ABSTRACT
This paper addresses the adaptive allocation of subcarrier, bit and power resources in the downlink of multicell OFDMA systems, where base stations allocate radio resources in a decentralized manner. Our algorithm uses discrete bit-loading values which is more applicable to the practical systems. Noncooperative game theoretic approach is adopted and we first only include the transmit power and throughput in the payoff function of each base station. Using the optimal solutions as the benchmark, the performance of this noncooperative game is obtained through computer simulations. Our simulation results show that in the multicell OFDMA systems with frequency reuse factor of one, such payoff function provides inadequate utilization efficiency due to the presence of high co-channel interference. We next incorporate the number of allocated subcarriers in the payoff function of each base station. We show that the new payoff function avoid neighboring base station from transmitting using the same subcarrier when interference is large. This resembles the use of interference avoidance technique in the algorithm, and can achieve better resource utilization when compared to the water-filling counterpart.

INTRODUCTION
Although radio transmission environment is hostile, the diverse channel conditions seen by users can be exploited to provide better radio resources utilization. How to efficiently allocate radio resources to achieve multiuser diversity gain has attracted many research interests. Earlier works mainly dealt with single cell systems, where the adaptive subcarrier and power allocation in multiuser OFDM systems was formulated, aiming at minimizing the total transmit power [2]. To satisfy multiple quality-of-service (QoS) requirements in term of bit-error-rate (BER) performance, a mixed integer nonlinear programming (MINLP) was formulated in [3], and complexity-reduced algorithms were also proposed by replacing the objective function with a sixth order polynomial to ensure convexity. Further on that, the MINLP problem was converted to an equivalent binary linear programming (BLP), with drastically reduced complexity in computation time [4].

In multicell OFDMA systems, the decisions of resource allocation can be made at a central unit located at the radio network controller (RNC) and the problem can be similarly formulated. With a frequency reuse factor (FRF) of one, the high co-channel interference (CCI) interrelates the assignment of the subcarriers in all the cells and results in nonlinear objective functions and constraints. Recently a method is proposed to convert the MINLP of the multicell problem to its equivalent BLP to reduce the complexity of optimization [5], so that the optimal solution can be obtained much easier and can be used as a benchmark of performance evaluation for other algorithms.

On the other hand, the amount of information that needs to be exchanged between the central unit and the base stations (BSs) can be very huge in practice, and the potential delay due to centralized computation and signaling can be very high. To overcome these problems, a suboptimal approach was proposed to have the decision of subcarrier allocation made at the RNC, followed by the bit and power allocations made at the individual BSs [6]. More algorithms were proposed to have the resource allocation made centralized at each BS but decentralized across the BSs [7]–[9]. To handle the conflicts in competitions for resource among BSs, game theory has been applied to these decentralized, multi-agent systems, where the concept of Nash Equilibrium (NE) was used to study the steady states in these noncooperative game models [10]–[12].

The noncooperative setting of the games implies that the players behave selfishly to maximize their own payoff or utility functions. When the players are the BSs in multicell systems, each of them tends to occupy all the available subcarriers in the whole spectrum [4] by effectively performing water-filling (WF) over the subcarriers. Although pricing on the transmit power is used to regulate the amount of interference among the players of the games, the effectiveness varies under different situations of the system. We show in this paper that from the overall system perspective, avoiding unnecessary interference on some of the
subcarriers among the BS could lead to better performance. To apply such an interference avoidance (IA) technique to the autonomous players in the games, we introduce a spectrum usage pricing in the payoff functions of the players. By using an appropriate spectrum cost factor, strong interference among the BSs could be alleviated and better resource usage can be achieved, without adding complexity to the systems. Moreover, since discrete values are used in the bit-loading process, our algorithms are more readily applicable to practical systems.

**SYSTEM MODEL AND NOTATIONS**

In this paper, we consider the resource allocation problem in the downlink of multicell OFDMA systems with $K$ BSs. There are $L_k$, $k \in \mathcal{K}$ users uniformly distributed in BS $k$, where $\mathcal{K} = \{1, \ldots, K\}$ denotes the set of BSs. The total bandwidth of the system is equally divided into $N$ OFDM subcarriers, in such a way that subcarriers are subject to flat and uncorrelated fading. We assume that intersymbol interference resulting from multipath can be removed through the use of cyclic prefix. The maximum total transmit power of each BS over all subcarriers is limited to $P_{\text{max}}$.

