Competitive Cell Association and Antenna Allocation in 5G Massive MIMO Networks

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***Abstract*—Massive MIMO will be one of the technologies adopted in 5G cellular networks due to its ability to enhance transmission performance. However, resource management issues remain unsolved, especially with quality of service (QoS) requirements from users. This paper focuses on cell association and antenna allocation problems in such networks. We analyze the competitive situations where users in different classes with different QoS (i.e., data rate) requirement can choose to associate with any cell rationally and independently. Likewise, access points can allocate their antennas to different users. The users and access points are self-interested to maximize their own benefits in terms of data rate and total revenue, respectively. We formulate a hierarchical evolutionary game framework which is composed of the games for cell association and antenna allocation. We apply both deterministic and stochastic approaches to obtain the equilibrium solutions of the game.**

***Index Terms*—Cell association, antenna allocation, evolutionary game**

I. Introduction

Massive MIMO is one of the important candidate technologies for 5G cellular networks [1], [2]. By deploying a number of antennas at a base station and access point, with massive MIMO the network can achieve much higher performance than that of 4G [3]. Massive MIMO can be deployed in heterogeneous networks (HetNets) which are composed of a variety of cells (e.g., a macrocell and small-cells) [4]. Additionally, in [4], the authors highlight some major issues of such an integration, i.e., interference management and energy efficiency. However, due to complex network design and implementation, the cell association for users and resource allocation for base stations (e.g., antenna allocation) in massive MIMO networks arise. For example, in [5], the authors introduced an energy-efficient resource allocation scheme for a network with large number of antennas. An optimization was formulated and solved to meet per user quality of service (QoS) requirement. In [6], a power control algorithm was proposed for a network with massive MIMO and noncooperative beamforming. The aim of the algorithm is to meet QoS requirement of users especially at cell edges.

Cell association or traditionally called network selection is an important issue for 5G heterogeneous networks (HetNets). Users have to associate with the most suitable cell so that their performance is maximized. To analyze the network selection, evolutionary game can be applied [7]. The problem of cell association was considered in [8]. Specifically, an optimization problem was formulated for load balancing which assigns a portion of resource blocks from different cells to different users to meet some fairness criteria. However, the paper did not consider independent and competitive cell association and antenna allocation performed by the users and access points, respectively. However, the cell association and resource allocation become more complex when the network lacks centralized coordination and control (e.g., in a distributed environment) and the users as well as the base stations are self-interested to maximize their own benefits.

In this paper, we consider jointly the cell association and antenna allocation problem of 5G massive MIMO networks. We formulate a hierarchical evolutionary game framework to analyze rational users' decisions to perform cell association to maximize their own data rate and to meet QoS requirement. Similarly, the framework can analyze self-interested access points' actions to perform antenna allocation to maximize their own revenue. First, the antenna allocation game is played by the access points after observing cell association decisions of users. Then the cell association game is played by the users based on the data rate achieved as a result of antenna allocation decisions. We apply deterministic and stochastic evolutionary game approaches to analyze the solutions. For the deterministic approach, we use replicator dynamics and the solution is a fixed point of the difference equation. For the stochastic approach, we use a Markov chain and the solution is a stochastically stable state whose steady state probability is non-zero. These solutions are similar to a Stackelberg equilibrium, where the access points are leaders and the users are followers of the hierarchical evolutionary game.

The rest of this paper is organized as follows. Section II describes the system model and assumptions used in this paper. Section III presents the hierarchical evolutionary game formulation. The deterministic and stochastic approaches based on replicator dynamics and Markov chain, respectively, are presented. Section IV shows the numerical performance evaluation results. Section V summarizes the paper.

II. System Model

We consider a network with N access points offering data transmission services to users (Fig. 1). The access point n has totally A_n antennas communicating with multiple users, each of which has a single antenna (i.e., multi-user MIMO).

