A Game Theoretic Load-Aware Network Selection

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***Abstract*—This paper presents a load-aware network selection model to help users to determine whether or not to connect to a macro cell (MC) or a WiFi access point (AP) in a vertically integrated cellular WiFi system. The problem is formulated as a game theoretic model in which users selfishly maximize their throughput. Unlike most existing work, we do not assume that users have complete information about the other users' dynamics, which is more realistic in a communication network with distributed users where conveying such information would create enormous overhead. To do so, we provide a simple procedure that introduces a full hierarchy among the users reflecting in an accurate way their channel quality and then allowing them to sequentially choose their preferred network. Interestingly, the result for each user in the payoff is not far from his optimum.**

I. Introduction

Nowadays, with the recent proliferation of wireless devices and the ubiquity of wireless networks, users can connect to WiFi wireless networks through hot-spots or access points in most public areas. As the cellular networks usually have a broader range of coverage, the WiFi networks are smaller in its reachable range but more densely deployed. From a standardization point of view, 3GPP has been working on a number of initiatives to improve WiFi/cellular interworking, including ways to improve the selection of WiFi networks by cellular devices and options for integrating WiFi networks into the cellular core [1].

The device is in the unique position to make the best final determination of when traffic can be transported over WiFi (e.g., based on real-time radio conditions, type of pending traffic, device conditions such as mobility and battery status, etc.). Indeed, the device can make network selection decisions based on policies from the operator and knowledge of the local operating environment (LOE). The LOE is a set of information that the device can use along with other information (e.g. knowledge about network load, operator policies and user preferences) as inputs to operator intelligent network selection (INS) to select the most *suitable* access for routing the traffic, and has been left unspecified since it is based on specific implementations and the information available inside the device. This has led to user-centric network selection schemes. However, new network selection approaches must be tailored to the specific challenges dictated by the new network topology, and there are significant technical issues that still need to be addressed for successful rollout and operation of these approaches. Network conditions are a key factor in making INS decisions. In the existing solutions, there is no standardized means of capturing these conditions and distributing them to users to influence selection decisions. There is a variety of network-based information that can be leveraged to help make network selection and traffic steering decisions, and a number of conceivable ways in which to distribute that information to devices. Some examples of this information can include network-distributed selection and steering policies, real time network conditions in the cellular and WiFi networks, subscriber profiles and analytics based on historical data, etc. As an example, downlink scheduling decisions are basically made depending on the QoS class identifier (QCI) and the channel quality indicator (CQI).

In this paper, we provide a network-assisted user-centric model for maximizing per-user throughput in an integrated cellular WiFi system. Specifically, a simple procedure allowing users to connect to a network which will form an approximate Nash equilibrium in our model. Our approach is based on introducing a full hierarchy among the users reflecting in an accurate way the quality of channels they have at their disposal and then allowing them to sequentially choose their preferred network. As it will turn out, this kind of procedure results for each user in the payoff not far from his optimum, while balancing the load over cells.

The approach proposed in this paper, while profiting from these new capabilities, presents a key to understand the actual benefits brought by WiFi integration. In fact, although WiFi integration have spurred great interest and excitement in the community, many of the fundamental theoretical questions on the limits of such approach remain unanswered.

The structure of the paper is as follows: The system model related aspects are described in Sec. II. Next, in Sec. III, we present the game theoretic framework adopted for the considered association problem. Two algorithms are presented: one for dense network and one for sparse network. We derive analytically the utilities of the users and compute equilibria. We then characterize the performance of the proposed solution. In Sec. IV, we provide numerical results to illustrate the theoretical solutions derived in the previous sections. Sec. V concludes the paper.

II. System Model

Consider an integrated cellular WiFi system, where the WiFi networks are tightly integrated with the cellular network in terms of the radio frequency coordination and network management. A user can choose a network from his reachable networks, which takes its index from the two network set

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spaces $\mathcal{M} = \{1, \ldots, M\}$ and $\mathcal{W} = \{1, \ldots, W\}$ for MeNBs and WiFi APs respectively.

A. WiFi Throughput

The measurement of average throughput of a node in a wireless LAN is done by the time it takes to transfer the files between the WiFi AP and the wireless clients. Typically, one would transfer a file from a wired server to a wireless client by means of an AP bridging wired and wireless networks. The throughput depends on the bit rate at which the wireless mobile communicates to its AP. On the other hand, as already mentioned, if there is at least one host with a lower rate, a WLAN network presents a performance anomaly in the sense that the throughput of all the hosts transmitting at higher rate is degraded below the level of the lower rate [2]–[4]. We can accordingly consider that the throughput of a WiFi connection is equal to a constant, say v_k, which only depends on the load of AP k regardless of differences in users' channel data rate, namely

$$v_k = \frac{D_k}{\sum_{i=1}^{n_k}(1 - a_{ik})b_i}; \qquad \text{for } k \in \mathcal{W} \tag{1}$$

where D_k is the peak data rate of AP k, n_k is the number of users with access to AP k, b_i is the demand of user i (with $b_i = 1$ when there exists a demand, and 0 otherwise) , a_{ik} is user i's action defined by the user decision to connect to RAN k (with $a_{ik} = 1$ when the user chooses MC k, and 0 when the user chooses WiFi AP k).

