Non-Cooperative Association Of Mobiles To Access Points Revisited

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***Abstract*—We consider in this paper games related to the association problem of mobiles to an access point. It consists of deciding to which access point to connect. We consider the choice between two access points or more, where the access decisions may depend on the number of mobiles connected to each one of the access points. We obtain new results using elementary tools in congestion and crowding games.**

I. Introduction

There has been a growing interest in last years in modeling access decisions to networks as non-competitive games. Indeed, it is quite frequent that the network leaves it to the user to decide to which access point to connect. The association problem is in fact related in nature to the channel selection problem. This motivates the use of games with incomplete information, also known as Bayesian games, where the partial information refers to the system load in [1] or to the channel quality in [2].

The access point may differ from one another by their technology and by the quality of radio channels between each of them and each mobile. Such state dependent competitive decision making in networking have been modeled in the past as stochastic games and structure of equilibrium policies has been derived for one or two dimensional problems. By one dimensional problem we mean problems in which each mobile has a choice between an access point in which resources are shared and between a dedicated channel. In such problem the information needed for taking the association decision is how many mobiles are connected to the shared resource (therefore the information is said to be one-dimensional). An example for a problem that falls into this category is [3]. The equilibrium policy there consists of a threshold policy with randomization at the threshold. In [4] the author study a two dimensional problem in which the choice is between accessing a 3G wireless cellular network or a wireless local area network. The information available is of two dimensions: the number of mobiles in each one of the networks. In [5] equilibrium policies were shown to have a switching curve form with possible randomization at the boundary between regions corresponding to connecting to different access point. A problem of association to one of several cellular network was considered in [6]. In all the above problems we assumed that once a connection decision is made, the mobile stays connected to the access point till the end of the call.

In contrast, in this paper we consider the problem where at any time period, mobiles can update their association decision. We consider the choice between two access points or more, where the access decisions may depend on the number of mobiles connected to each one of the access points. We obtain new results using elementary tools in congestion and in crowding games. We show in particular that at equilibrium, mixed (randomized) actions are not required. We moreover show the convergence of sequence of best response strategies.

Our results are based on congestion games [7] and on crowding games [9]. We further study (i) multi-homing in which a user can connect simultaneously to more than one access point. (ii) the "elastic" case in which there is also an option not to connect at all.

II. The generic game problem

There is a set Σ containing r resources and a set M of m users (players). Player i has access to a subset $\Sigma_i \subset \Sigma$ of these and has to choose to which resource it associates. We assume that the cost C_{ji} for player i of associating with resource j only depends on the number n_j (including himself) of players that use this resource. Each one of the costs C_{ji} is assumed to be monotonically non-decreasing in n_j. We wish to know whether an equilibrium exists, i.e. whether each player can choose one resource such that no player can get a strictly cheaper resource by deviating unilaterally. We further are interested to know when do we have convergence to equilibrium. Before answering these questions, we first introduce applications to the association problem of mobiles to base station.

We study below problems where each one of m mobiles has to decide to which one of r base stations to associate. We assume that the association is determined by the downlink conditions.

A. Association to a base station (BS): TDMA

Mobiles are served cyclically by the BS they associate to. Thus, if $n_j > 0$ mobiles connect to BS j then the time dedicated to transmission to each mobile is one frame in every n_j consecutive frames.

The utility of a user is the difference between a payoff and some cost. Here is an example of utilities and costs.

1) The throughput as payoff: We assume that each BS has its own frequency so that there is no interference. We further introduce the concept of effective bandwidth [12] which allows us to associate an effective bandwidth to each mobile depending on its class and location relative to a target cell. Assume that a maximum of L users are allowed to be served by a BS. The utility that player i obtains can be expressed as

$$u_i(j, n_j) = \begin{cases} \underbrace{\frac{W_{ji} \log\left(1 + \frac{|h_{ji}|^2 P_{ji} d_{ji}^{-\alpha}}{\rho}\right)}{n_j}}_{\text{throughput}} - \underbrace{\frac{\delta \tilde{P}_j}{n_j}}_{\text{cost}}, & \text{if } n_j \leq L; \\ -\infty, & \text{otherwise.} \end{cases} \tag{1}$$

where W_{ji} is the bandwidth that BS j allocates to the mobile i, h_{ji} captures the effects of fading between mobile i and BS j, d_{ji} is the distance between BS j and mobile i, α is the path loss exponent, ρ is the variance of additive noise, P_{ji} is transmitted power from BS j to mobile i and δ is called the *price* of switching on a BS which bears $\tilde{P}_j$ power cost if the corresponding BS is the jth one.