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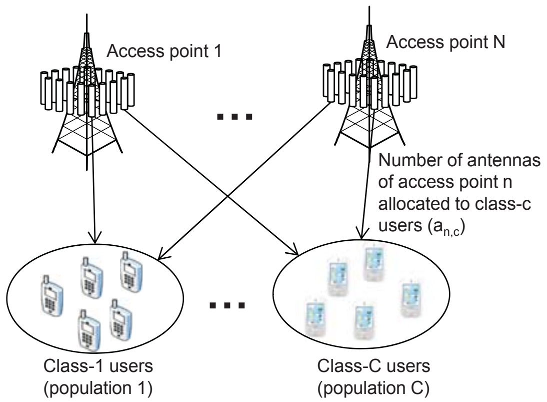

Fig. 1. A system model.

We consider service differentiation among different classes of users. There are totally C classes. Class c has M_c users. Each class has the data rate requirement denoted by R_c. The access point n can allocate $a_{n,c}$ antennas to a group of class-c users. The users can choose one of the N access points to associate with. However, if their data rate requirement cannot be met, the users can disassociate from the network. If a class-c user associates with access point n, the user has to pay a price $p_{n,c}$ to the access point. We assume that the users are uniformly distributed in the network.

To address the double competition of users for cell association and access points for antenna allocation, we propose a hierarchical evolutionary game framework. The framework is composed of evolutionary games for cell association in a lower level and for antenna allocation in a higher level. That is, the users are the followers and the access points are the leaders of the hierarchical evolutionary game framework. The hierarchical equilibrium, similar to a Stackelberg equilibrium, for the users and access points is considered as a solution of the framework.

We consider the data rate of a user as a major performance measure. The transmission rate of a user can be obtained, e.g., as in [10]. Ignoring estimation noise with the simple channel model and matched filter, the SINR can be obtained from [10]

$$\overline{\gamma}(a_{n,c}, M_{n,c}) = \frac{1}{\frac{\overline{L}}{\rho a_{n,c}} + \frac{M_{n,c}}{P}\overline{L}^2 + \alpha(\overline{L}-1)} \quad (1)$$

where $\overline{L} = 1 + \alpha(L-1)$, $a_{n,c}$ represents the number of antennas allocated to class-c users by access point n, $M_{n,c}$ represents the number of class-c users associated with access point n, L represents the number of cells, α represents the intercell interference factor, P represents the number of degree of freedom (DoF), and ρ represents the transmit SNR. The associated rate can be obtained from

$$\overline{r}(a_{n,c}, M_{n,c}) = \log_2(1 + \overline{\gamma}(a_{n,c}, M_{n,c})). \quad (2)$$

Here, we define the SINR and the associated rate as a function of the number of antennas $a_{n,c}$ and the number of users $M_{n,c}$ since they depend on the cell association and antenna allocation strategies.

III. Hierarchical Evolutionary Game Formulation

In this section, we present the hierarchical evolutionary game framework. Firstly, we introduce game definitions for cell association and antenna allocation. Then the deterministic and stochastic evolutionary game approaches are presented.

A. Game Definition

1) Cell Association Game: The game formulation of the cell association for users is composed of the following components. The *players* are users, and the *population* is a group of users in the same class, where M_c is the size (i.e., the number of class-c users) of class-c population. The *strategy* is to choose one of the available access points to associate with or disassociate from the network if the data rate is lower than the requirement. The strategy is denoted by $s \in \mathcal{S} = \{0, 1, \ldots, N\}$, where 0 corresponds to the disassociation action. The *payoff* is the data rate. Given a fixed and optimized transmission parameters, the data rate of class-c users given the number of allocated antennas from an access point n, i.e., $a_{n,c}$ can be obtained, for example, as in [10].

Let $s_{c,m}$ denote a strategy used by user m in class c and $\mathbf{s}_c$ be its vector, i.e., $\mathbf{s}_c = \begin{pmatrix} s_{c,1} & \cdots & s_{c,m} & \cdots & s_{c,M_c} \end{pmatrix}$. The number of class-$c$ users choosing access point n is obtained from

$$M_{n,c} = \sum_{m'=1}^{M_c} 1_{s_{c,m'}=n} \quad (3)$$

where $1_{\text{condition}}$ returns one if the condition is true and zero otherwise. The payoff of class-c users can be expressed as follows:

$$U_m(s_{c,m}, \mathbf{s}_{c,-m}, a_{n,c}) = \begin{cases} \overline{r}(a_{n,c}, M_{n,c}), & s_{c,m} = n > 0, \\ R_c, & s_{c,m} = 0 \end{cases} \quad (4)$$

where $\mathbf{s}_{c,-m}$ represents a vector of the strategies of other class-c users except user m, i.e., $\mathbf{s}_{c,-m} = \begin{pmatrix} s_{c,1} & \cdots & s_{c,m-1} & s_{c,m+1} & \cdots & s_{c,M_c} \end{pmatrix}$. There are two cases. If a user chooses any access point, the payoff will be the data rate. However, if a user chooses to disassociate from the network, its virtual payoff will be the data rate requirement. This virtual payoff is used as a cutoff point for the user to take the disassociation action. In particular, if the received data rate is lower than the requirement, it is better for the user to disassociate from the network. As a result, the user will prefer the strategy to associate with any access point only if it yields the data rate higher than the requirement.

2) Antenna Allocation: The game formulation of antenna allocation for access points is composed of the following components. The *players* are the access points in the network. The *strategy* is the antenna allocation to all classes of users, i.e., $a_{n,c}$ for access point n and $\mathbf{a}_c$ is the vector of antenna allocation to class-c users by all access points, i.e., $\mathbf{a}_c = \begin{pmatrix} a_{1,c} & \cdots & a_{n,c} & \cdots & a_{N,c} \end{pmatrix}$. We also call this $\mathbf{a}_c$ as an antenna allocation. Again, $\mathbf{a}_{-n,c}$ is a vector of antenna allocation of all access points except access point n, i.e., $\mathbf{a}_{-n,c} = \begin{pmatrix} a_{1,c} & \cdots & a_{n-1,c} & a_{n+1,c} & \cdots & a_{N,c} \end{pmatrix}$. The *payoff* is the total revenue earned from serving users in all classes choosing to associate with this access point. The revenue earned from class-c users is expressed as follows:

$$P_{n,c}(a_{n,c}, \mathbf{a}_{-n,c}) = p_{n,c} M_{n,c} \quad (5)$$

$$= p_{n,c} \left(\sum_{m'=1}^{M_c} 1_{s_{c,m'}=n} \right) \quad (6)$$

where again $p_{n,c}$ is the price that a class-c user pays to access point n. We can see that the payoff of the access points depends on the strategies of the users. Therefore, the cell association and antenna allocation are interrelated. The total revenue of access point n is obtained from

$$P_n(\mathbf{a}_n, \mathbf{a}_{-n}) = \sum_{c=1}^{C} P_{n,c}(a_{n,c}, \mathbf{a}_{-n,c}) \quad (7)$$

which is defined as a function of the antenna allocations of access point n, i.e., $\mathbf{a}_n$ and other access points, i.e., $\mathbf{a}_{-n}$.

The typical solution of the games is a Nash equilibrium. For the antenna allocation game, the Nash equilibrium denoted as $a^*_{n,c}$ is defined as follows:

$$P_n(\mathbf{a}^*_n, \mathbf{a}^*_{-n}) \geq P_n(\mathbf{a}_n, \mathbf{a}^*_{-n}) \quad (8)$$

for all n. The Nash equilibrium can be obtained as a solution of the best response defined as follows:

$$\mathbf{a}^*_n = \arg\max_{\mathbf{a}_n} P_n(\mathbf{a}_n, \mathbf{a}^*_{-n}) \quad (9)$$

for all n.