B. Macro Cell Throughput

As opposed to WiFi, the macro cell throughput can vary greatly depending on the link conditions due to interference and noise impairments. We then model the utility experienced by a user that is connected to macro cell by the capacity of Shannon [5]. Assuming that there is no interference between the macro cell and the WiFi network (as they operate on different frequency bands), the throughput of a user i connected to the macro cell k is given by

$$r_{ik} = \log_2\left(1 + \frac{p\, h_{ik}\, a_{ik}\, b_i}{\sigma^2 + p\sum_{\substack{j\neq i\\ k'\neq k}} h_{jk'}\, a_{jk'}\, b_j}\right); \text{ for } k \in \mathcal{M} \tag{2}$$

where h_{ik} is the downlink channel from MeNB k to user i, p is the transmit power and σ^2 is the noise variance.

III. The Approximately Optimal Network Selection

In this section, we suppose that each user i measures all the CQI values h_{ik} and sends some information about them to an MC. Then, based on them and other known primitives of the model, each MC computes an approximate equilibrium and connects the users to one of the WiFis or one of MCs. We will show that an approximate equilibrium in this model can be computed using a simple algorithm, which can be implemented in a **partially** distributed way. Further, we show that implementing this algorithm in practice will be difficult, as it will be profitable to lie about the measured values of CQIs.

A. The Game Theoretic Formulation

The basic solution concept for multi-agent multi-objective systems like the one considered here is given by non-cooperative game theory under the name of Nash equilibrium (NE) [6]. It is a vector of strategies (referred to hereafter and interchangeably as actions) $\mathbf{p}^{NE} = p_1^{NE}, \ldots, p_N^{NE}$, one for each player, such that no player has incentive to unilaterally change his strategy, i.e., $u_n(p_n^{NE}, \mathbf{p}_{-n}^{NE}) \geq u_n(p_n, \mathbf{p}_{-n}^{NE})$ for every action $p_n \neq p_n^{NE}$, where the $-n$ subscript on vector $\mathbf{p}$ stands for "except user n", i.e., $\mathbf{p_{-n}} = \{p_1, \ldots, p_{n-1}, p_{n+1}, \ldots, p_N\}$. If there exists an $\epsilon > 0$ such that $(1+\epsilon)u_n(p_n^{\epsilon NE}, \mathbf{p}_{-n}^{\epsilon NE}) \geq u_n(p_n, \mathbf{p}_{-n}^{\epsilon NE})$ for every action $p_n \neq p_n^{\epsilon NE}$, we say that the vector $\mathbf{p}^{\epsilon NE} = p_1^{\epsilon NE}, \ldots, p_N^{\epsilon NE}$ is an ϵ-Nash equilibrium. ϵ-Nash equilibrium can be regarded as a solution which bounds the possible profit from a unilateral deviation from it by some small constant, which makes it unlikely e.g., in the case when computing a profitable change of strategy is difficult algorithmically.

In our model, the strategy for user i is the number of network he chooses or, to make the notation easier to read, a pair $P_i = (\mathcal{N}, k)$, where $\mathcal{N} \in \{\mathcal{M}, \mathcal{W}\}$ denotes the type of network he chooses to connect to, while $k \in \mathcal{M}_i$ if $\mathcal{N} = \mathcal{M}$ is the number of MeNB he chooses, and $k \in \mathcal{W}_i$ is the number of WiFi AP he chooses, with $\mathcal{M}_i \subset \mathcal{M}$ and $\mathcal{W}_i \subset \mathcal{W}$ denoting the sets of MeNBs and WiFi APs available to user i. Then, the utility of user i is defined as

$$u_i(P) = \begin{cases} r_{ik} & \text{if } P_i = (\mathcal{M}, k) \\ v_k & \text{if } P_i = (\mathcal{W}, k) \end{cases}$$

B. The Network Selection Algorithm

Our goal will be to provide a simple procedure allowing users to connect to a network which will form an approximate Nash equilibrium in our model. Our approach will base on introducing a full hierarchy among the users reflecting in an accurate way the quality of channels they have at their disposal and then allowing them to sequentially choose their preferred network. As it will turn out, this kind of procedure will result for each user in the payoff not far from his optimum.

Below, we present our main algorithm. The computations made there are distributed among all MeNBs and all users. A small value $\delta > 0$ and an optional parameters H, γ_M and γ_W (if we do not want to use them, we can always set Hm γ_M and γ_W to 1)[1] are the parameters of the algorithm.