Remark 2.1: In the above formulation, L denotes the capacity constraints of a BS (maximum number of mobiles that can be associated with a BS). We included implicitly capacity constraints, by assigning an infinite cost to joining a BS j if the total number of mobiles that associate to this BS exceeds L. Instead of using $-\infty$ one can use any other number sufficiently small. In both cases any equilibrium solution will have the property that all capacity constraints are satisfied for all players. Note that crowding games with capacity constraints and a special cost structure have been studied already in [9]. By assigning sufficiently negative utilities to association to BSs for the case that the number of mobiles exceeds some threshold, we manage to include these constraints in the framework of [7].

We notice that the throughput that a player gains decreases when some group of players are served by the same BS. However, the cost that the corresponding player has to pay decreases as well. Note that the utility function is player-specific.

Finally, we assume that a mobile has the option not to connect to any BS in which case its utility is zero.

2) Monotonicity of utility: In order the considered game to be a crowding game, the utility must be a monotonically decreasing function, i.e. $\partial u_i(j,k)/\partial k \leq 0$. Therefore,

$$\frac{\partial u_i(j,k)}{\partial k} = -\frac{W_{ji} \log\left(1 + \frac{|h_{ji}|^2 P_{ji} d_{ji}^{-\alpha}}{\rho}\right) - \delta \tilde{P}_j}{k^2} \leq 0 \tag{2}$$

$$\delta \leq \frac{W_{ji} \log\left(1 + \frac{|h_{ji}|^2 P_{ji} d_{ji}^{-\alpha}}{\rho}\right)}{\tilde{P}_j}, \quad \forall j, i. \tag{3}$$

Let us assume that the bandwidth W_{ji} allocated to a player be a component of a set $\mathcal{W}$ (the set of different bandwidth classes), i.e. $W_{ji} \in \mathcal{W}$, and the SNR takes a value from the set $\mathcal{G}$, i.e. $SNR_{ji} = \frac{|h_{ji}|^2 P_{ji} d_{ji}^{-\alpha}}{\rho} \in \mathcal{G}$. Also, the operational power cost $\tilde{P}_j \in \mathcal{P}$. In order to determine the upper bound of pricing δ, we need to calculate the following

$$\min_{j,i} \frac{W_{ji} \log(1 + SNR_{ji})}{\tilde{P}_j}. \tag{4}$$

B. Association to a base station (BS): HSDPA

We adopt the model of S. Borst [10] for opportunistic scheduling according to the proportional fairness criterion. Time is divided into slots, and each BS schedules at each slot transmission to one mobile among those connected to it. A weakly symmetric channel model is used in which the channel statistics from BS j to mobile i are such that the throughput available to that mobile, if the channel is assigned to it is a random variable of the form $R_{ji} = Q_{ji} Y_{ji} Z_j$ where for each given j, $\{Y_{ji}\}$ are independent and identically distributed random variables, Z_j is some random variable (that may be used to bring correlation) with a unit mean, and Q_{ji} is representing the time-average rate of user i [10]. Thus, the probability distribution of the normalized available throughput of all the mobiles connected to BS j are the same. The proportional fair allocation at BS j schedules transmission to the connected mobile for which the normalized rate (i.e. ratio R_{ji}/Q_{ji}) is the largest. The expected average throughput of mobile i when connecting to BS j is then given by $G(n_j)/n_j$ times its rate R_{ji}, where $G(k) := \max_{i=1,\ldots,k} Y_{ji}$ is the opportunistic gain. Hence, the utility of player i is given by

$$u_i(j, n_j) = \begin{cases} R_{ji} \frac{G(n_j)}{n_j} - \frac{\delta \tilde{P}_j}{n_j}, & \text{if } n_j \leq L; \\ -\infty, & \text{otherwise.} \end{cases} \tag{5}$$

By the law of iterated logarithm we know that $G(k)/k$ converges to 0.

In particular,

- for the Gilbert channel [11] in which Y_{ji} can take two values, say a and b with $b \geq a$ and with corresponding probabilities p and $1-p$, we have $G(k) = b(1-p^k) + ap^k$. Let us analyze in which condition the utility is always monotonically decreasing:

$$\frac{\partial u_i(j,k)}{\partial k} = \frac{-bR_{ji} + \tilde{P}_j \delta + (a-b)p^k R_{ji}(k \ln p - 1)}{k^2} \leq 0 \tag{6}$$

  We would like to know the value of pricing δ in which the monotonically decreasing property maintains. Hence,

$$\delta \leq \min_{j,i} \frac{R_{ji}\left(b + p^k(b-a)(k \ln p - 1)\right)}{\tilde{P}_j}, \tag{7}$$

