_n)^2} \\ &= \frac{1 + 2\lambda(N-1)}{N}. \end{aligned} \tag{39}$$

■

According to Theorem 5. when R_N^0/R_1^0 increases, λ can take a larger value. Then, the JFI for the sum-MOS maximization goal gets larger, since it increases with λ. When $R_1^0 = \ldots = R_N^0$, λ can take 1/2, thus the JFI reaches 1.

V. Simulation Results

In this section, we evaluate the performance of the proposed algorithm by Matlab simulations.

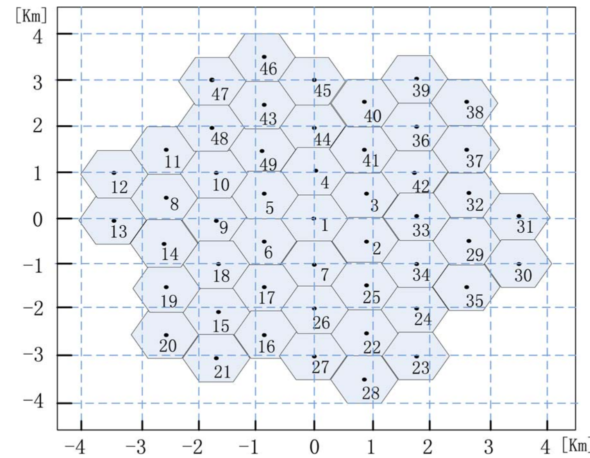

Fig. 4. Simulated network configuration with 49 cells.

TABLE I
Transmitted Video Streams

Video name	Desired data rate ($R^{4.5}$)	Ratio ($R^{4.5}/R^{1.0}$)
Foreman	2156 kbit/s	18
Mother	447 kbit/s	26
News	638 kbit/s	11
Container	1159 kbit/s	22
Salesman	2265 kbit/s	40
Bus	4141 kbit/s	7
City	2202 kbit/s	13
Crew	2677 kbit/s	15

A. System Description and Parameters Setting

Similar to [2], [23], we consider a 49-cell OFDMA network configuration, as shown in Fig. 4. Each hexagonal cell has a radius of 500 meters, and each BS is located at the center of its serving cell, and adjacent BSs are separated by $\sqrt{3}/2$ km from each other. To investigate the case of severe inter-cell interference, 8 remote users (each with a separate video stream) are generated as a uniform distribution within the edge-region of each cell (at least 400 meters away from the BS). Parameters of the videos [10] are summarized in Table I and the weight of each user is set to be 1 for simplicity. The maximal transmit power of each BS is set to be 46 dBm, and is equally split across subchannels. The BER gap Γ is set to be 1. The total bandwidth B is divided into $M = 16$ subchannels similar to [23] and the bandwidth of each subchannels is set to be 200 KHz. $G_{l,n}^k = |H_{l,n}^k|^2$ is the channel power gain from BS l to user n on subchannel k, which is expressed as $G_{l,n}^k = (d_{l,n})^{-\theta}\varepsilon_{l,n}^k$, where $d_{l,n}$ is the distance between BS l and user n, θ is the path loss exponent and $\varepsilon_{l,n}^k$ is the fading coefficient. Rayleigh fading model is considered in the simulation, and the channel gains are exponentially distributed with unit-mean. The pass loss exponent θ is set to be 3.7 and the noise power experienced at each receiver is assumed identical and has a power of -130 dBm.

In the proposed algorithm, the obtained solution is closer to optimum given a larger β, at the cost of convergence time [43]. To achieve a tradeoff between optimality and convergence speed, we choose $\beta = t/10$ in the simulation, where t is the iteration step.

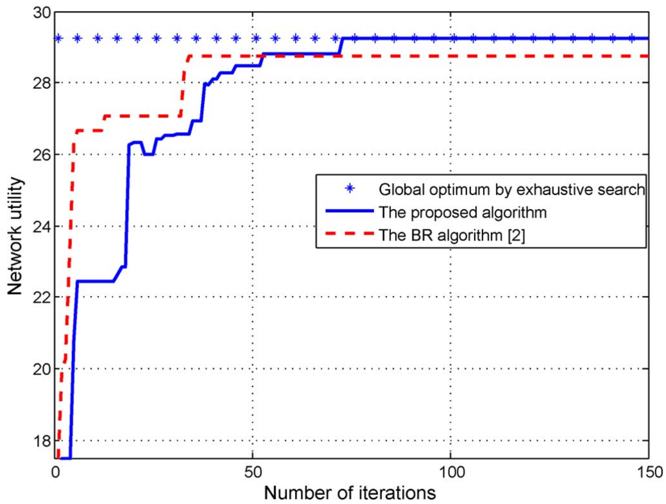

Fig. 5. Convergence behavior in a single trial.