Algorithm 1. Phase A:
Each user i, $i = 1, \ldots, N$, sends $K_i := |\mathcal{M}_i + \mathcal{W}_i|$ and $H_i = \max_{k\in\mathcal{M}_i} h_{ik}$ to (exactly) one of MeNBs from $\mathcal{M}_i$.
Each MeNB k simultaneously *does the following steps:*

A.1) It sorts triplets (K_i, H_i, i) of all users who sent their information to this MeNB using first coordinate in an increasing order obtaining vectors $(K^k(1), \ldots, K^k(N_k))$, $(H^k(1), \ldots, H^k(N_k))$ and π^k.

A.2) It sets $l_0^k = 0$, $\nu = 1$ and does $l_\nu^k = K^k(l_{\nu-1}^k + 1) + l_{\nu-1}^k$, $\nu = \nu + 1$ while $N_k > K^k(l_{\nu-1}^k + 1) + l_{\nu-1}^k$.

[1]The meaning and optimal selection of these parameters will be further discussed after Proposition 1.

Then, it sets $m_k = \nu$ *and* $l^k_{m_k} = N_k$*, and creates lists* $\mathcal{L}^k_1 = (\pi^k(l^k_0+1), \dots, \pi^k(l^k_1)), \dots, \mathcal{L}^k_{m_k} = (\pi^k(l^k_{m_k-1}+1), \dots, \pi^k(l^k_{m_k}))$.

Phase B: *(done* simultaneously *by each MeNB)*

B.1) Each MeNB k *sets* $\underline{\alpha}^k_1 = 0, \dots, \underline{\alpha}^k_{m_k} = 0$, $\overline{\alpha}^k_1 = 1, \dots, \overline{\alpha}^k_{m_k} = 1$, $\alpha^{*k}_1 = 0, \dots, \alpha^{*k}_{m_k} = 0$ *and* $\pi^*_k = \pi^k$.

B.2) It computes $\overline{H}^k_1 = \mu \sum_{s \neq 1} \max\{H^k(l^k_{s-1}+1), \dots, H^k(l^k_s)\}, \dots, \overline{H}^k_{m_k} = \mu \sum_{s \neq m_k} \max\{H^k(l^k_{s-1}+1), \dots, H^k(l^k_s)\}$ *and* $\overline{m}_k = \gamma_W M m_k$*, and sends* $(\overline{H}^k_s, \overline{m}_k)$ *to each user on list* $\mathcal{L}^k_s$ *for* $s = 1, \dots, m_k$*, where*

$$\mu = \begin{cases} \frac{M m_k \gamma_M - 1}{m_k - 1} & \text{if } m_k \neq 1 \\ M\gamma_M - 1 & \text{otherwise.} \end{cases}$$

B.3) Each user $j \in \mathcal{L}^k_s$ *computes* $\overline{\Psi}_j = \max\left\{ \max_{l \in \mathcal{M}_j} \log_2\left(1 + \frac{p h_{jl}}{\sigma^2 + p\overline{H}^k_s}\right), \max_{l \in \mathcal{W}_j} \frac{D_l}{\overline{m}_k} \right\}$ *and* ρ_{jl}, $l = 1, \dots, M + W$*, as follows:* $\rho_{jl} = \frac{\log_2\left(1 + \frac{p\overline{h}_{jl}}{\sigma^2 + p\overline{H}^k_s}\right)}{\overline{\Psi}_j}$ *if* $l \leq M$ *and* $\rho_{jl} = \frac{D_{l-M}}{\overline{m}_k \overline{\Psi}_j}$ *if* $l > M$ *and* $l - M \in \mathcal{W}_j$ *with* $\rho_{jl} = 0$ *otherwise.*

B.4) Then, for each $s \in \{1, \dots, m_k\}$ *the following steps are repeated until the loop is interrupted in point B.4.1):*

B.4.1) MeNB k *computes* $\overline{\alpha}^k_s - \underline{\alpha}^k_s$*. If* $\overline{\alpha}^k_s - \underline{\alpha}^k_s < \delta$ *or* $\underline{\alpha}^k_s > H$*, then it stops the loop, putting* $\alpha^{*k}_s = \underline{\alpha}^k_s$*. Otherwise it takes* $\alpha^{*k}_s = \frac{\overline{\alpha}^k_s + \underline{\alpha}^k_s}{2}$ *and announces* α^{*k}_s *to the users on list* $\mathcal{L}^k_s$.

B.4.2) Each user $j \in \mathcal{L}^k_s$ *computes* $K_j = |\{l : \rho_{jl} \geq \alpha^{*k}_s\}|$ *and sends it back to MeNB* k.