- choose the distribution of the mean SNR as a bi-modal distribution either SNR_1 or SNR_2 with equal probability. If the instantaneous rate R is linear in the instantaneous SNR, i.e. $R = W \times SNR$, then the relative fluctuations $\{Y_{ji}\}$ have an exponential distribution, and the gain factor can be derived in closed form as $G(n_j) = \max_{i=1,\ldots,n_j} Y_{ji} = \sum_{i=1}^{n_j} 1/i$ [10]. The harmonic numbers are given by $H^l(k) = \sum_{i=1}^{k} 1/i^l$ with $H(k) = H^1(k)$. It is suitable for both symbolic and numerical manipulation. The monotonically decreasing property requires the following

$$\delta \leq \min_{j,i} \frac{R_{ji}(H(n_j) - n_j \psi(n_j+1))}{\tilde{P}_j} \tag{8}$$

where $\psi(k)$ is the logarithmic derivative of the gamma function, given by $\psi(k) = \Gamma'(k)/\Gamma(k)$. Denote $\Delta(k) = H(k) - k\psi(k+1)$. Figure 1 plots how $\Delta(k)$ changes with respect to k. $k = 1$ minimizes $\Delta(k)$ which is $\Delta(1) = 2 - \frac{\pi^2}{6} = 0.355$.

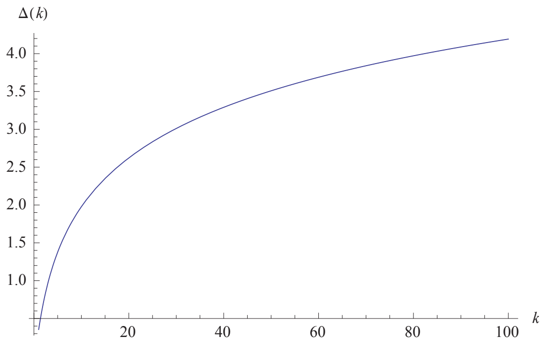

Fig. 1. The change of Δ with respect to number of mobiles that share the same BS.

III. Crowding Games Preliminaries

We first introduce crowding games and then show that our problems can be transformed into such games. This allows us then to use a wide spectrum of tools available there for studying our problems.

A crowding game is represented by triple $\Gamma = \langle M, \Sigma^m, (u_i)_{i \in M} \rangle$ where $M = \{1, 2, \ldots, m\}$ is the set of *players*, Σ is the set of *strategies* shared by all the players and $u_i : \sigma \to \Re$ is the *utility function* of player $i \in M$. Each player $i \in M$ chooses exactly one element from the r alternatives in Σ. The choices of players are represented by $\sigma = \{\sigma_1, \sigma_2 \ldots, \sigma_m\} \subseteq \Sigma^m$ which is called the *strategy-tuple* (σ_i shows the strategy chosen by player i).

The utility that player i receives for playing the jth strategy is monotonically non-increasing function u_i of the total number of n_j of players playing the jth strategy [7]. The number of players playing each strategy corresponding to σ can be presented by a *congestion vector* $n = (n_1, n_2, \ldots, n_r)$, where $n_j \geq 0$ is the number of players who have chosen a $j \in \Sigma$. The strategy-tuple σ is a Nash equilibrium iff each σ_i is a best-reply strategy [7]:

$$u_i(n_{\sigma_i}) \geq u_i(n_j + 1) \quad \forall i \in M \text{ and } \forall j \in \Sigma. \tag{9}$$

A crowding game becomes a congestion game (symmetric crowding game) if all players share the same set of utility functions. Clearly, the crowding games arise if there exist *player-specific* utility functions. Nonsymmetric crowding games, however, generally do not admit a potential function (for further information about potential function, refer to [8]).

An Algorithm for Finding Nash Equilibrium

Milchteich establishes the following [7]:

Theorem 3.1: Consider a crowding game. Assume that the utility of player i for choosing resource j is

- a function of i, j and the number of players that choose resource j,
- decreasing in this number

Then

- (i) There exists a pure Nash equilibrium,
- (ii) There exists a sequence of best responses of players that converges to an equilibrium within finitely many steps.
- (iii) Assume that the number of resources is 2. Consider any sequence of best responses in which each player has infinitely many opportunities to change its decision. Then already after a finite number of steps, the sequence reaches an equilibrium.