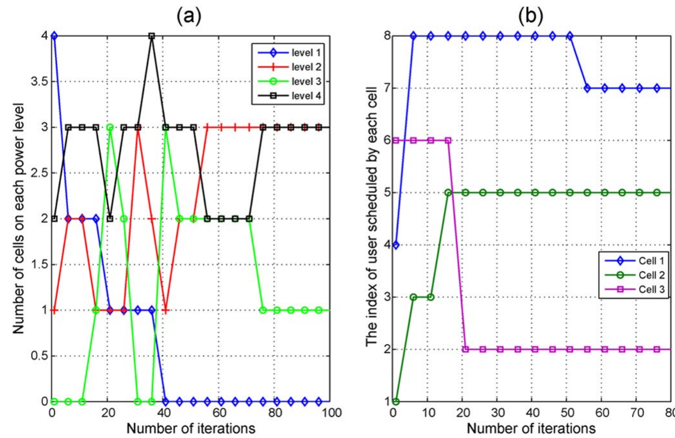

Fig. 6. The evolution of power allocation and user scheduling strategy versus the number of iterations in a single trial.

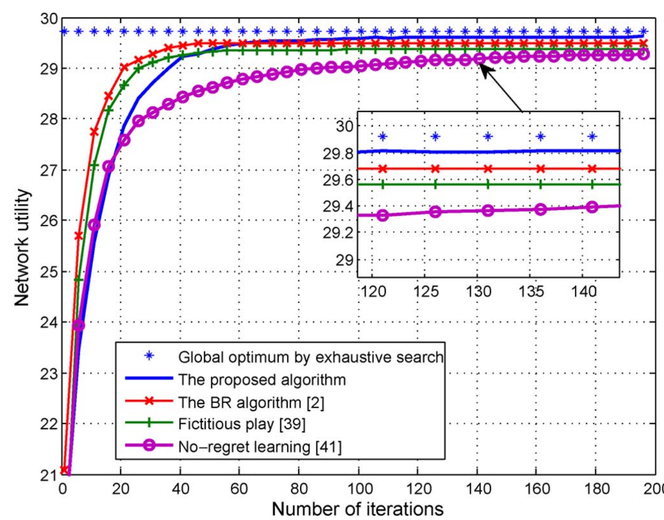

Fig. 7. Performance comparison of different algorithms.

B. Convergence and Optimality

The convergence curve of the proposed algorithm is shown in Fig. 5, and the convergence curve of the best response (BR) algorithm in [2] is presented for comparison. In order to capture the convergence behavior, the results are achieved by single simulation trial. Moreover, the globally optimal solution is plotted by exhaustive search to evaluate the optimality of our proposed algorithm. Because the global optimum cannot be found by existing computing techniques in large scale networks, this figure studies a 7-cell small network (cell 1–7 in Fig. 4). The number of power levels is set to be 4. As shown in Fig. 5, the network utilities by the two algorithms are updated in each iteration and both greatly improved at the convergence time. Furthermore, our proposed algorithm can achieve the global optimum with an arbitrarily high probability, while the BR algorithm in [2] only obtains a local optimum. It should be noted that the BR algorithm in [2] converges faster than our proposed algorithm, since the probabilistic updating is employed in our algorithm for global optimum. Additionally, our proposed algorithm shares the same amount of signaling exchange and communication overhead as the BR algorithm. The detailed signaling overhead analysis and comparison can be found in [2], and the interested readers can refer to [2] for further reading.

Next, Fig. 6(a) and (b) present the power allocation and user scheduling strategy updating versus the number of iterations, respectively. The evolution of number of players selecting different power levels is shown in Fig. 6(a). It is seen that the number of players on different power levels remains unchanged in about 80 iterations, which further validates the convergence of the proposed algorithm. Additionally, the user scheduling strategy updating is presented in Fig. 6(b), where only 3 cells' strategies are shown. In fact, the other cells' strategy updating is quite similar, which is omitted for concision and brevity.