B.4.3) MeNB k *sorts pairs* (K_j, j) *where* $j \in \mathcal{L}^k_s$ *using its first coordinate in an increasing order obtaining vectors* $\overline{K}$ *and* $\overline{\pi}$*. If* $\overline{K}(l) < l$ *for some* $l \leq l^k_s - l^k_{s-1}$ *it puts* $\overline{\alpha} = \alpha^{*k}_s$ *and returns to point B.4.1).*

B.4.4) MeNB k *puts* $\pi^*_k(l^k_{s-1}+1, \dots, l^k_s) = \overline{\pi}$, $\underline{\alpha} = \alpha^{*k}_s$ *and returns to point B.4.1).*

Phase C: *(done* simultaneously *by users from the lists of each MeNB)*

For $i = 1, \dots, N_k$ *repeat:*

C.1) User $\pi^*_k(i)$ *connects to the network* l *(MeNB* l *or WiFi AP* $l - M$*) with the highest* $\rho_{\pi^*_k(i)l}$ *which is not already chosen by one of the users* $\pi^*_k(l^k_s+1), \dots, \pi^*_k(i-1)$*, where* s *is such that* $l^k_s < i \leq l^k_{s+1}$.

In case of a sparse network ($M >> N$) Algorithm 1 can be reduced to (Phase A is not necessary and Phases B and C can be significantly simplified as a consequence):

Algorithm 2. *Each user* i *computes* $\Psi_i = \max\left\{ \max_{k \leq M} \log_2\left(1 + \frac{p h_{ik}}{\sigma^2}\right), \max_{l \in \mathcal{W}_i} D_l \right\}$ *and* $\rho_{ik} = \frac{\log_2\left(1 + \frac{p h_{ik}}{\sigma^2}\right)}{\Psi_j}$ *if* $k \leq M$ *and* $\rho_{ik} = \frac{D_{k-M}}{\Psi_i}$ *if* $k > M$ *and* $k - M \in \mathcal{W}_i$ *with* $\rho_{ik} = 0$ *otherwise.*

A designated MeNB starts with $\underline{\alpha} = 0$, $\overline{\alpha} = 1$, $\alpha^* = 0$ *and* $\pi^* = [1 \dots N]$.

The following steps are repeated until the loop is interrupted in point 1):

1) *The MeNB computes* $\overline{\alpha} - \underline{\alpha}$*. If* $\overline{\alpha} - \underline{\alpha} < \delta$ *or* $\underline{\alpha} > H$*, then it stops, putting* $\alpha^* = \underline{\alpha}$*. Otherwise it takes* $\alpha^* = \frac{\overline{\alpha} + \underline{\alpha}}{2}$ *and* $\pi = \mathbf{0}_{1 \times M+W}$ *and announces* α^* *to the users.*
2) *Each user computes* $K_i = |\{k : \rho_{ik} > \alpha^*\}|$ *and sends it back to the MeNB*[2].
3) *The MeNB sorts pairs* (K_i, i) *using its first coordinate in an increasing order obtaining vectors* $(K(1), K(2), \dots, K(N))$ *and* π*. If* $K(l) < l$ *for some* $l \leq M + W$ *it puts* $\overline{\alpha} = \alpha^*$ *and returns to point 1).*
4) *The MeNB puts* $\pi^* = \pi$, $\underline{\alpha} = \alpha^*$ *and returns to point 1).*

For $i = 1, \dots, N$:

1) *User* $\pi^*(i)$ *chooses the network with the highest utility that is not already chosen by some other player.*

To understand the sense of Algorithms 1 and 2 first note that the fraction ρ_{ik} appearing in both algorithms can be interpreted as a measure of disutility of player i from choosing MeNB k or WiFi $k - M$ instead of his best network. In case of the simplified algorithm we assume that no two different players can be connected to the same network, so the utilities are always of the form $\log_2\left(1 + \frac{p h_{ik}}{\sigma^2}\right)$ or D_l. Maximizing the value of ρ_{ik} is thus equivalent to choosing the network with highest utility. Given the interpretation of ρ_{ik} given above, the α^* appearing in the algorithm can be interpreted as the maximal disutility for any player from not choosing his network first, that is the worst-case[3] ratio of utility of any of the players who do not choose their networks first to their utility if they were the first ones to choose. The sense of Algorithm 2 is thus finding the ordering of the players which minimizes this disutility. It is done by putting on i-th coordinate of ordering π^* a player (his index), who has at least i good networks to choose from (by which we mean i networks with utility better than α^* times his best possible utility if he was a leader). α^* found by Algorithm 2 is the minimal value (computed with a δ toleration) for which such an ordering is possible.

In case of Algorithm 1, the situation is more complex, as the number of available networks can (and usually will be) much smaller than the number of users. In that case, avoiding any interference is no longer possible and so instead of trying to create a situation where there will be no interference between users we try to minimize it. Doing it consists of two steps done in Phases A and B of the algorithm. First, in Phase A, we divide the set of users into the smallest number of layers, each of which contains only users with a number of networks available which is not smaller than the number of users in that layer. This means that for such a layer we can use the same idea as that used in Algorithm 2 to find the ordering of the players in which they will choose their networks, which minimizes the disutility from not being the first in the layer to choose. This is done in Phase B of the algorithm. In this case however the values of ρ_{ik} used to find this ordering cannot be exactly computed, as exact information about the

[2]If the user has no access to the designated MeNB, he sends the data to some other MeNB, which then transfers it to the MeNB doing computations through X2 interface.