Consider user $l$ in BS $k$ on subcarrier $n$, $l \in \mathcal{L}_k$, $k \in \mathcal{K}$ and $n \in \mathcal{N}$, where $\mathcal{L}_k = \{1, \ldots, L_k\}$ denotes the set of users in BS $k$ and $\mathcal{N} = \{1, \ldots, N\}$ denotes the set of frequency subcarriers. With frequency reuse factor of one, all $N$ subcarriers are available to each BS. Depending on the interference level and channel conditions, the effective bit rates can be achieved by suitably selecting one of the available $M$-QAM modulations, where $M \in \{4, 16, 64\}$.

Instead of separately defining the subcarrier and the modulation index assignment variables, we integrate them into a group of subcarrier-and-bit assignment variables denoted by $a_{lkq}^{nq}$, where $q \in Q = \{1, \ldots, Q\}$ is the set of modulation indices. $a_{lkq}^{nq} = 1$ if subcarrier $n$ is allocated to user $l$ in BS $k$ with modulation index $q$, and $a_{lkq}^{nq} = 0$ otherwise. $Q = 3$ is used with $q = 1, 2$ and 3 correspond to the cases where 4-QAM, 16-QAM and 64-QAM are chosen, respectively. Each user therefore transmits $2q$ bits per OFDM symbol on the assigned subcarrier. The total data rate of user $l$ in BS $k$ can thus be expressed as

$$r_{lk} = \sum_{n=1}^{N} \sum_{q=1}^{Q} 2q \cdot a_{lkq}^{nq}, \quad \forall l \in \mathcal{L}_k, k \in \mathcal{K}.$$  \hspace{1cm} (1)

Take note that the subcarriers assigned to a user can have different modulation indices, while a subcarrier in each BS can only be assigned one modulation index.

Denote $p_{lkq}^{nq}$ as the required power for user $l$ in BS $k$ to transmit on subcarrier $n$ at modulation index $q$, so that the user can recover the signal with a specific BER. The total transmit power on subcarrier $n$ in BS $k$ is given by

$$p_{lkq}^{nq} = \sum_{l=1}^{L_k} \sum_{q=1}^{Q} a_{lkq}^{nq} p_{lkq}^{nq}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}.$$  \hspace{1cm} (2)

Denote $G_{lkq}^{nq}$ as the channel gain of subcarrier $n$ from BS $j$ ($j \in \mathcal{K}$) to user $l$ in BS $k$. We refer to the channel gains from a BS $k'$ to its intended users as the main channel gains, $G_{lkq}^{nq} \cdot \forall l \in \mathcal{L}_{k'}$, and those from the neighboring BSs as interference gains, $G_{lkq}^{nq} \cdot j \neq k'$. Assuming that there is no sharing of a subcarrier among users in a BS, the amount of CCI on subcarrier $n$ experienced by user $l$ in BS $k$ is given by

$$I_{lkq}^{nq} = \sum_{j=1}^{K} \sum_{q=1}^{Q} a_{ljq}^{nq} p_{ljq}^{nq}, \quad \forall l, k, n.$$  \hspace{1cm} (3)

A 3-cell system is illustrated in Fig. 1 as an example, where each cell has two users. The user $l$ in BS $k$ is denoted as $m_{lk}$. The solid line represents the signal from the respective BS of the designated receiver, while those dotted lines represent interfering signals from the adjacent BSs.

To support multiple service classes, the QoS requirement of each user is specified by $\{R_{lk}, B_{lk}^{ER}\}$, which are the minimum data rate and BER requirements for user $l$ in BS $k$, respectively. For a particular $q$, the signal-to-interference-and-noise ratio (SINR) threshold is a function of symbol error rate (SER) [13]. Under the usual operating conditions of low BER ($B_{lk}^{ER} < 10^{-3}$), we have $S_{lk}^{ER} \approx 2q \cdot B_{lk}^{ER}$ [14]. The average SINR required to
achieve \( B_{lk}^{ER} \) is thus given by
\[
\frac{C_{lk}^{nk} P_{lk}^{nk}}{I_{lk} + N_0} \geq \gamma_{lk}^{q}, \quad \forall q, l, k, n, \tag{4}
\]
where \( \gamma_{lk}^{q} \) denotes the SINR threshold for user \( l \) in BS \( k \) when modulation index \( q \) is used. The power spectral density (PSD) of the white Gaussian noise, \( N_0 \), is assumed to be identical on all subcarriers for all users.