B. Deterministic Model

To reach the solutions of cell association and antenna allocation, we apply replicator dynamics in the deterministic model of evolutionary game. Firstly, we consider the cell association game. Let $x_{s,c}$ denote a proportion of class-c users choosing strategy $s \in \mathcal{S}$, and $\mathbf{x}_c$ is its vector, i.e., $\mathbf{x}_c = \begin{pmatrix} x_{0,c} & x_{1,c} & \cdots & x_{s,c} & \cdots & x_{N,c} \end{pmatrix}$. The discrete replicator dynamics of the cell association game is based on difference equation [11]. It models the change of a proportion of class-c users choosing different strategies as follows:

$$x^{(t+1)}_{s,c}(\tilde{\mathbf{a}}_c) = x^{(t)}_{s,c}(\tilde{\mathbf{a}}_c) \frac{\beta + U_{s,c}(\mathbf{x}^{(t)}_c(\tilde{\mathbf{a}}_c))}{\beta + \overline{U}^{(t)}_c} \quad (10)$$

where $x^{(t)}_{s,c}$ is the proportion at time step t. $U_{s,c}(\mathbf{x}^{(t)}_c(\tilde{\mathbf{a}}_c))$ is the payoff of a class-c user choosing strategy s, and $\overline{U}_c$ is the average payoff of a class-c user over all the strategies. Here, $\tilde{\mathbf{a}}_c$ is a vector of strategies (i.e., the number of antennas of all access points allocated to class-c users), which is defined as $\tilde{\mathbf{a}}_c = \begin{pmatrix} a_{1,c} & \cdots & a_{n,c} & \cdots & a_{N,c} \end{pmatrix}$. β is the variable to control the strategy adaptation. The larger value of β will lead to faster convergence rate, but higher chance of unstability.

The payoff is obtained as follows:

$$U_{s,c}(\mathbf{x}_c(\tilde{\mathbf{a}}_c)) = \begin{cases} \overline{r}(a_{n,c}, M_c x_{s,c}(\tilde{\mathbf{a}}_c)), & s > 0 \\ R_c, & s = 0 \end{cases} \quad (11)$$

and the average payoff is obtained from

$$\overline{U}_c = \frac{\sum_{s \in \mathcal{S}} U_{s,c}(\mathbf{x}_c(\tilde{\mathbf{a}}_c))}{|\mathcal{S}|} \quad (12)$$

where $|\mathcal{S}|$ is the Cardinality of a set $\mathcal{S}$ (i.e., the total number of strategies). The fixed point of the discrete replicator dynamics for the cell association game $x^*_{s,c}$ meets the following condition

$$x^*_{s,c}(\tilde{\mathbf{a}}_c) = x^{(t+1)}_{s,c}(\tilde{\mathbf{a}}_c) = x^{(t)}_{s,c}(\tilde{\mathbf{a}}_c) \quad (13)$$

for all s. The fixed point implies that the users stop changing their strategy. That is, the users cannot switch to a new strategy to gain higher payoff (i.e., an equilibrium).

Similarly, we apply discrete replicator dynamics to model the strategy adaptation of access points in the antenna allocation game. Let $y_{n,\mathbf{a}_n}$ denote the frequency (e.g., percentage of time) that access point n applies the allocation $\mathbf{a}_n$ to users in all classes, and $\mathbf{y}$ is its vector. The discrete replicator dynamics of the antenna allocation game is defined as follows:

$$y^{(k+1)}_{n,\mathbf{a}_n} = \frac{\delta + P_n(\mathbf{a}_n, \mathbf{y}^{(k)})}{\delta + \overline{P}_n(\mathbf{y}^{(k)})} \quad (14)$$

where again δ is the variable to control the strategy adaptation. $P_n(\mathbf{a}_n)$ is the average payoff of access point n over the strategies of all other access points, i.e.,

$$P_n(\mathbf{a}_n, \mathbf{y}) = \sum_{\mathbf{a}_{-n}} P_n(\mathbf{a}_n, \mathbf{a}_{-n}) \left(\prod_{n' \neq n} y_{n',\mathbf{a}_{n'}} \right) \quad (15)$$

$$= \sum_{\mathbf{a}_{-n}} \sum_{c=1}^{C} p_{n,c} M_c x^*_{s=n,c} \left(\prod_{n' \neq n} y_{n',\mathbf{a}_{n'}} \right) \quad (16)$$

where $\mathbf{a}_{-n}$ is a vector of antenna allocations of all access points except access point n (i.e., its element is $\mathbf{a}_{n'}$). $\overline{P}_n$ is the average payoff of access point n over all its possible strategies, i.e.,

$$\overline{P}_n(\mathbf{y}) = \sum_{\mathbf{a}_n} P_n(\mathbf{a}_n, \mathbf{y}) y_{n,\mathbf{a}_n}. \quad (17)$$

Note that $y^{(k)}_{n,\mathbf{a}_n}$ is the frequency at iteration k. Each iteration of the antenna allocation game contains a number of time steps of the cell association game (i.e., much larger than that required by the cell association game to converge).