[3]Worst-case here means that such a big disutility will only be possible if different users' private ordering (from best to worst) of the networks is similiar.

possible other users interfering with any given player cannot be recovered (as the connections of different players are done simultaneously). Thus we use some available estimates which can well describe the interference we'll be dealing with. One more important feature of Algorithm 1 we need to note is that this interference will be limited to at most one user per layer. Thus, as in Phase A the number of layers was minimized, the interference will also be significantly bounded. More exact bounds on the disutility perceived by the users when Algorithms 1 and 2 are used to allocate them to networks, as well as some other useful properties of these algorithms, are enumerated in the following proposition and its immediate corollary.

Proposition 1. *Let Ψ_i be the highest utility that user i could obtain if all the users were trying to maximize his utility and define the following constants:*

$$\alpha^* = \min_{k\le M, s\le m_k} \alpha_s^{*k}, \quad \overline{H} = \sum_{k=1}^{M}\sum_{s=1}^{m_k} \max_{i\in\mathcal{L}_s^k} H_i,$$
$$\overline{\lambda} = \min_{l\le M, s\le m_l} \frac{\overline{m}_l\left(\sigma^2+p\overline{H}\right)}{\sum_{k=1}^M m_k\left(\sigma^2+p\overline{H}_s^l\right)},$$
$$\underline{\lambda} = \min_{l\le M, s\le m_l} \frac{\sum_{k=1}^M m_k\left(\sigma^2+p\overline{H}_s^l\right)}{\overline{m}_l\left(\sigma^2+p\overline{H}\right)},$$
$$\lambda = \min\{\overline{\lambda},\underline{\lambda}\}, \quad \theta = \min\left\{\frac{1}{1+\frac{p}{\sigma^2}\overline{H}}, \frac{1}{\sum_{k=1}^M m_k}\right\}.$$

Suppose[4] *that $\overline{H}_s^k \le \overline{H}$ for every $k\le M$ and $s\le m_k$. Then, the choice of network selections done by Algorithm 1 satisfies the following:*

1) *It gives each player i the utility not smaller than $\alpha^*\lambda\theta\Psi_i$.*
2) *It is a $\frac{1-\alpha^*\lambda\theta}{\alpha^*\lambda\theta}$-equilibrium in the game.*
3) *The sum of utilities of all the players in our game when they use network selections defined by it is not smaller than $\alpha^*\lambda\theta$ times the sum of utilities of all the players at the social optimum.*

The proof of this proposition is given in the appendix.

We need to know that Proposition 1 does not give exact information about the quality of the algorithm proposed, just upper bounds which may be far from exact. In particular the bounds on the quality of equilibrium and distance from the socially optimal selection could be further improved if we introduced additional notation. The main reason to state the proposition in this form is to show that some quantities which are maximized in Algorithm 1 are proportional to lower bounds on the quality of the solution. First, note that α^* appearing in these bounds was maximized in Phase B of the algorithm. Next, see that the value of θ increases as the number of user layers $\sum_{k=1}^M m_k$ decreases (both expressions appearing there do). Phase A of the algorithm is designed exactly to minimize this number. Finally, the magnitude of λ is not directly related to the choices made by the algorithm – it mainly depends on the choices of the parameters γ_M and γ_W. If they are both equal to 1, $\overline{m}_k = Mm_k$ is a natural estimate of the value of $\sum_{l=1}^M m_l$ based on the information available to MeNB k. Similarly, $\overline{H}_s^k$ can be viewed as an estimate of $\overline{H}$ based on the information available to users in layer $\mathcal{L}_s^k$. If both these estimates are of good quality, λ should be close to 1 in that case. In practice however both γ_M and γ_W will be taken significantly smaller than 1, whence λ can be smaller. The reason why we will take them this way is the intuitive meaning of these parameters. Note that when γ_M and γ_W appear in Algorithm 1, $\overline{m}_k$ is meant to estimate the number of users connected to an average WiFi AP rather than the number of all the layers. The factor γ_W by which we multiply the total number of layers will thus describe the probability that in an average layer there will be a player who can connect to this WiFi. As a consequence, it makes sense to take γ_W proportional to the size of the area covered by an average WiFi divided by the area covered by all the macro cells. Similarly, γ_M should be be seen as the probability that in an average layer there is a player who can connect to one particular MeNB. Hence, taken proportional to the average size of the area covered by a single MeNB divided by the size of the entire area covered by all macro cells. Paradoxically, this will result in worse bounds on the quality of the assignment obtained with the help of Algorithm 1, but at the same time it should make the assignments made in Phase C of the algorithm more accurate, so in practice it should improve the performance of the algorithm. As it suggests, the bounds obtained in Proposition 1 will in many cases be pretty rough, so further analysis of the quality of the solutions obtained and their dependance on the parameters of the algorithm will be done numerically.