**NONCOOPERATIVE RESOURCE ALLOCATION GAME**

**A. Noncooperative Games**

A noncooperative game is denoted in strategic form as
\[
\Gamma = (\mathcal{G}, \mathcal{S}, \{\Phi_i\}_{i \in \mathcal{G}}),
\]
where \( \mathcal{G} \) denotes the set of \( G \) players and \( \mathcal{S} \) is the strategy space of the game. In this paper we consider only pure strategies of the game, where the selection of a strategy is deterministic rather than probabilistic. All players in a noncooperative game are assumed to behave rationally and selfishly so that each of them tries to maximize his own payoff. With the strategy space of player \( i \) denoted as \( \mathcal{S}_i \), each of the players \( i \in \mathcal{G} \) selects a strategy \( s_i \in \mathcal{S}_i \) to maximize its payoff \( \Phi_i \). Strategy spaces of all players constitute the joint strategy space which is denoted as the Cartesian product of the individual strategy spaces: \( \mathcal{S} = \times_{i \in \mathcal{G}} \mathcal{S}_i \). An element \( s \in \mathcal{S} \) is called a strategy profile, defined as the chosen strategies of all players. Opponents of player \( i \), referred to as all the players belonging to \( \mathcal{G} \) except \( i \) itself, are designated by \( -i \). Thus we refer to the collective strategies of the opponents as \( s_{-i} \in \mathcal{S}_{-i} \), where \( \mathcal{S}_{-i} = \mathcal{S} \setminus \mathcal{S}_i \). The payoff function, \( \Phi_i(s) \), quantifies the payoff of player \( i \) in the game for a given strategy profile \( s \), hence is a scalar-valued function \( \Phi_i(s) : \mathcal{S} \rightarrow \mathbb{R} \). By convention, it is often denoted as \( \Phi_i(s_i, s_{-i}) = \Phi_i(s_1, \ldots, s_{i-1}, s_i, s_{i+1}, \ldots, s_{-i}) \) to emphasize the payoff for different strategies of player \( i \) with a given strategy profile of his opponents.

A very important concept in game theory is called *Nash equilibrium* (NE), a strategy profile with which the game has arrived at a balanced state.

**Definition 1** A strategy profile \( s^* \in \mathcal{S} \) is a NE if \( \forall i \in \mathcal{G}, \Phi_i(s_i^*, s_{-i}^*) \geq \Phi_i(s_i, s_{-i}^*) \), \( \forall s_i \in \mathcal{S}_i \). \( \tag{5} \)

In other words, if the game is at a NE point, no player can improve its payoff with a unilateral deviation, given all other players’ chosen strategies. If there exists a game-master, she would suggest a NE to the players, on which they will agree and will not deviate in the absence of coordination, as each player has obtained his maximum achievable payoff value given his opponents’ strategies.

Repeated games are those games played in multiple stages, in such a manner that the players update their strategies sequentially or simultaneously in each stage. Based on the opponents’ strategies that one observed, the player generally chooses the best response with maximum payoff in return.

**Definition 2** The *best response* of player \( i \) to the profile of strategies \( s_{-i} \) is a strategy \( s_i' \) such that:
\[
s_i'(s_{-i}) = \arg \max_{s_i \in \mathcal{S}_i} \Phi_i(s_i, s_{-i}). \tag{6}\]

With this definition, we can see that a NE is actually such a strategy profile that all the selected strategies are best responses to all the corresponding players in the game.

**B. Game Modeling in Multicell OFDMA Systems**

Radio resource allocation in multicell OFDMA system has been modeled as a noncooperative resource allocation game (NRAG), where each BS allocates the available resources such as subcarriers, modulation indices and power in such a way to maximize the payoff. All BSs in the system are considered players of the game, each of which monitors the radio environment around itself, receives feedback information from its users, and allocates radio resources to fulfill the QoS requirements of their users. Decisions are made locally at each BS, and we assume that no information are exchanged among the BSs. The NRAG can be expressed in a strategic form as
\[
\Gamma_{NRAG} = (\mathcal{K}, \mathcal{A}_k^K \times \mathcal{P}_K, \{u_k\}_{k \in \mathcal{K}}),
\]
where the set of players is denoted as \( \mathcal{K} \), i.e. the set of BSs. \( \mathcal{A}_k = \{a_{lk}^{nk}\}_{q, l, k, n} \) is the subcarrier-and-bit assignment space, and \( \mathcal{P}_K \) is the power allocation space, both for a player. The payoff function of BS \( k \) is defined as [11]:
\[
u_k = \mu \sum_{l=1}^{L_k} r_{lk} - c \sum_{n=1}^{N} p_k^n, \quad \forall k \in \mathcal{K}, \tag{7}\]
where \( r_{lk} \) and \( p_k^n \) are the total data rate and transmit power as defined in (1) and (2), respectively. The power cost factor, \( c \), is used to make the throughput and power which have different units to have the basis to sum together, and \( \mu \) is a weighing factor. The function \( u - K \) can be considered as the payoff to BS \( k \), resulted from subtracting the rewards (total user rate in this case) by the expenses (the cost of transmit power).