In Fig. 7, we compare the proposed algorithm with state-of-the-art algorithms (best response (BR) algorithm [2], [37], fictitious play [39], [40], no-regret learning [41]). The results are obtained by simulating 500 independent trials and then taking the average value. The stop criterion for each trial is that the maximum number of iterations (200 iterations) is reached. It is noted that the average utility achieved by the proposed algorithm may not reach global optimum within finite number of iterations, as analyzed in Section IV-C. Among these 500 trials, the globally optimal solution was reached by the proposed algorithm for 69 trials within about 170 iterations, and in the remaining 431 trials the global optimum cannot be found within 200 iterations. However, the result at 200th iteration is close to the global, and the marginal gain decreases while the marginal cost increases significantly. Therefore, the result at the 200th iteration is a good approximation of the optimal one.

Besides, Fig. 7 shows that the average utilities achieved by different algorithms all increase with the number of iterations. In specific, the BR algorithm and the fictitious play converge fastest, the proposed algorithm converges relatively slower, and the convergence speed of the no-regret learning algorithm is slowest. However, all algorithms converge within 200 iterations. In terms of the achieved network utility, all the algorithms present good performance. In more details, the proposed algorithm is near-optimal, the BR algorithm and the fictitious play follow, while the performance of the no-regret algorithm is relatively worse. It is theoretically proved that the BR algorithm [37] and the fictitious play [39] can converge to

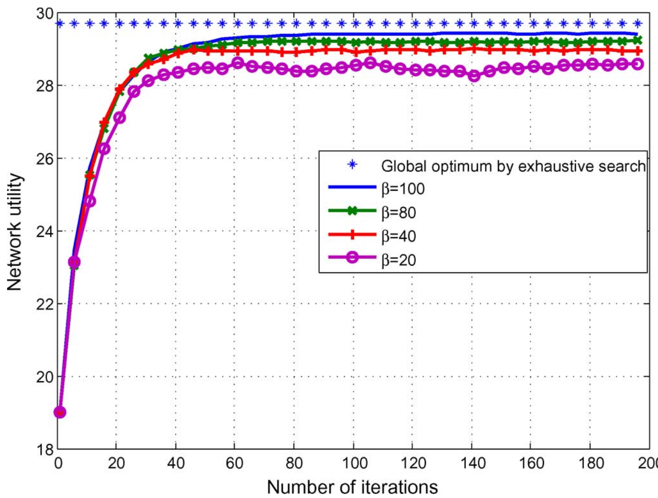

Fig. 8. Evaluation of performance loss when different β are selected.

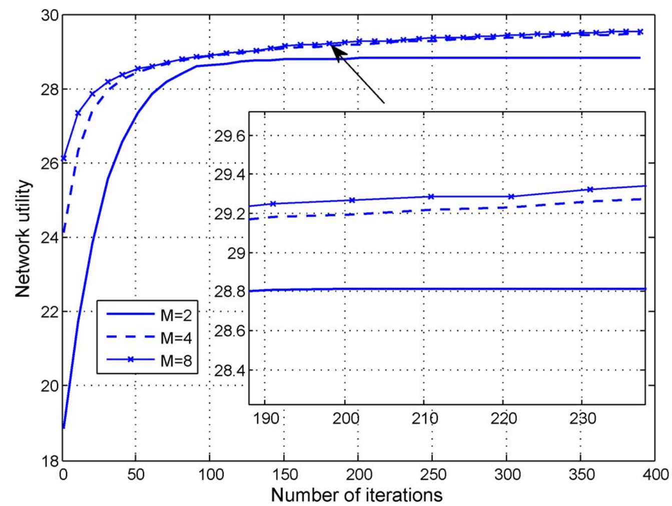

Fig. 10. Improvement of utility versus number of iterations for different power levels $(M = 2, 4, 8)$.