In view of this Theorem, we can use a best response algorithm to compute an equilibrium. We are guaranteed that it will converge within a finite time if the number of resources is two, or if there is a unique best response decision at every step. Under these conditions it can be used as an algorithm that yields convergence to an equilibrium within a finite number of steps. The Algorithm is summarized below (see Algorithm 1).

Proof: The proof of Theorem 3.1 is given in the proof of Theorem 2 of [7]. ■

IV. Application to the BS association problem

Theorem 4.1: Consider the association problem described in Section II-A. Then the conclusions of Theorem 3.1 hold.

Proof: The game described in Section II-A satisfies the conditions of Theorem 3.1 except possibly two condition.

1) If for some mobile i and BS j, we have

$$W_{ji} \log\left(1 + \frac{|h_{ji}|^2 P_{ji} d_{ji}^{-\alpha}}{\rho}\right) < \delta \tilde{P}_j$$

then the utility of player i to associate with BS j increases with the number n_j that associate to that BS. Let H_1 be the set of pairs (i, j) that have this property.

2) In the [7], if a resource is available to one player then it is available to all players. Let H_2 be the set of pairs (i, j) for which j is not available for i.

Let $H = H_1 \cup H_2$. Consider a new game in which all BSs are accessible to all players. We set $u_i(j, n_j) = -1$ for all $(i, j) \in H$. This is a crowding game that satisfies the conditions of Theorem 3.1. Moreover, any best response

Algorithm 1 Utility and Strategy-tuple in Nash Equilibrium

function nashequilibrium $(M, \Sigma, (P_{ji}, \tilde{P}_j, h_{ji}, W_i)_{j\in\Sigma, i\in M}, \delta, \alpha)$

$\sigma(0) \leftarrow \{0, 0, \ldots 0\}$ Set the initial strategy-tuple

$$u_i(\sigma(0)) \leftarrow 0, \forall i \in M$$

$c \leftarrow 0$ Set the convergence variable to zero
$p \leftarrow 1$ Set the player variable to 1
$l \leftarrow 1$ Set the step variable of strategy-tuple to 1
while $c == 0$ **do**
Find the best-reply strategy of player p: $\sigma_p^*(l)$
Calculate $u_i(\sigma(l)), \forall i \in M$
if $u_p(\sigma_p^*(l)) \geq u_p(\sigma_p^*(l-1))$ **then**
$l \leftarrow l + 1$
if $p < m$ **then**
$p \leftarrow p + 1$
else
$p \leftarrow 1$
end if
else
$u_p(\sigma_p^*(l)) \leftarrow u_p(\sigma_p^*(l-1))$
$\sigma_p(l) \leftarrow \sigma_p(l-1)$
$l \leftarrow l + 1$
if $p < m$ **then**
$p \leftarrow p + 1$
else
$p \leftarrow 1$
end if
end if
if $l > m + 1$ **then**
if $\sigma_p(l-1) == \sigma_p(l-2) \forall p \in M$ **then**
$c \leftarrow 1$
end if
end if
end while
end

TABLE I
UTILITY MATRIX

		Mobile 2		
		BS 1	BS 2	BS 3
Mobile 1	BS 1	$(2, 1.3)$	$(4^*, 8^*)$	$(4, 6.3)$
	BS 2	$(5.2, 2.6)$	$(2.7, 4)$	$(5.2^*, 6.3^*)$
	BS 3	$(2, 2.6)$	$(2, 8)$	$(1, 3.15)$

sequence in the original game is also a best response in this game since any player i will never chooses a BS j with $(i, j) \in H$ as a best response since choosing not to connect at all gives a strictly better utility (of zero). This establishes the proof. ∎

V. Example Scenario

In this section, we show by an example scenario how the introduced algorithm converges to an equilibrium in the context of throughput competition.

In Figure 2, it is depicted the utilities for each BS-mobile pair when one mobile uses one BS. For example, the utility is $u_1(1) = 4$ if mobile 1 is served by BS_1. In case of multiple usage, the utility decreases, for example: $u_1(2) = 2$, $u_2(2) = 1.3$ if both mobile 1 and mobile 2 use BS_1 which results in the strategy tuple $\sigma = \{\sigma_1, \sigma_2\} = \{BS_1, BS_1\}$.

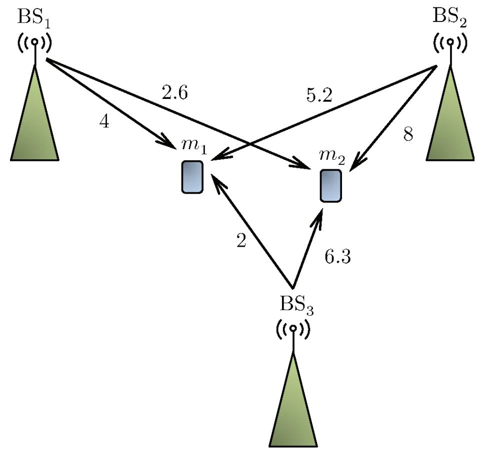

Fig. 2. Example scenario.