[4]For γ_M significantly smaller than 1, which will be our natural choice of this parameter, it should be naturally satisfied.

To finish this section, we present two results describing the properties of Algorithm 2. The first one follows directly from Proposition 1.

Corollary 1. *Suppose N, $\mathcal{M}_i$ and $\mathcal{W}_i$, $i=1,\ldots,N$ are such that there exists an assignment of networks to players which assigns each player to a different network. Then, the choice of network selections done by Algorithm 2 satisfies the following:*

1) *It gives each player i the utility not smaller than $\alpha^*\Psi_i$.*
2) *It is a $\frac{1-\alpha^*}{\alpha^*}$-equilibrium in the game.*
3) *The sum of utilities of all the players in our game when they use network selections defined by it is not smaller than α^* times the sum of utilities of all the players at the social optimum.*

The second result describes another useful property of the selections made by Algorithm 2.

Proposition 2. *Suppose the assumptions of Corollary 1 are satisfied. If in addition $\alpha^*\ge\frac{1}{2}$ and*

$$\alpha^* \ge \frac{1}{\Psi_i}\log_2\left(1+\frac{\sigma^2(e^{\Psi_i}-1)}{\sigma^2+ph_{jk}}\right) \text{ for each } i,j,\ i\ne j \text{ and } k\le M \quad (3)$$

then, the network selections done by Algorithm 2 form an equilibrium in the game.

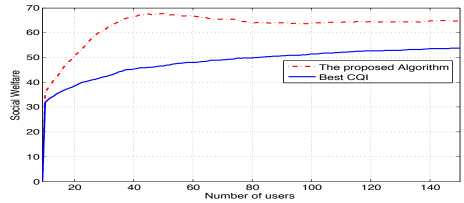

Fig. 1. The social welfare.

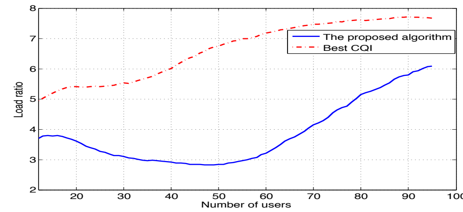

Fig. 2. The load ratio.

The proof is given in the appendix. The meaning of this proposition is that for some value of α^* increasing its value in the first part of Algorithm 2, even if it is still possible, may have no sense as it will not result in any further improvement of the network assignment (which is already a NE assignment). This is why we have introduced the optional parameter H into the algorithm. Similar statement should be true with regard to the Phase B of Algorithm 1, although writing any inequalities that could serve as counterparts of Equation (3) is problematic.

IV. Performance Evaluations

The proposed algorithm is implemented in an LTE compliant system level simulator [7]. As for MC deployment, general hexagonal structure with three sector MC is assumed, where WiFi APs are overlaid on the MCs randomly and operated in the same frequency band than MeNBs. Users are scattered into the 19 omni-directional MCs in the same way as WiFi APs. $\gamma_W = \gamma_M = 0.5$, $p = 10$. For the sake of comparison, we will consider the best CQI scheme (in which users connect to the wireless network with the highest CQI) as a benchmark scenario.

Social welfare: As we can see from Fig. 1, for all algorithms social welfare grows fast for small number of users, and then slows down, stabilizing finally at some level. This is natural, as for a small number of users interference is not a serious issue, so each additional user can use almost all the available capacity for his transmission. When number of cells outnumbers the number of available networks, interference starts to affect the overall utility. In the case of our algorithm, load balancing between networks implies that all the networks become equally saturated more or less at the same time (around 50 users), which stabilizes the social welfare at some threshold level. In the case of best CQI choice, networks become saturated successively, so the utility increases even for more than 100 users, yet the overall utility never reaches the level obtained by the proposed algorithm. This is also natural, as the main idea of design of Algorithms 1 and 2 is to minimize the interference between users, which is not done for best CQI choice.

Load balancing: In order to get good intuition on the load balancing characteristics, we plot in Fig. 2 the load ratio defined as the ratio between the most loaded cell and the average cell load. We can see that in the proposed algorithm the macro cell load is in general smaller than that for best CQI choice. To understand it, note that in our algorithm to avoid interference we force users to use almost all the networks available (it is only through proper ordering of users that we achieve relatively small utility loss caused by using an MC with lower CQI which a user is forced to). In particular, a significant number of users is forced to use WiFi APs rather than MeNBs. What we also notice is that with an increasing number of users there is a general tendency to use WiFi more often as macro cells become more saturated, which can be seen in the decrease of the macro cell load for up to 50 users. When WiFi networks become congested as well, the macro cell load starts to increase again approximately proportionally to the total number of users.

V. Conclusions

We have proposed in this paper a load-aware network selection method in an integrated cellular WiFi system, which is a practical network resource allocation problem related to the new IEEE and 3GPP standards. Both analytical and simulation results have shown that the proposed scheme based on the network selection game achieves a good load balancing while improving system throughput with respect to traditional network selection schemes. Then, since we deal with user-centric network selection decision, we have shown how a user misrepresenting his signal to the MeNB can maximize his throughput.