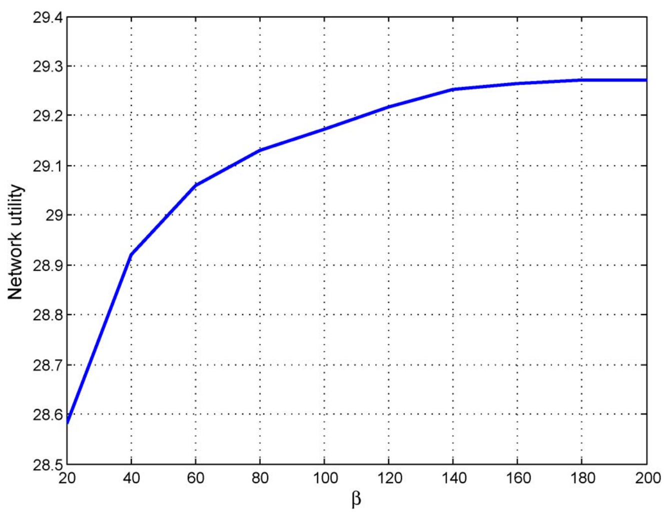

Fig. 9. The achieved network utility versus parameter β.

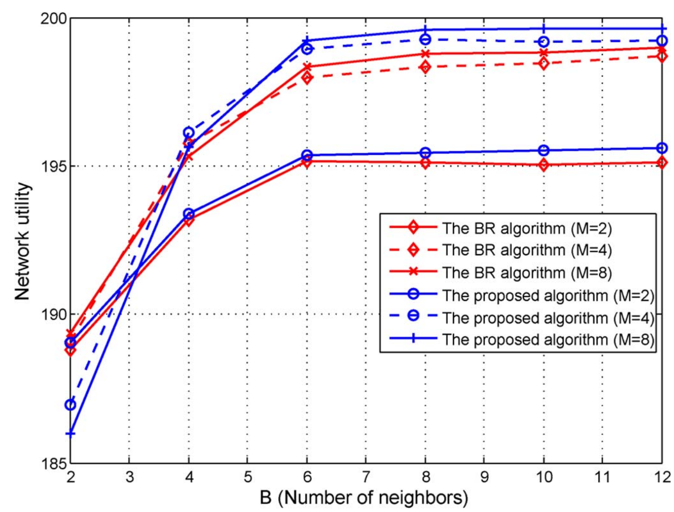

Fig. 11. Improvement of utility versus the size of in-neighbor set.

NE in potential games, which is either globally or locally optimal solution of this problem. However, the no-regret learning proves to converge only to the correlated equilibrium (CE) [41], which does not show a clear relationship with the global/local optimum. Therefore, the no-regret algorithm presents relatively worse performance.

As analyzed in Section IV-C, there exists a tradeoff between performance and complexity (convergence speed). In order to get a clear understanding of the performance loss, we present in Fig. 8 the network utility achieved by the proposed algorithm when different values of β are selected. Fig. 8 shows that the larger β is, the closer to optimum the proposed algorithm can achieve. However, the smaller β is, BSs are more inclined towards uniformly playing all their actions, which yields lower performance gains [13]. Moreover, when β is small, the convergence curve fluctuates, since it may oscillate around several good solutions. Besides, we plot Fig. 9 to further evaluate how the selection of parameter β affects the achieved network utility. As shown in Fig. 9, larger β yields higher network utility, but further increasing β beyond 140 only obtains marginal gains of network utility.

C. Network Utility

In Fig. 10, we evaluate the performance of our proposed algorithm in terms of different power levels $(M = 2, 4, 8)$. Similar to [2], the normalized power levels are set to be $\{0, 1\}$, $\{0, 1/4, 1/2, 1\}$ and $\{0, (\sqrt{2})^i/8, i = 0, \ldots, 6\}$ for $M = 2, 4, 8$, respectively. As we can see from Fig. 10, increasing M from 2 to 4 brings significant performance gain, while further increasing the number of power levels beyond 4 only achieves marginal benefits. Moreover, the increase of the number of power levels makes the convergence of the algorithm slow down.