Let us then find the Nash equilibrium of this scenario. We have two players and three strategies. First, we show the utility matrix of this game (Table 1). From the utility matrix, we find easily the equilibria $(4, 8)$ and $(5.2, 6.3)$.

Secondly, we run the algorithm for this example scenario that is introduced in Algorithm 1. Let us assume that in the step $l = 0$, the initial strategy-tuple be as $\sigma(0) = \{BS_1, BS_1\}$. Then the utilities become

$$u_1(\sigma(0)) = 2, u_2(\sigma(0)) = 1.3, \tag{10}$$

in which $u_i(\sigma(l))$ represents the utility of player i in case of strategy-tuple $\sigma(l)$.

We set player 1 as the first player which looks for the best-reply strategy. Player 1 finds out that the best-reply strategy $\sigma_1(1) = BS_2$ in the step $l = 1$. The utilities are calculated as

$$u_1(\sigma(1)) = 5.2, u_2(\sigma(1)) = 2.6, \tag{11}$$

where $\sigma(1) = \{BS_2, BS_1\}$. In the next step, $l = 2$, player 2 searches the best-reply strategy which turns out to be $\sigma_2(2) = BS_3$. The strategy-tuple then is as $\sigma(2) = \{BS_2, BS_3\}$ which results in the following utilities

$$u_1(\sigma(2)) = 5.2, u_2(\sigma(2)) = 6.3. \tag{12}$$

In the next step, player 1 can not find a best-reply strategy. Consequently, the algorithm converges to the Nash equilibrium which coheres with the one of utility matrix that we found as $(5.2, 6.3)$.

VI. Computational Results

In this section, we show the computational results that are performed in the context of crowding games for non-cooperative association of mobiles to access points.

The mean of any variable x was calculated by Monte Carlo simulations by running the algorithm for different generated

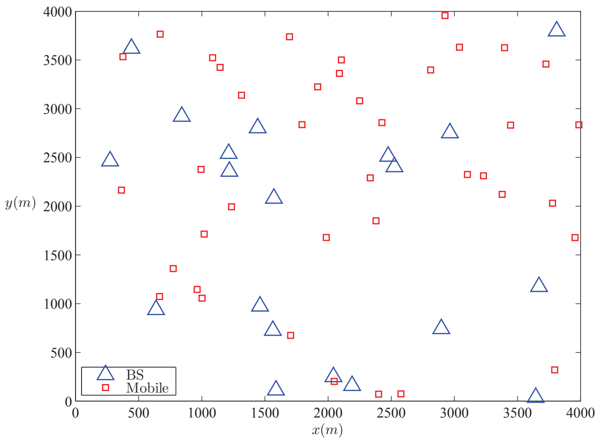

Fig. 3. Distribution of BSs and mobiles in 2D plane. $r = 20$, $m = 40$

values x for some iteration number t and taking the mean of the result, which can be given by

$$\begin{aligned} x_s(i+1) &= x_s(i) + x, \quad i = 1, \ldots, t \\ \bar{x} &= \frac{x_s}{t}. \end{aligned} \tag{13}$$

A. Scenario 1: The Rayleigh Fading and Path Loss Model

The deployment scenario in the Figure 4 and 5 is considered to be a small cell network context instead of macro or micro cells. Clearly, the general term "small cell networks" covers a range of radio network design concepts which are all based on the idea of deploying BSs much smaller than typical macro cell devices to offer public or open access to mobile terminals [13]. Therefore, we consider the deployment of BSs as random rather than a hexagon-type. The cellular network model consists of BSs arranged according to uniform distribution of r points over an area A in the Euclidean plane. Also, we consider an independent collection of mobile users, located according to uniform distribution of m points over the same area A. In MATLAB, we used the following code to produce the collection of BSs and mobiles:

```
pointsOfBSs = sqrt(A)*rand(r,2);
xOfBSs = pointsOfBSs(:,1); % x axis
yOfBSs = pointsOfBSs(:,2); % y axis
pointsOfMobiles = sqrt(area)*rand(m,2);
xOfMobiles = pointsOfMobiles(:,1); % x axis
yOfMobiles = pointsOfMobiles(:,2); % y axis
```

We also assume that within 200 meters a BS is deployed. The area over which the BSs and mobiles are distributed is supposed to increase as $A = (200r)^2\ m^2$. Furthermore, we enumerate the BSs and mobiles according to the distance between the corresponding node (BS, mobile) and the origin assumed to be $(0, 0)$ (Figure 3).