The fixed point of the discrete replicator dynamics for the antenna allocation game $y^*_{n,\mathbf{a}_n}$ meets the following condition

$$y^*_{n,\mathbf{a}_n} = y^{(k+1)}_{n,\mathbf{a}_n} = y^{(k)}_{n,\mathbf{a}_n} \quad (18)$$

for all $\mathbf{a}_n$. The fixed point implies that the access points stop changing their strategies as they cannot do so to improve the payoffs.

Algorithm 1 shows the major steps to obtain numerically the equilibrium solutions for both the cell association and antenna selection games. ϵ is a tolerable difference between two consecutive time steps and iterations.

Algorithm 1 Computation of an equilibrium in deterministic evolutionary game

for All access points n **do**
  for All strategy $\mathbf{a}_n$ **do**
    Initialize $t \leftarrow 0$, $x_{s,c}^{(t)}(\tilde{\mathbf{a}}_c)$
    repeat
      Use (10) to update $x_{s,c}^{(t)}(\tilde{\mathbf{a}}_c)$ for the cell association game.
      $t \leftarrow t+1$
    until $\max_s \max_c |x_{s,c}^{(t)}(\tilde{\mathbf{a}}_c) - x_{s,c}^{(t-1)}(\tilde{\mathbf{a}}_c)| < \epsilon$
  end for
end for
Initialize $k \leftarrow 0$, $y_{n,\mathbf{a}_n}^{(k)}$
repeat
  Use (14) to update $y_{n,\mathbf{a}_n}^{(k)}$ for the antenna allocation game.
  $k \leftarrow k+1$
until $\max_n \max_{\mathbf{a}_n} |y_{n,\mathbf{a}_n}^{(k)} - y_{n,\mathbf{a}_n}^{(k-1)}| < \epsilon$

C. Stochastic Model

In addition to replicator dynamics which is a deterministic approach to obtain a solution of evolutionary game, the stochastic approach based on a Markov chain can be applied. The stochastic approach can incorporate noise of players' decision in the model. Firstly, the Markov chain for the cell association game is defined. The state space of the class-c users is as follows:

$$\Omega_c = \left\{ (\omega_0, \omega_1, \ldots, \omega_s, \ldots, \omega_N); \sum_{s=0}^{N} \omega_s = M_c \right\} \quad (19)$$

where ω_s is the number of class-c users applying strategy s. We define the state $\omega = \begin{pmatrix} \cdots & \omega_s & \cdots & \omega_{s'} & \cdots \end{pmatrix}$ and the state $\omega_{s\rightarrow s'} = \begin{pmatrix} \cdots & \omega_s - 1 & \cdots & \omega_{s'}+1 & \cdots \end{pmatrix}$. In particular, one user switches from strategy s to strategy s'. The transition rate from state ω to state $\omega_{s\rightarrow s'}$ is given as follows:

$$\rho_{\omega,\omega_{s\rightarrow s'}}(\tilde{\mathbf{a}}_c) = \begin{cases} \omega_s \sigma, & U_{s,c}(\omega_{s\rightarrow s'}, \tilde{\mathbf{a}}_c) > U_{s,c}(\omega, \tilde{\mathbf{a}}_c) \\ \varepsilon_{\mathrm{C}}, & \text{otherwise} \end{cases} \quad (20)$$

where $U_{s,c}(\omega, \tilde{\mathbf{a}}_c)$ is the payoff of class-c users with strategy s given the antenna allocations of all access points to this class-c users $\tilde{\mathbf{a}}_c$. σ is the rate of users to change their strategy and $\sigma \gg \varepsilon_{\mathrm{C}}$. This payoff is obtained from

$$U_{s,c}(\omega, \tilde{\mathbf{a}}_c) = \begin{cases} \overline{r}(a_{n,c}, \omega_s(\tilde{\mathbf{a}}_c)), & s > 0, \\ R_c, & s = 0. \end{cases} \quad (21)$$

In (20), a user switches from strategy s to strategy s' if the latter yields higher payoff. However, the user can make an irrational strategy switching (i.e., noise) with a small rate of ε_{C}.