In Fig. 11, we study the performance of our proposed algorithm under different sizes of the in-neighbor set in the whole 49-cell network, and the algorithm in [2] is also plotted for comparison. By properly selecting the interference threshold IM_l^0, the size of the in-neighbor set, $|\mathcal{B}_l^{\mathrm{in}}|, \forall l$, is set to be B, which is varied from 2 to 12 in the simulation. Increasing B is beneficial since a larger number of interfering BSs are coordinated; however, increasing B inevitably increases signaling overhead as well as computational complexity in each iteration of the distributed procedure. Furthermore, when B is larger

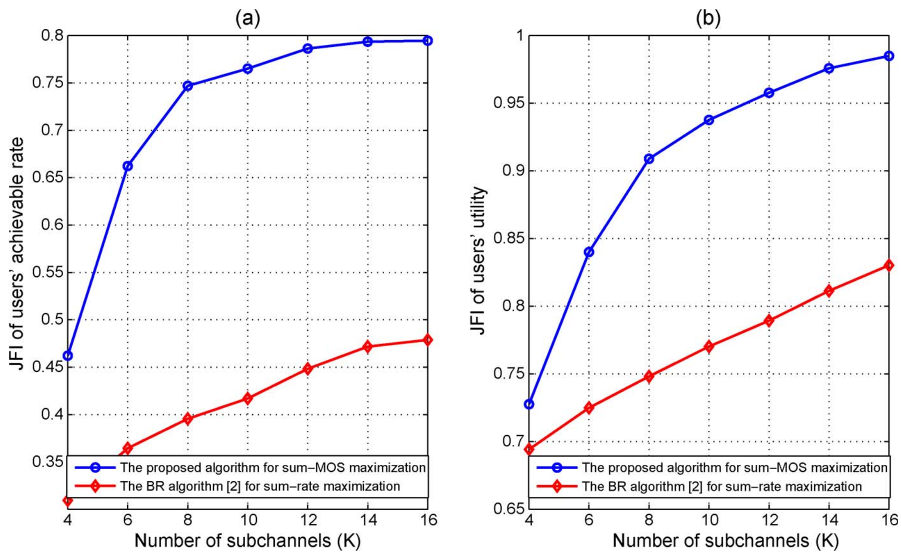

Fig. 12. Improvement of JFI versus the number of subchannels.

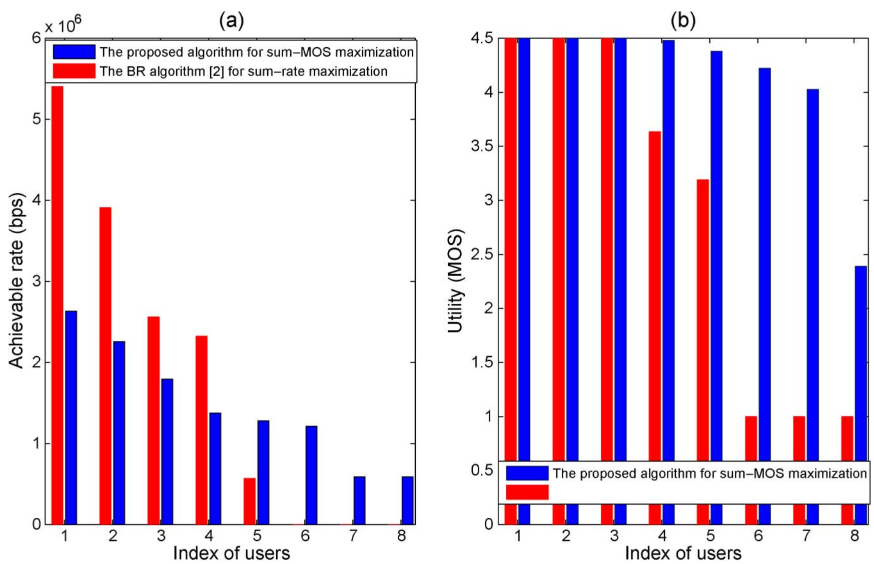

Fig. 13. The achieved rate and utility of each user by different algorithms $(K = 16)$.

than 6, increasing B cannot bring substantial performance improvement. In practical implementation, we should make a tradeoff between performance and signaling overhead. Based on the simulation results, setting the size of the in-neighbor set to be 6 is appropriate in the studied large-scale network for good performance. Moreover, Fig. 11 also shows that our proposed algorithm outperforms the existing algorithm (especially when B is larger than 6). Additionally, increasing the number of transmit power levels beyond 4 will not obtain significant benefits by both algorithms.

D. Fairness Evaluation

In this part, we perform the fairness comparison of the two different algorithms with different optimization goals. Since we focus on the fairness among users, users in a single cell are investigated. Fig. 12 shows the evolution of Jain's fairness index (JFI) versus the number of available subchannels, K. The JFIs in terms of achievable rate and utility are presented. The JFI of utility is higher than that of rate, because the utility function reduces the gap between users' rates to minor difference of MOS values (1 to 4.5).