The path loss model is supposed to be in the form $P_r = P_t(1 + d)^{-\alpha}$ where P_r is the received power while the transmission power is P_t.

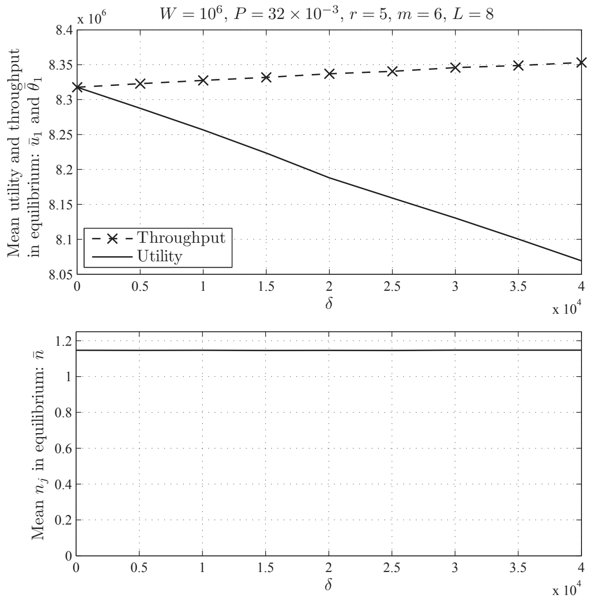

Fig. 4. Mean utility, throughput and number of mobiles sharing the same BS with respect to pricing in case of Rayleigh and path loss model.

In Figure 4 and 5, we set $W_{ji} = 1Mhz$, $P_{ji} = 32mW, \forall j \in \Sigma, \forall i \in M$, and $\rho = 10^{-12}$, $\tilde{P}_j = 12W, \forall j \in \Sigma$. All channels were assumed to be subject to slow varying Rayleigh fading which is a result of a circularly symmetric complex Gaussian random variable with zero mean and unit variance. Moreover, we adjust the simulations such that the minimum SNR cannot be lower than $-4dB$, i.e. $SNR_{min}(dB) = -4dB$. Moreover, the multiple access model is assumed to be TDMA. Consequently, the upper bound of pricing δ is given by

$$\delta \leq \frac{W \log(1 + SNR_{min})}{\tilde{P}} = \frac{10^6 \log\left(1 + 10^{-4/10}\right)}{12}, \tag{14}$$

$$\delta \leq 40289.6 \tag{15}$$

In Figure 4 and 5 the change of mean utility, throughput and number of mobiles that share the same BS of player 1[1] ($\bar{u}_1$, $\bar{\theta}_1$ and $\bar{n}$ respectively) with regards to pricing and number of mobiles, respectively are plotted. It is an inevitable result that mean utility in equilibrium decreases while the pricing goes up. But mean throughput, conversely, increases. In equilibrium, mean throughput depends on δ. Let us consider the following representation of the utility of player 1,

$$u_1(\delta, m, r) = \frac{c_1(m, r) - \delta\tilde{P}}{n(m, r)} \tag{16}$$

where n represents the mean number of mobiles that are served by the same BS with player 1 and c_1 is the capacity of player 1. Notice that the throughput of player 1 is $\theta_1(m, r) = c_1(m, r)/n(m, r)$ which depends on m and r but

[1]Without lose of generality, in all simulations, we plot the functions according to player 1. The same characteristics are valid for each player.

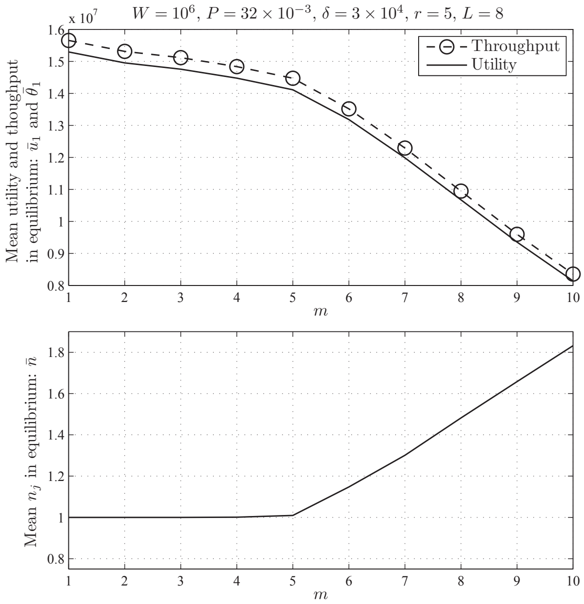

Fig. 5. Mean utility, throughput and number of mobiles sharing the same BS with respect to m in case of Rayleigh and path loss model.