Let the steady state probability of the state ω be denoted by $\pi_\omega(\mathbf{a})$. Any state $\omega^*(\mathbf{a}) \in \Omega_c$ is stochastically stable if the steady state probability is non-zero when the noise (i.e., ε_{C}) is small. Note that this stochastically stable state $\omega^*(\mathbf{a})$ is a function of antenna allocation strategy $\mathbf{a}$ of all access points.

Similarly, we apply stochastic evolutionary game to analyze the antenna allocation game. The Markov chain for the antenna allocation game has the state space defined as follows:

$$\Theta = \Big\{ (a_{1,1}, \ldots, a_{1,C}, a_{2,1}, \ldots, a_{N,1}, \ldots, a_{N,C}); \sum_{c=1}^{C} a_{n,c} = A_n \ ; \forall n \Big\}. \quad (22)$$

The state is a collection of antenna allocations by all access points to all classes of users. We define the state $\mathbf{a} \in \Theta$ as $\mathbf{a} = \begin{pmatrix} a_{1,1} & \cdots & a_{n,c} & \cdots & a_{N,C} \end{pmatrix}$ and the state $\mathbf{a}_{n,c\rightarrow c'} = \begin{pmatrix} \cdots & a_{n,c}-1 & \cdots & a_{n,c'}+1 & \cdots \end{pmatrix}$. In particular, access point n changes the antenna allocation for class-c users to class-c' users, making state transition from $\mathbf{a}$ to $\mathbf{a}_{n,c\rightarrow c'}$. The transition rate from state $\mathbf{a}$ to state $\mathbf{a}_{n,c\rightarrow c'}$ is as follows:

$$\phi_{\mathbf{a},\mathbf{a}_{n,c\rightarrow c'}} = \begin{cases} \theta, & P_n(\mathbf{a}_{n,c\rightarrow c'}) > P_n(\mathbf{a}) \\ \varepsilon_{\mathrm{A}}, & \text{otherwise} \end{cases} \quad (23)$$

where θ is a strategy switching rate of an access point, and $\theta \gg \varepsilon_{\mathrm{A}}$. $P_n(\mathbf{a})$ is derived in the same way as in (7), i.e.,

$$P_n(\mathbf{a}) = \sum_{c=1}^{C} p_{n,c} \omega_c^*(\mathbf{a}) \quad (24)$$

where $\omega_c^*(\mathbf{a})$ is a component of stochastically stable state $\omega^*(\mathbf{a})$ given antenna allocation $\mathbf{a}$.

Again, let the steady state probability of the state $\mathbf{a}$ be denoted by $\psi_{\mathbf{a}}$. Any state $\mathbf{a}^* \in \Theta$ is stochastically stable if the steady state probability is non-zero when the noise (i.e., ε_{A}) is small. Algorithm 2 shows the algorithm to solve the stochastic evolutionary game for cell association and antenna allocation.

Algorithm 2 Computation of an equilibrium in stochastic evolutionary game

for All access points n **do**
  for All strategy $\mathbf{a}_n$ **do**
    Solve for stochastically stable state $\omega^*(\mathbf{a})$.
  end for
end for
Solve for stochastically stable state $\mathbf{a}^*$.

IV. Performance Evaluation

A. Parameter Setting

We consider two access points with massive MIMO. The first and second access points have 50 and 60 antennas, respectively. We adopt the match filter user detection. However, the network can also adopt more sophisticated minimum-mean-square-error (MMSE) detection. Similar to [10], we use the following parameters: the intercell interference factor is $\alpha = 0.1$ and transmit SNR is $\rho = 0$dB. There are two classes of users, i..e, class-1 and class-2. Unless otherwise stated, the data rate requirements are 1 and 2 b/s/Hz for class-1 and class-2 users, respectively. There are 50 users in each class. The prices of cell association are 1 and 2 monetary units (MUs) for class-1 and class-2 users, respectively. For the deterministic evolutionary game, we set $\beta = \delta = 0.1$. For an initial connection, users choose access points 1 and 2 uniformly. For the stochastic evolutionary game, we set $\varepsilon_{\rm C} = \varepsilon_{\rm A} = 10^{-4}$.