In noncooperative games, every player determines the best action to maximize his own payoff, based on the information available locally. We assume that the game is repeated in a round-robin manner, such that the players take turns to find their respective best responses sequentially. The game is assumed to be a so-called *myopic game*, where the players are short-sighted optimizers each tries to
follows: overall network payoff, given by function defined in the centralized optimization [5] as the desires of the network operator, we choose the objective equilibrium point that is highly inefficient. To reflect the BS is ensured by the constraints in (12).

exclusive assignment of a subcarrier to only one user in a and the maximum power limit of a BS, respectively. The satisfy the minimum rate requirement for individual users In the above formulation, constraints in (10) and (11) are to in (9) in a single-cell BS is effectively the same as performing WF over all the subcarriers. In multicell systems, since each BS makes decision independently, not all the channel information can be made available to the BSs. Even if CCI together with the thermal noise can be measured at the receiver, by making each BS operating at their own optimal solution does not guarantee that the global optimum of the whole system can be obtained [16]. It was shown that the optimal solution in a single-cell system tends to load the data bits over all the subcarriers [4]. However, multicell systems which apply some kind of IA techniques can achieve better overall network payoff.

We use a 2-BS system, where the number of available subcarriers is 2 and each BS has 4 bits of data to transmit, to illustrate this concept. If WF approach is used, both BS will transmit 2 bits on each subcarrier, resulting in CCI to each other. Alternatively, to avoid unnecessary interference, a BS could also choose a higher modulation index to transmit the 4 bits on a single subcarrier different from the other BS. This results in zero CCI such that the required transmit power is constant, depending only on $N_0$. It can be seen from Fig. 2 that when interference is low, WF requires less power than IA due to its lower modulation level. As the interference increases, however, the power needed in WF eventually arrives at a crossover point, beyond which it becomes higher than that of IA. Similar conclusion was observed for 6 bits to be loaded on 3 subcarriers. The example shows that WF algorithm might not result in desirable solution from the system perspective, especially in interference-limited environments.

Since OFDMA multicell systems have a FRF of one, IA would be a more effective way to alleviate the strong CCI among the BSs. However, IA cannot be achieved by the players autonomously due to the lack of coordination perspective, it is preferable to have each player to use an objective function that can reflect the operator’s desires, which gives rise to the following questions: how can a network designer lead the players to reach a desirable equilibrium point in NRAG, or how to modify the game to have more preferable NEs?

**Mechanism design** looks into how to put in incentive mechanisms or to obtain optimal design parameters of a game, in order to achieve a more desirable outcome from the system point of view. Particularly, pricing has been used as a technique to regulate the usage of a certain resource. In NRAG, pricing on the transmit power has been incorporated in the payoff function, e.g., in [11], to lessen possible severe CCI among the BSs. We will show that, however, such a pricing mechanism is not the most effective way in multicell OFDMA systems.

The process of maximizing (9) in a single-cell BS can be expressed as an optimization problem as follows:

$$\max_{a_{lk}^{nq}} u_k = \sum_{n=1}^{N} \sum_{l=1}^{L_k} \sum_{q=1}^{Q} (\mu \cdot 2q - cp_{lk}^{nq}) a_{lk}^{nq}, \quad \forall k \in K \tag{9}$$

subject to

$$\sum_{n=1}^{N} \sum_{l=1}^{L_k} \sum_{q=1}^{Q} a_{lk}^{nq} \geq R_{lk}, \quad \forall l \in L_k, \quad \tag{10}$$

$$\sum_{n=1}^{N} \sum_{l=1}^{L_k} \sum_{q=1}^{Q} p_{lk}^{nq} a_{lk}^{nq} \leq P_{\text{max}}, \quad \tag{11}$$

$$L_k, Q \sum_{l=1}^{L_k} a_{lk}^{nq} \leq 1, \quad \forall n, \quad \tag{12}$$

$$a_{lk}^{nq} \in \{0, 1\}. \quad \tag{13}$$

In the above formulation, constraints in (10) and (11) are to satisfy the minimum rate requirement for individual users and the maximum power limit of a BS, respectively. The exclusive assignment of a subcarrier to only one user in a BS is ensured by the constraints in (12).

