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To lie or not to lie in non-cooperative user-centric networks: Is lying worth it?

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Abstract—This paper¹ presents a load-aware network selection model intended to help users to determine whether or not to connect to a macro cell (MC) or a WiFi access point (AP) in non-cooperative user-centric networks. The problem is formulated as a game theoretic model in which users selfishly maximize their throughput. Unlike in most existing work, we do not assume that users have complete information about the other users' dynamics, which makes it more realistic in a communication network with distributed users. Then, because the network selection decision depends crucially on truthful reporting of channel states by the users, we explore the idea of non-cooperative users sending signals that are likely to induce the scheduler to behave in a manner beneficial to them. We provide five procedures which consist of introducing hierarchy among the users reflecting their channel quality and dividing them into groups interfering with each other, but not within themselves. Having done this, we allow them to sequentially choose their preferred network. We also propose a solution to compel users to reveal the truthful signals to the macro eNodeB (MeNB) by designing an additional immunity parameter mainly meant to keep lying users from harming truthful users. Particularly noteworthy is the fact that the additional immunity parameter does not only decrease the gain of liars, but it further improves the overall system performance. We provide extensive system level simulation results comparing our procedures between themselves and with traditional schemes. It is shown that the proposed solutions outperform classical approaches in almost every respect.

Index Terms—Ultra dense network, macro cell, WiFi, integrated cellular WiFi network, network selection, traffic steering, load balancing, channel state information, game theory, network-centric, user-centric, truthful reporting, fairness.

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 their 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 [2]. 3GPP has also defined several wireless local area network (WLAN) offloading mechanisms which rely on the connection between the LTE core network and WLAN.

Following the same trend, the cellular industry has converged on a single mobile broadband standard which has facilitated WiFi/cellular integration work. Simultaneously, the emergence of Hotspot 2.0 and Next Generation Hotspot (NGH) provides a number of standardized features for improving user experience on WiFi networks and should further simplify integration with mobile networks [3]. As a result, many mobile operators who are thinking strategically about investing in 5G are also considering how WiFi can complement and enhance their existing infrastructure deployments. Among the interesting challenges, resulting from the coexistence of WLAN and LTE, network selection has greatly attracted attention in the academia and industry community. The network selection can be network-centric, such as in [4]–[6], where a central controller chooses networks for the users to achieve the global optimum, or user-centric, such as in [7], [8], where users choose the network by themselves. The former approaches can achieve better performance, but require global information, while the latter can provide better individual service with less overhead.

WiFi access selection of today strongly depends on the device implementation. This means that in typical implementations, the device selects WiFi whenever it is available. Examples of when it would be beneficial for the user experience to remain in a 3GPP mobile system include situations when the WiFi radio quality is worse than the LTE quality and when the WiFi backhaul is congested. Different devices may also have different implementations, leading to different user experiences. From the operator's point of view, it would be good to have more control on the access selection to be able to provide a more uniform experience. In fact, with the integration of WiFi on the radio access network (RAN) levels, there is a focus on providing operators with more control over WiFi access selection. This control may be gained through network-centric mobility mechanisms (e.g., direct handover command or redirection to WiFi), or by device-centric mechanisms (e.g., more careful specification of the access-selection algorithm in the terminal). The association schemes actually implemented by network operators are fully centralized: the operator tries to maximize his utility (revenue) by assigning the users to different systems [9]. However, distributed joint radio resource management (JRRM) mechanisms are gaining in importance – users may be allowed to make autonomous decisions in a distributed way. This has led to game theoretic approaches to the network selection problems in heterogeneous wireless networks, as can be found in [10]–[13].

¹The material in this paper has been presented in part at [1]. The work of P. Wiecek was supported by Wrocław University of Science and Technology under the project 8211104160 MPK: 9130740000.

In [14], the authors proposed a UE association and selection framework where the eNB selects the users to aggregate the service with AP, so that the user experiencing least service gets aggregated first. They used the Received Signal Strength Indicator (RSSI) value of the users as the main parameter for aggregating a particular user for a contract period with LTE and WiFi. In [15], the authors considered a heterogeneous network model which is composed of diverse network LTE BSs and WiFi APs. They tried to maximize the total quality of experience (QoE) of users constrained by the bandwidth capacity. They showed that the proposed algorithm reduces the number of handovers and improves the QoE experienced by users. Authors of [16] considered the LTE-A offloading to WiFi. The authors proposed a network selection and offloading scheme based on the queueing model of M/G/1 in order to satisfy the delay budget of UEs and the global load balancing. The authors of [17] investigated the impact of integrating LTE-U and WiFi from an economic perspective and showed that the welfare impacts are subtle, depending in part on the amount of unlicensed spectrum and the number of entrants. Authors of [18] presented a flexible analytical model for the performance evaluation and the efficient design of user assignment and RAT selection schemes using a Markovian agent formalism.