B. Numerical Results

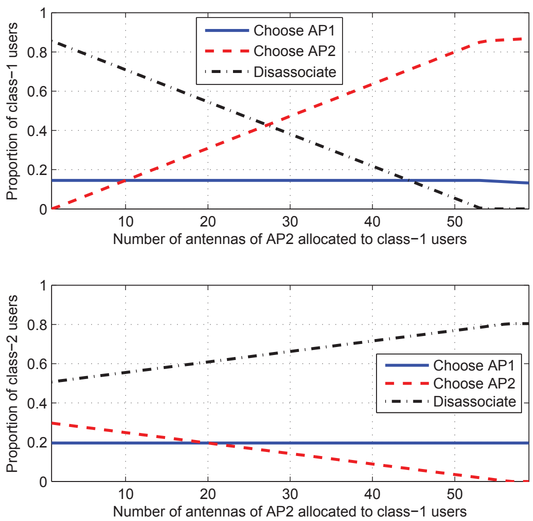

Fig. 2. Proportions of class-1 and class-2 users choosing access points (APs) 1 and 2.

Figure 2 shows the proportions of class-1 and class-2 users choosing access points 1 and 2 when the number of antennas allocated by access point 2 to class-1 users is varied. Here the number of antennas allocated by access point 1 to class-1 users is fixed at 10. Firstly, we observe that if the number of users is too many, not all users can achieve the data rate requirement. Some of them will be disconnected from the network. As a result, the proportions of class-1 and class-2 users disassociated from the network are not zero. The number of disassociated users can be high as shown in the figure that the access points has to improve its performance to reduce the unsatisfactory users.

When the access point 2 allocates more antennas to class-1 users (i.e., fewer antennas allocated for class-2 users), the data rate of class-1 users increases and some disassociated class-1 users switch to connect to access point 2. Until there is no disassociated class-1 users, some class-1 users choosing access point 1 will start switching to choose access point 2. In this case, access point 1 will gain higher revenue while access point 2 earns less revenue. By contrast, since there are fewer antennas allocated for class-2 users, the data rate of class-2 users decreases, and some class-2 users will switch from choosing access point 2 to disassociate from the network.

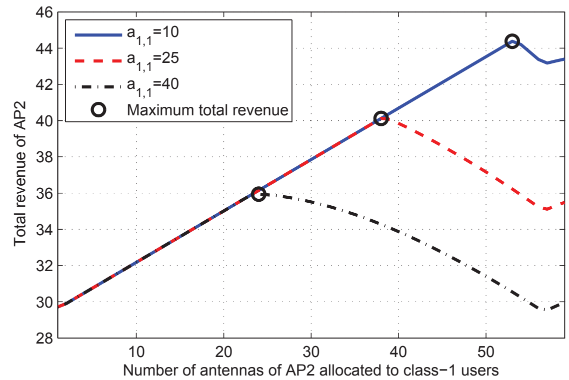

Fig. 3. Total revenue of access point (AP) 2 under different number of allocated antennas.

Based on the varied number of antennas allocated to class-1 users by access point 2, its total revenue is shown in Fig. 3. We observe that when this number of antennas increases, first the total revenue increases since access point 2 earns more from class-1 users. However, at a certain point, the total revenue decreases, this is due to the loss of revenue from class-2 users. Clearly, there is an optimal point that yields the highest total revenue for access point 2. This optimal point depends on the number of antennas allocated to class-1 users by access point 1 also. This behavior can be well analyzed using game theory, where access points compete by allocating their antennas to different classes of users.