Secondly, the JFIs in both subfigures of Fig. 12 get improved with the increasing number of subchannels due to the multi-channel diversity gain, which is the advantage of OFDMA in frequency-selective channels. A user experiencing fading on one subchannel, can be scheduled on another when it meets a better channel, if there are enough subchannels.

Last but not least, Fig. 12 further validates the claim in Theorem 5 that the proposed algorithm for sum-MOS maximization can achieve significant fairness improvement against the existing sum-rate optimal scheme, since sum-rate optimization tends to privilege users with better channel conditions, who are generally closer to the base-station. To better illustrate how the sum-MOS optimal scheme performs, the rate and utility achieved by each user are shown in Fig. 13, where the users are sorted in descending order of their performance.

VI. Conclusion

In this paper, we have investigated the multicell coordination among multiple BSs for interference mitigation in the QoE-oriented resource allocation. A game-theoretic approach has been proposed in which the existence of the joint-strategy NE has been proved. Then, the globally optimal solution for the network sum-utility maximization has been obtained using a decentralized iterative algorithm with an arbitrarily high probability, where only local information exchange is involved. The proposed algorithm has been analyzed and proved to converge to the best NE (i.e., global optimum). Moreover, fairness among users has been improved with theoretical analysis. Simulation results have validated the effectiveness of the proposed algorithm.

For our future work, we will extend the presented model to the case where base stations have multiple antennas. It is also interesting and challenging to extend the model to the heterogeneous networks such as a mixture of macrocells and small cells. In addition, considering the negative impact to the environment caused by CO_2 emissions and the depletion of non-renewable energy resources, energy efficiency is another potential topic.

References

[1] A. S. Hamza, S. S. khalifa, H. S. Hamza, and K. Elsayed, "A survey on inter-cell interference coordination techniques in OFDMA-based cellular networks," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 4, pp. 1642–1670, 2013.

[2] H. Zhang *et al.*, "Weighted sum-rate maximization in multi-cell networks via coordinated scheduling and discrete power control," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 6, pp. 1214–1224, Jun. 2011.

[3] E. Björnson, N. Jaldén, M. Bengtsson, and B. Ottersten, "Optimality properties, distributed strategies, measurement-based evaluation of coordinated multicell OFDMA transmission," *IEEE Trans. Signal Process.*, vol. 59, no. 12, pp. 6086–6101, Dec. 2011.

[4] J. Zheng, Y. Cai, and D. Wu, "Subcarrier allocation based on correlated equilibrium in multi-cell OFDMA systems," *EURASIP J. Wireless Comm. Netw.*, vol. 2012, pp. 233–245, 2012.

[5] D. Lee *et al.*, "Coordinated multipoint transmission and reception in LTE-Advanced: Deployment scenarios and operational challenges," *IEEE Commun. Mag.*, pp. 148–155, Feb. 2012.

[6] W. Yu, T. Kwon, and C. Shin, "Multicell coordination via joint scheduling, beamforming and power spectrum adaptation," *IEEE Trans. Wireless Commun.*, vol. 12, no. 7, pp. 1–14, Jul. 2013.

[7] S. G. Kiani, G. E. Øien, and D. Gesbert, "Maximizing multicell capacity using distributed power allocation and scheduling," in *Proc. IEEE WCNC*, Hong Kong, Mar. 2007, pp. 1690–1694.

[8] D. Gesbert and M. Kountouris, "Rate scaling laws in multicell networks under distributed power control and user scheduling," *IEEE Trans. Inf. Theory*, vol. 57, no. 1, pp. 234–244, Jan. 2011.

[9] "Methods for Subjective Determination of Transmission Quality," Geneva, Switzerland, ITU-T Recommendation P.800, Aug. 1996.

[10] A. Saul and G. Auer, "Multiuser resource allocation maximizing perceived quality," *EURASIP J. Wireless Commun. Netw.*, vol. 2009, pp. 1–15, Jan. 2009, Article ID 341689.

[11] C. Sacchi, F. Granelli, and C. Schlegel, "A QoE-oriented strategy for OFDMA radio resource allocation based on min-MOS maximization," *IEEE Commun. Lett.*, vol. 15, no. 5, pp. 494–496, May 2011.