**NRAG WITH INTERFERENCE AVOIDANCE**

In the NRAG, each player wants to maximize his payoff but the competitions among the players can arrive at an equilibrium point that is highly inefficient. To reflect the desires of the network operator, we choose the objective function defined in the centralized optimization [5] as the overall network payoff, given by

$$U = \sum_{k=1}^{K} u_k, \quad \tag{14}$$

where $u_k$ is defined in (7). This also ensures that both the centralized optimization and NRAG have a common basis to compare their performance. From the network perspective, it is preferable to have each player to use an objective function that can reflect the operator’s desires, which gives rise to the following questions: how can a network designer lead the players to reach a desirable equilibrium point in NRAG, or how to modify the game to have more preferable NEs?
among the BSs in the NRAG. To discourage the BSs from excessively occupying the subcarriers in the system, we include the number of subcarriers used by the BSs as a cost factor in the players’ payoff functions. Define

\[
v_k = \sum_{n=1}^{N} \sum_{l=1}^{L_k} \sum_{q=1}^{Q} (2q - cp_{lk}^{\text{h}}) a_{lk}^{nq} - b \sum_{n=1}^{N} \sum_{l=1}^{L_k} a_{lk}^{nq}, \quad \forall k \in \mathcal{K},
\]

(15)

where \(b\) is the spectrum cost factor, a value set to tradeoff bit rate with the number of allocated subcarriers, with unit bits/\text{MHz}. Since \(\sum_{n=1}^{N} \sum_{l=1}^{L_k} \sum_{q=1}^{Q} a_{lk}^{nq}\) corresponds to the total number of subcarriers occupied by BS \(k\), \(b\) can also be considered as the unit cost of using the a subcarrier in the spectrum.

By introducing such a pricing mechanism to the spectrum usage, a BS would refrain from using those subcarriers that are undergoing deep fades and will cost more than their possible return. On the other hand, the BSs still transmitting on these subcarriers will experience reduced interference and incur less power cost, resulting in higher payoff values for the individual players as well as the network as a whole. The original game has now become a NRAG with IA (NRAGIA):

\[
\Gamma'_{\text{NRAGIA}} = \left< \mathcal{K}, \mathbb{A}^K \times \mathbb{P}^K, \{v_k\}_{k \in \mathcal{K}} \right>.
\]

With appropriate values of \(b\), the new payoff function (15) can prevent players in the NRAG from unnecessarily occupying all the subcarriers and causing strong interference to the others, thus incorporates the behaviors similar to IA. The complexity of the NRAGIA remains the same as NRAG, as the new utility function, \(v_k\), has a similar structure to the original one, \(u_k\). The value of \(b\) can be determined by a central unit, such as the RNC, according to the network conditions and traffic load, and then be broadcast to the players before the game starts. Simulation results show that (15) is effective in improving the overall performance of the multicell systems, details of which are provided in the next section.

**NUMERICAL RESULTS**

In order to compare the performance between the centralized and game theoretic approach which uses different payoff functions, we conducted simulations for a 3-cell OFDMA system, where each cell has a radius of 100 m and is separated by 100\sqrt{3} m among each other. BSs are located at the center of the cells, and the locations of two users in each cell are randomly generated. The propagation model takes into consideration the path loss, shadowing and fast fading. The path loss (in dB) at a distance \(d\) from the BS is taken as \(L(d) = L(d_0) + 10\alpha \log_{10}(d/d_0)\), with \(d_0 = 10\text{m}\) being the reference point (\(L(d_0) = 0\text{dB}\)) and \(\alpha = 3.8\). The shadowing effect is modeled as a lognormal random variable with 10dB standard deviation. The four-path Rayleigh model is used to model the frequency selective fading with an exponential power profile. We consider a multicell OFDMA system with 16 subcarriers. The receiver thermal noise is -70dBm, and the required BER is 10^{-5} for every user. The maximum total transmit power for each BS is 40dBm.