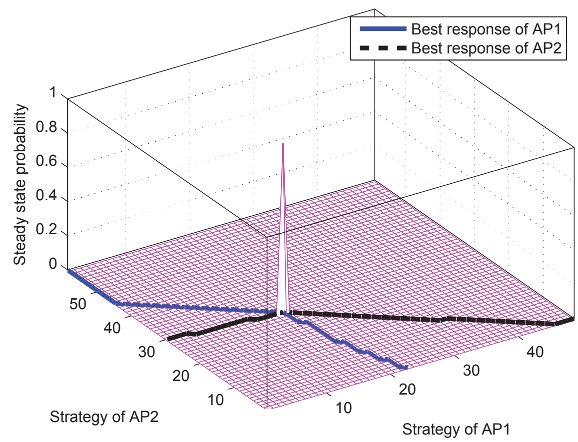

Fig. 4. Best responses of access points (APs) 1 and 2 and steady state probability for data rate requirement of class-2 user is 1 b/s/Hz.

Figure 4 shows the steady state probabilities of equilibrium(s) for when the data rate requirement of class-2 user is 1.0 and 2.0, respectively. Additionally, these figures show the best responses in a noncooperative game context of access points 1 and 2. Based on the best responses, their intersection are the Nash equilibrium. Clearly, from a stochastic evolutionary game framework, the steady state probability of these points are non-zero.

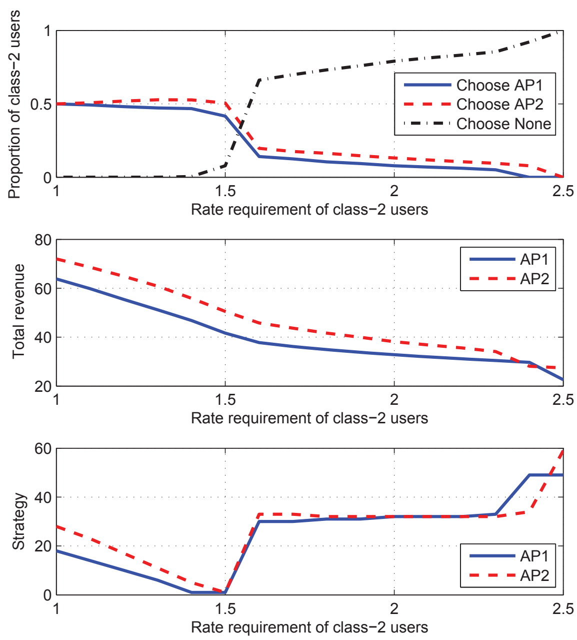

Fig. 5. Proportion of users, total revenue, and strategy under varied data rate requirement of class-2 users.

With the hierarchical evolutionary game framework, Fig. 5 shows the proportions of users choosing different access points, total revenue and strategies of the access points when the data rate requirement of class-2 users is varied. At the equilibrium solution, when the data rate requirement of class-2 users increases, the number of class-2 users associated with any access points decreases, while the number of disassociated class-2 users increases. This is due to the fact that the increasing data rate requirement cannot be met by any antenna allocation strategy. Consequently, the total revenues of both access points decrease. Note that we observe an interesting result for the antenna allocation strategies of both access points. First, the number of allocated antennas to class-1 users decreases (i.e., more antennas are allocated to class-2 users). This is to meet the increasing data rate requirement of class-2 users. However, at a certain point, the number of allocated antennas to class-1 users increases. This is from the fact that the data rate requirement of class-2 users is too high. Therefore, it is better for the access points to put more resources (i.e., antennas) to class-1 users to gain higher revenue.

V. Summary

We have considered the cell association and antenna allocation jointly in the 5G massive MIMO networks. We have developed the hierarchical evolutionary game framework, which is composed of the cell association game played by users and the antenna allocation game played by access points. The users in different classes aim to maximize their data rate, while meeting their data rate requirements. The access points have the objective to maximize their total revenue. We have applied the deterministic evolutionary game to obtain an equilibrium solution defined as a fixed points of the replicator dynamics. Alternatively, we have adopted the stochastic evolutionary game to obtain the solution defined based on steady state probability of the Markov chain. The numerical studies have shown a few important features of the proposed games including the impact of data rate requirements.

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