[12] A. B. Reis, J. Chakareski, A. Kassler, and S. Sargento, "Distortion optimized multi-service scheduling for next-generation wireless mesh networks," in *Proc. IEEE INFOCOM*, San Diego, CA, USA, Mar. 2010.

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

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

[15] J. Deng, R. Zhang, L. Song, Z. Han, and B. Jiao, "Truthful mechanisms for secure communication in wireless cooperative system," *IEEE Trans. Wireless Commun.*, vol. 12, no. 9, pp. 4236–4245, Sep. 2013.

[16] D. Wu, Y. Cai, and J. Wang, "A coalition formation framework for transmission scheme selection in wireless sensor networks," *IEEE Trans. Veh. Technol.*, vol. 60, no. 6, pp. 2620–2630, Jul. 2011.

[17] D. López-Pérez, X. Chu, A. V. Vasilakos, and H. Claussen, "On distributed and coordinated resource allocation for interference mitigation in self-organizing LTE networks," *IEEE/ACM Trans. Netw.*, vol. 21, no. 4, pp. 1145–1158, Aug. 2013.

[18] L. Liang and G. Feng, "A game-theoretic framework for interference coordination in OFDMA relay networks," *IEEE Trans. Veh. Technol.*, vol. 61, no. 1, pp. 321–332, Jan. 2012.

[19] I. Koutsopoulos and L. Tassiulas, "Cross-layer adaptive techniques for throughput enhancement in wireless OFDM-based networks," *IEEE/ACM Trans. Netw.*, vol. 14, no. 5, pp. 1056–1066, Oct. 2006.

[20] H. Burchardt, S. Sinanovic, Z. Bharucha, and H. Haas, "Distributed and autonomous resource and power allocation for wireless networks," *IEEE Trans. Commun.*, vol. 61, no. 7, pp. 2758–2771, Aug. 2013.

[21] H. Kwon and B. G. Lee, "Distributed resource allocation through noncooperative game approach in multi-cell OFDMA systems," in *Proc. IEEE ICC*, Istanbul, Turkey, Jun. 2006.

[22] Y. Hua, Q. Zhang, and Z. Niu, "Resource allocation in multi-cell OFDMA-based relay networks," in *Proc. IEEE INFOCOM*, San Diego, CA, USA, Mar. 2010.

[23] L. Venturino, N. Prasad, and X. Wang, "Coordinated scheduling and power allocation in downlink multicell OFDMA networks," *IEEE Trans. Veh. Technol.*, vol. 58, no. 6, pp. 2835–2848, Jul. 2009.

[24] Z. Liang, Y. H. Chew, and C. C. Ko, "On the modeling of a noncooperative multicell OFDMA resource allocation game with integer bit-loading," in *Proc. IEEE GLOBECOM*, Honolulu, HI, USA, Dec. 2009, pp. 1–6.

[25] G. Lv, S. Zhu, and H. Hui, "A distributed power allocation algorithm with inter-cell interference coordination for multi-cell OFDMA systems," in *Proc. IEEE GLOBECOM*, Honolulu, HI, USA, Nov./Dec. 2009.

[26] A. Y. Zahrani and F. R. Yu, "A game theory approach for inter-cell interference management in OFDM networks," in *Proc. IEEE ICC*, Kyoto, Japan, Jun. 2011.

[27] Y. Xu, J. Wang, Q. Wu, A. Anpalagan, and Y. Yao, "Opportunistic spectrum access in cognitive radio networks: Global optimization using local interaction games," *IEEE J. Sel. Topics Signal Process.*, vol. 6, no. 2, pp. 180–194, Apr. 2012.

[28] J. Zheng, Y. Cai, Y. Xu, and A. Anpalagan, "Distributed channel selection for interference mitigation in dynamic environment: A game-theoretic stochastic learning solution," *IEEE Trans. Veh. Tech.*, vol. 63, no. 9, pp. 4757–4762, Nov. 2014.

[29] J. Zheng, Y. Cai, W. Yang, Y. Wei, and W. Yang, "A fully distributed algorithm for dynamic channel adaptation in canonical communication networks," *IEEE Wireless Commun. Lett.*, vol. 2, no. 5, pp. 491–494, Oct. 2013.