not on δ. However, in equilibrium the throughput is a function of δ. Mean throughput in equilibrium of player 1 is given by

$$\bar{\theta}_1(\delta, m, r) = \bar{u}_1(\delta, m, r) + \frac{\delta \tilde{P}}{\bar{n}(m, r)} \tag{17}$$

in which mean number of mobiles that share the same BS with player 1 $\bar{n}$ does not depend on δ (we observe this result from Figure 4).

Let us now answer the question why does mean throughput increase while mean utility decreases? (recall Figure 4). In fact, consider the issue reversely. The payoff (throughput) of the player can not compensate the cost $\delta\tilde{P}/\bar{n}$ while the pricing is augmented. Thus, the profit (utility) of the player diminishes.

From Figure 5 we conclude that for a specific value of pricing $\delta = 3 \times 10^4$ while m increases $\bar{u}_1$ and $\bar{\theta}_1$ diminishes as well as $\bar{n}$ increases. Since $r = 5$, $\bar{n}$ remains constant for $m \leq 5$. This means that there are more resources than players. Consequently, the players tend to be alone in one resource resulting in one player per resource: $\bar{n} = 1$. On the other hand, since the capacity depends on m mean throughput and consequently mean utility decreases while m is increased.

B. Scenario 2: The Bi-modal Distribution of Mean SNR

We suppose that mean SNR possesses a bi-modal distribution. Hence, the SNR takes a component from $\mathcal{G} = \{SNR_1, SNR_2\} = \{-4dB, 2dB\}$ which occurs with probability 0.5. Moreover, we set $W_{ji} = W, \forall j, i$ and $\tilde{P}_j = 12, \forall j$. Let us calculate the upper bound of pricing from (4) and (8)

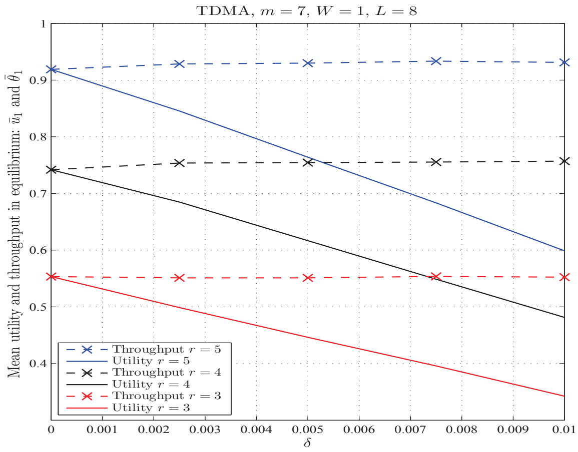

Fig. 6. The effect of pricing in case of TDMA for Scenario 2: Mean utility and throughput for different values of r.

for TDMA and HSDPA cases, respectively

$$\delta_{TDMA} \leq \frac{W \log(1 + 10^{-4/10})}{12} = 0.0403W, \tag{18}$$

$$\delta_{HSDPA} \leq \frac{W \times 10^{-4/10}\Delta(1)}{12} = 0.0118W \tag{19}$$

1) TDMA Case: Figure 6 plots the curve of $\bar{u}_1$ and $\bar{\theta}_1$ with respect to δ for different values of $r = \{3, 4, 5\}$. Furthermore, we set $m = 7$, $W = 1$ and $L = 8$. The figure demonstrates the same characteristic of mean utility and throughput in equilibrium like in Figure 4. In addition, we observe that while the number of resources increases, mean utility and throughput in equilibrium also go up.

Figure 7 depicts the change of $\bar{u}_1$ and $\bar{n}$ with respect to L for $\delta = \{0, 2 \times 10^4, 4 \times 10^4\}$ where $r = 3$, $m = 12$ and $W = 10^6$. In the figure, the region $L < 4$ implies that some players can not join to the game. For example, let $L = 2$. If each BS serves to 3 mobiles, there will be 6 mobiles receiving transmission. Within the region $L \leq 4$, we observe from the figure that $\bar{n} = L$. For $L > 4$, $\bar{n}$ remains constant which is due to the fact that the ratio $\lceil m/r \rceil$ gives mean number of mobiles served by the same BS.

2) HSDPA Case: The interpretations of Figure 8 and 9 are the same like for Figure 6 and 7, respectively.