An example to compare the performance of \(\Gamma'_{\text{NRAG}}\) when WF is used (defined by (9)), \(\Gamma'_{\text{NRAG}}\) when IA is used (defined by (15)), and the centralized approach can be found in Fig. 3. For illustrative purpose, we reduce the number of subcarriers to 3, and every BS has only one user each requires a minimum data rate of 6 bits. Results of the repeated plays are taken at the end of the tenth iteration. It can be seen that in \(\Gamma'_{\text{NRAG}}\), the players put the bits on more than one subcarriers, as contrast to the optimal case where every BS loads all the bits on a distinctive subcarrier so that no interference among each other. Using the new payoff function (15), the outcome of \(\Gamma'_{\text{NRAG}}\) happened to be exactly the same as the optimal case. Although it does not guarantee to result in the optimal solution every time, \(\Gamma'_{\text{NRAG}}\) which uses the new payoff function generally achieves better overall system payoff over \(\Gamma_{\text{NRAG}}\).

To further investigate the performance of games with the optimal solution, the respective network utilities are shown in Fig. 4(a). The simulation settings are \(N = 16\),
Fig. 3. Comparison of subcarrier-and-bit allocation: (a) Optimal (b) Game with WF (c) Game with IA.

$R_{lk} = 12$, $c = 100$, $b = 2$ and $\mu = 30$, and the results are averaged over $10^3$ instances of simulation. It can be seen that the network payoff resulting from WF NRAG is only slightly over one third of the optimal, whereas the IA NRAG can achieve more than half of the optimal. Since the total number of bits and the transmit power resulting from the three approaches are not the same, we define a Figure of Merit (FOM) to make fairer comparison:

$$FOM = \frac{1}{\sum_{k=1}^{K} \sum_{l=1}^{L_k} r_{lk}} \left( \sum_{k=1}^{K} \sum_{n=1}^{N} p_n k \right).$$

The FOM can be considered as the efficiency of data transmission per unit power. From Fig. 4(b), it can seen that the FOM of the optimal solution is more than 10% above $c$, while that of the game with WF is much lower than $c$. Albeit still below $c$, the game with IA has a better FOM than that with WF. Hence, the final system payoff is improved without the need to perform extra coordination among the BSs. It should be noted that the new payoff for the IA NRAG tends to increase the stability of the game as well, which is also reflected in the figure.

Based on our observations during the simulations, we would like to make a few comments regarding the existing and convergence of the games. Under light to moderate system load, both the NRAG and NRAGIA games converged for most of the channel realizations. In some cases, however, the solution appears oscillating, i.e., solution cycles through a number of states. Such a phenomenon could be illustrated by a simple example. Initially there is no BS transmitting and BS1 chooses to start its transmission at a low power level $p_l$. If BS2 finds that the interference caused by BS1 is acceptable and start to transmit, BS1 will detect that the interference level has gone up and increase its transmit power to a higher level $p_h$ to maintain the required SINR threshold. At this point if the new interference level becomes too high for BS2 to continue its transmission and ceases its transmission, the transmit power of BS1 is then reverted back to $p_l$. This again reduces the interference to BS2 and hence BS2 will begin to transmit again and solution appears ‘oscillatory’ and hence a NE solution does not exist. Conditions on the existence of NEs have been discussed in game models using an information theoretic approach, e.g. in [11] and [17], where the continuous bit allocation is assumed. There are currently still lack of similar investigation when discrete values are used. More detailed discussion will be reported in the journal version of the paper.

CONCLUSION

The adaptive subcarrier, bit and power allocation in the downlink of multicell OFDMA systems with a FRF of one is considered. The problem is modeled as a noncooperative resource allocation game, with the decisions of resource allocation being made centralized in a BS while decentralized across the BSs. Since resource allocation is made at each BS locally, such a game-theoretic approach can achieve lower complexity than the centralized optimization model, at the expense of deteriorated performance in the system as a whole. Since the NRAG with payoff function that only imposes pricing on the power is performing WF in the multicell environment, it could result in strong CCI among the BSs. In interference-limited environments, we show that the IA technique can lead to an increase value of the overall network payoff, which is more desirable for a network operator. By proposing a new payoff function used by the BSs, we introduce the IA mechanism which includes
pricing on the spectrum usage implicitly to the NRAG. The optimal solution to the centralized optimization is then used as the benchmark to compare the performance of NRAG with and without IA, where the simulation results show that games with IA result in higher network utility than those with WF. Finally, as discrete values are used in the bit-loading process, our results are more applicable to practical systems than those using information theoretic approaches where real values are computed.

References