[30] Z. Han, Z. Ji, and K. J. R. Liu, "Non-cooperative resource competition game by virtual referee in multi-cell OFDMA networks," *IEEE J. Sel. Areas Commun.*, vol. 25, no. 6, pp. 1079–1090, Aug. 2007.

[31] S. Buzzi, G. Colavolpe, D. Saturnino, and A. Zappone, "Potential games for energy-efficient power control and subcarrier allocation in uplink multicell OFDMA systems," *IEEE J. Sel. Topics Signal Process.*, vol. 6, no. 2, pp. 89–103, Apr. 2012.

[32] L. Zhou, X. Wang, W. Tu, G. Mutean, and B. Geller, "Distributed scheduling scheme for video streaming over multi-channel multi-radio multi-hop wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 28, no. 3, pp. 409–419, Apr. 2010.

[33] T. Jiang, H. Wang, and A. V. Vasilakos, "QoE-driven channel allocation schemes for multimedia transmission of priority-based secondary users over cognitive radio networks," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 7, pp. 1215–1224, Aug. 2012.

[34] J. A. Hassan, M. Hassan, S. K. Das, and A. Ramer, "Managing quality of experience for wireless VOIP using noncooperative games," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 7, pp. 1193–1204, Aug. 2012.

[35] W. Sheen, S. Lin, and C. Huang, "Downlink optimization and performance of relay-assisted cellular networks in multicell environments," *IEEE Trans. Veh. Technol.*, vol. 59, no. 5, pp. 2529–2542, Jun. 2010.

[36] R. Y. Chang, Z. Tao, J. Zhang, and C.-C. J. Kuo, "Multicell OFDMA downlink resource allocation using a graphic framework," *IEEE Trans. Veh. Technol.*, vol. 58, no. 7, pp. 3494–3507, Sep. 2009.

[37] D. Monderer and L. S. Shapley, "Potential games," *Games Econ. Behav.*, vol. 14, no. 1, pp. 124–143, May 1996.

[38] H. Kameda and E. Altman, "Inefficient noncooperation in networking games of common-pool resources," *IEEE J. Sel. Areas Commun.*, vol. 26, no. 7, pp. 1260–1268, Sep. 2008.

[39] J. Marden, G. Arslan, and J. Shamma, "Joint strategy fictitious play with inertia for potential games," *IEEE Trans. Automat. Control*, vol. 54, no. 2, pp. 208–220, Feb. 2009.
[40] L. Rose, S. Lasaulce, S. M. Perlaza, and M. Debbah, "Learning equilibria with partial information in decentralized wireless networks," *IEEE Commun. Mag.*, pp. 136–142, Aug. 2011.
[41] S. Hart and A. Mas-Colell, "A simple adaptive procedure leading to correlated equilibrium," *Econometrica*, vol. 68, no. 5, pp. 1127–1150, 2000.
[42] H. P. Young, *Individual Strategy and Social Structure*. Princeton, NJ, USA: Princeton Univ. Press, 1998.
[43] Y. Song, C. Zhang, and Y. Fang, "Joint channel and power allocation in wireless mesh networks: A game theoretical perspective," *IEEE J. Sel. Areas Commun.*, vol. 26, no. 7, pp. 1149–1159, Sep. 2008.
[44] S. Zhong and Y. Zhang, "How to select optimal gateway in multi-domain wireless networks: Alternative solutions without learning," *IEEE Trans. Wireless Commun.*, vol. 12, no. 11, pp. 5620–5630, Nov. 2013.
[45] P. J. M. van Laarhoven and E. H. L. Aarts, *Simulated Annealing: Theory and Applications*. Amsterdam, The Netherlands: Reidel, 1987.
[46] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*. Cambridge, MA, USA: MIT Press, 1998.
[47] J. Marden, G. Arslan, and J. Shamma, "Cooperative control and potential games," *IEEE Trans. Syst., Man, Cybern.*, vol. 39, no. 6, pp. 1393–1407, Dec. 2009.
[48] R. Jain, D. Chiu, and W. Haws, "A Quantitative Measure of Fairness and Discrimination for Resource Allocation in Shared Computer System," Digit. Equip. Co., Tech. Rep., 1984.

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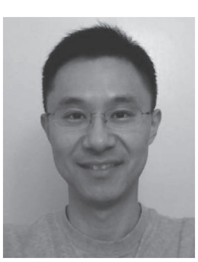

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