However, if compare $\bar{u}_1$ and $\bar{\theta}_1$ of TDMA and HSDPA, we conclude that in case of HSDPA, mean utility and throughput in equilibrium is always better than that of TDMA. For example, in case of TDMA (Figure 6) for $\delta = 0.005$ and $r = 3$, player 1 has $\bar{u}_1 = 0.4463$ and $\bar{\theta}_1 = 0.5512$ while in HSDPA (Figure 8) the same player gains $\bar{u}_1 = 0.9697$ and $\bar{\theta}_1 = 0.9960$.

VII. Conclusion

In this paper, we studied the association problem of mobiles in wireless networks in the downlink transmission. We considered the problem as a crowding game in which the utility

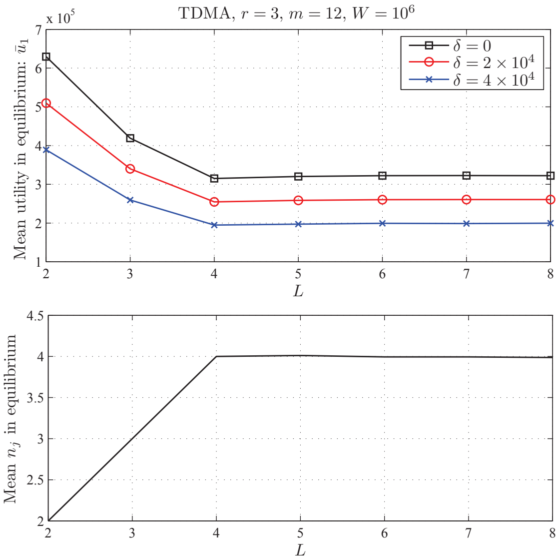

Fig. 7. Mean utility, throughput and number of mobiles sharing the same BS with respect to L in case of TDMA for Scenario 2.

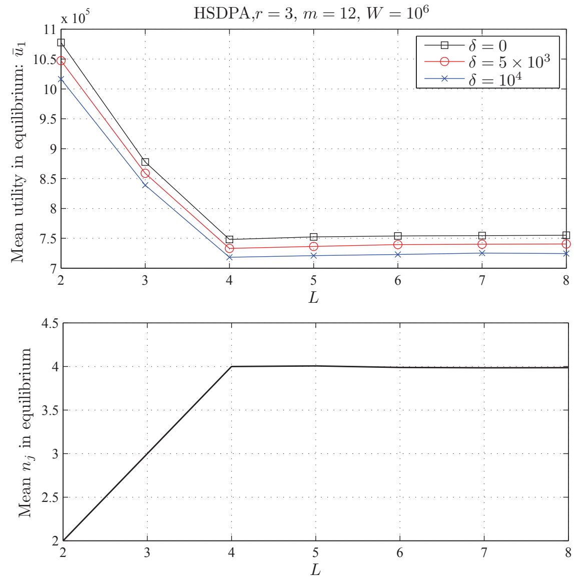

Fig. 9. Mean utility, throughput and number of mobiles sharing the same BS with respect to L in case of HSDPA for Scenario 2.

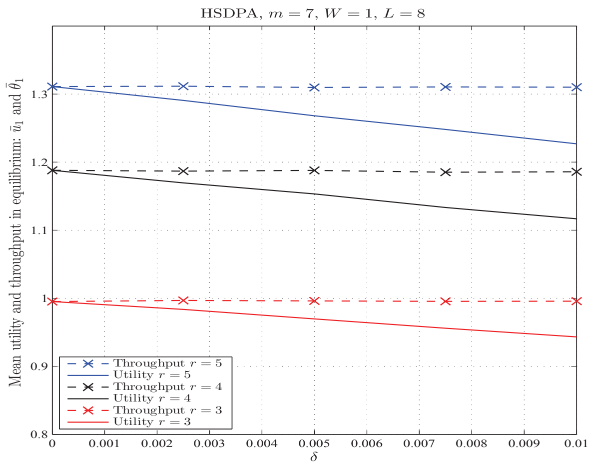

Fig. 8. The effect of pricing in case of HSDPA for Scenario 2: Mean utility and throughput for different values of r.

is specific to a player and a function of the number of the players that share the same resource. The throughput was taken as payoff and the cost has been considered to be a function of operational power cost of a BS. Using tools of crowding game we analyzed the problem for the TDMA and HSDPA cases. From the computational results, we observed for several metrics that mean utility and throughput in equilibrium that a player gains are always better compared to multiple access method is HSDPA.

VIII. Acknowledgement

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