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Appendix

A. Proof of Proposition 1

Proof: First, see that Algorithm 2 is always terminated at some step, as loops in parts A.2) and C.1) are repeated at most N times, while after each passage through points B.4.1)–B.4.3) of the loop in part B.4), $\overline{\alpha}_s^k - \underline{\alpha}_s^k$ decreases twice, thus at most after $\log_2(\delta^{-1})$ passages, $\overline{\alpha}_s^k - \underline{\alpha}_s^k < \delta$, which stops the loop.

For the remainder of the proof of part 1) of the proposition fix $k \in \{1,\dots,M\}$. Further, note that even if the loop in part B.4) of the Algorithm 2 constantly decreases α_s^{*k}, the final value $\alpha_s^{*k} = 0$ and the final ordering π_k^* satisfy

$$\rho_{\pi_k^*(j)k_{\pi_k^*(j)}} \geq \alpha_s^{*k} \geq \alpha^* \quad \text{for } j = l_{s-1}^k,\dots,l_s^k,\ s = 1,\dots,m_k, \tag{4}$$

where k_i denotes the network choice made by player j in part C.1) of Algorithm 1. The same inequalities are clearly satisfied if the algorithm is finished for some bigger value of α^*, as this is the condition which is checked any time the value of α_s^{*k} is increased.

Next note that when each of the players uses different network, player i choosing MeNB k_i may at most obtain utility $\log_2\left(1 + \frac{ph_{ik_i}}{\sigma^2}\right)$, while the biggest utility he can obtain from using WiFi l_i is D_{l_i}, which are both acheived when he is the only user connected to MeNB k_i or WiFi l_i. Thus the highest utility obtainable in the game for player i (if all others cooperate to maximize his utility) is Ψ_i.

In the rest of the proof of part 1) of the proposition let us pick some player $i = \pi_k^*(j)$, where $j \in \{l_{s-1}^k,\dots,l_s^k\}$ and the layer number s is chosen arbitrarly from $\{1,\dots,m_k\}$. to finalize the proof we will need to consider four cases depending on the type of network user i chooses and the type of network where utility Ψ_i is obtained. First suppose that the utility Ψ_i is obtained for a MeNB we will call B_i and his choice is a MeNB k_i. In this case his utility is at least

$$\log_2\left(1 + \frac{ph_{ik_i}}{\sigma^2 + p\overline{H}}\right),$$

as he may obtain interference from at most one user from each layer. From the concavity of the logarithm function and the assumption that $\overline{H}_s^k \leq \overline{H}$ this is not smaller than

$$\begin{aligned}\frac{\sigma^2 + p\overline{H}_s^k}{\sigma^2 + p\overline{H}}\log_2(1+\frac{ph_{ik_i}}{\sigma^2 + p\overline{H}_s^k}) &\geq \frac{\sigma^2 + p\overline{H}_s^k}{\sigma^2 + p\overline{H}}\alpha^*\log_2(1+\frac{ph_{iB_i}}{\sigma^2 + p\overline{H}_s^k})\\ &> \frac{\alpha^*\sigma^2}{\sigma^2 + p\overline{H}}\log_2(1+\frac{ph_{iB_i}}{\sigma^2}) = \frac{\alpha^*\Psi_i}{1 + \frac{p}{\sigma^2}\overline{H}} \geq \alpha^*\lambda\theta\Psi_i,\end{aligned}$$

where the first inequality follows from (4), the second from the concavity of the logarithm, and the last one from the definition of θ and the fact that $\lambda \leq 1$.

Now suppose that the value Ψ_i is obtained for WiFi AP $l_i^{\max}$. Then, as before, his utility in not smaller than

$$\begin{aligned}\frac{\sigma^2 + p\overline{H}_s^k}{\sigma^2 + p\overline{H}}\log_2\left(1 + \frac{ph_{ik_i}}{\sigma^2 + p\overline{H}_s^k}\right) &\geq \frac{\sigma^2 + p\overline{H}_s^k}{\sigma^2 + p\overline{H}}\alpha^*\frac{D_{l_i^{\max}}}{\overline{m}_k}\\ = \frac{\sum_{l=1}^M m_l(\sigma^2 + p\overline{H}_s^k)}{\overline{m}_k(\sigma^2 + p\overline{H})}\frac{\alpha^*\Psi_i}{\sum_{l=1}^M m_l} &\geq \frac{\underline{\lambda}\alpha^*}{\sum_{l=1}^M m_l}\Psi_i \geq \alpha^*\lambda\theta\Psi_i,\end{aligned}$$

where the first inequality follows from (4), while the second and the last one from the definitions of $\underline{\lambda}$, λ and θ.

Next assume that user i chooses a WiFi AP l_i. Then, his utility is not smaller than $\frac{D_{l_i}}{\sum_{l=1}^M m_l}$. In case Ψ_i is obtained for MeNB B_i this last value can be written as

$$\begin{aligned}\frac{\overline{m}_k}{\sum_{l=1}^M m_l}\frac{D_{l_i}}{\overline{m}_k} &\geq \frac{\overline{m}_k}{\sum_{l=1}^M m_l}\alpha^*\log_2\left(1 + \frac{ph_{iB_i}}{\sigma^2 + p\overline{H}_s^k}\right)\\ &> \frac{\overline{m}_k}{\sum_{l=1}^M m_l\left(1 + \frac{p}{\sigma^2}\overline{H}_s^k\right)}\alpha^*\log_2\left(1 + \frac{ph_{iB_i}}{\sigma^2}\right)\\ &= \frac{\overline{m}_k\left(1 + \frac{p}{\sigma^2}\overline{H}\right)}{\sum_{l=1}^M m_l\left(1 + \frac{p}{\sigma^2}\overline{H}_s^k\right)}\frac{\alpha^*}{1 + \frac{p}{\sigma^2}\overline{H}}\Psi_i \geq \overline{\lambda}\alpha^*\theta\Psi_i \geq \alpha^*\lambda\theta\Psi_i\end{aligned}$$

with the first inequality following from (4), the second from the concavity of the logarithm, while the last two from the definitions of $\overline{\lambda}$, λ and θ.

Finally, if user i chooses a WiFi AP l_i instead of another WiFi AP l_i^Ψ, by (4) his utility can be bounded below by

$$\frac{\alpha^* D_{l_i^{\max}}}{\sum_{l=1}^M m_l} = \frac{\alpha^*\Psi_i}{\sum_{l=1}^M m_l} \geq \alpha^*\theta\lambda\Psi_i,$$

where the last inequality is a consequence of the definition of θ and the fact that $\lambda \leq 1$. Thus, we have proved part 1) of the proposition. Parts 2) and 3) are immediate consequences of part 1) and the definitions of ϵ-Nash equilibrium and social optimum respectively. ■

B. Proof of Proposition 2

Proof: Assume that α^* satisfies $\alpha^* > \frac{1}{2}$ and (3). We will show that network selections chosen by Algorithm 2 form an equilibrium in the game. Suppose they do not, that is – there exists a player i who can gain by deviating form it. First note that he will not deviate to any of the networks that are not used by anyone, as the algorithm assures that player i always chooses his best available network at the time decision is made. Obviously the set of unoccupied networks may only shrink afterwards, so any network that is not used upon the termination of the algorithm can only decrease the utility for player i. Thus suppose that player i changes his network from MeNB k_i which he would choose in Algorithm 2 to some other MeNB k^*, used by some other player j. Then, his utility will change to

$$\begin{aligned}\log_2\left(1 + \frac{ph_{ik^*}}{\sigma^2 + ph_{jk^*}}\right) &\leq \log_2\left(1 + \frac{\sigma^2(e^{\Psi_i}-1)}{\sigma^2 + ph_{jk^*}}\right)\\ &\leq \alpha^*\Psi_i \leq \log_2\left(1 + \frac{ph_{ik_i}}{\sigma^2}\right),\end{aligned}$$

where the first inequality follows from the fact that by definition $\log_2\left(1 + \frac{ph_{ik^*}}{\sigma^2}\right) \leq \Psi_i$ which is equivalent to

$$ph_{ik^*} \leq \sigma^2(e^{\Psi_i} - 1), \tag{5}$$

the second one from (3) and the third one from part 1) of Corollary 1. This means he will not gain by changing his network. Similarly, when user i changes his network to a WiFi AP l^* used by some other player, his utility changes to

$$\frac{D_{l^*}}{2} < \alpha^* D_{l^*} \leq \alpha^*\Psi_i \leq \log_2\left(1 + \frac{ph_{ik_i}}{\sigma^2}\right),$$

where the first inequality follows from $\alpha^* \geq \frac{1}{2}$, the second from the definition of Ψ_i, while the last one from part 1) of Corollary 1. Thus such deviation is not profitable either. Next suppose that the network chosen by user i according to Algorithm 2 is WiFi AP l_i and that he tries to improve his utility by choosing MeNB k^* used by player j. His utility will then change to

$$\begin{aligned}\log_2\left(1 + \frac{ph_{ik^*}}{\sigma^2 + ph_{jk^*}}\right) &\leq \log_2\left(1 + \frac{\sigma^2(e^{\Psi_i}-1)}{\sigma^2 + ph_{jk^*}}\right)\\ &\leq \alpha^*\Psi_i \leq D_{l_i},\end{aligned}$$

where again the first inequality follows from (5), the second from (3) and the last from part 1) of Corollary 1. Finally, changing WiFi AP l_i to some other WiFi AP l^* used by some other player does not increase the utility of user i because

$$\frac{D_{l^*}}{2} \leq \frac{\Psi_i}{2} \leq \alpha^*\Psi_i \leq D_{l_i}.$$

■