MOTIVATION AND CONTRIBUTIONS

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. It has been left unspecified since it is based on specific implementations and the information available inside the device, which 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 making network selection and traffic steering decisions, and a number of conceivable ways to distribute that information to devices. The 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).

Because there are many channel responses that are proportional to the number of users, we have proposed a new communication scenario wherein a partial channel state information (CSI) of each user, rather than his full channel side information, is fed back to the MeNB. By conveying a partial CSI, the feedback burden can be greatly reduced. In this paper, we provide a network-assisted user-centric network selection 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 is proposed. 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.

Another noteworthy aspect when dealing with user-centric network selection problem is how the operator can compel users to reveal the truthful signals about their CQI. It has been shown in [19] that this requires implementing more complex policies (making use of more information) which would be robust against cheating. In this paper, we show that, in the presence of lying users, liars lose and gain more than non-liars and thus, the impact of lying is bigger with liars than non-liars, which suggests that the proposed algorithms are rather fair. We then present a simple procedure that tends to prevent users from lying, as they cannot gain much from being non-cooperative. 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 has spurred great interest and excitement in the community, many of the fundamental theoretical questions on the limits of such approach remain unanswered.

The contribution of this paper is threefold:

- Firstly, we provide five load-aware network selection algorithms. Simulation results show that all the proposed algorithms outperform classical approaches in almost every respect.
- Secondly, we explore the idea of non-cooperative users sending signals that are likely to induce the scheduler to behave in a manner beneficial to them.
- Thirdly, we propose a simple solution integrated into our algorithms, which intends to make them robust against lying.

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. Three algorithms are presented: one for sparse networks (which we call MERE) and three for dense networks (which we call PIXEL and ADROIT and BEST CQI). Sec. IV presents the offloading algorithm (which we call OFF). In Sec. V, we explore non-truthful reporting of users' channel state information, and in Sec. VI, we design a simple procedure which aims at making the proposed algorithms more immune to lying. For all the proposed solutions, we present



Fig. 1. A vertically integrated cellular WiFi system with $M = 3$ macro cells and $W = 9$ overlapping WiFi access points.

key properties and performance characteristics. In Sec. VII, we provide numerical results to illustrate the theoretical solutions derived in the previous sections and get a deep insight on the performances of the proposed solutions with respect to related works. Sec. VIII concludes the paper.

II. SYSTEM MODEL

Consider a vertically 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 (see Fig. 1). A user can choose a network from his reachable networks, which takes its index from the two network set spaces $\mathcal{M} = \{1, \dots, M\}$ and $\mathcal{W} = \{1, \dots, W\}$ for MeNBs and WiFi APs respectively. The various parameters used throughout the paper are listed in Table I.

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 [20], [21]. 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

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

where D_k is the peak data rate of AP k which takes into account the transmission protocol, 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 [22]. 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 by²:

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

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

The problem we tackled here is that of maximizing the sum of throughputs over all the MeNBs in \mathcal{M} and all the WiFi APs in \mathcal{W} . This problem is a high-dimension optimization problem with the objective function which is not convex, so traditional gradient-based optimization tools will work poorly here. Moreover, computing the centralized globally optimal solution results in excessive computational complexity and large signaling overhead. Therefore, a distributed and practical solution is highly desirable in this case. As a consequence, we are interested in finding an approximately optimal solution, which will be relatively easy to compute. We provide ways to compute such a solution and try to evaluate it both from global and individual point of view. The individual point of view (which in formal considerations leads to a Nash equilibrium solution) is important because a user who is not satisfied with his own performance may not want to connect where the algorithm tells him to or may want to cheat the algorithm in order to obtain a better connection as we will see in Section V. In both cases, this may degrade the overall performance of the system.

In our considerations, 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 WiFi APs or one of MCs. We show that an approximate equilibrium in this model can be computed using a simple algorithm, which can be implemented in a *partially* distributed way.

²Although this is not a restriction of the proposed model, we suppose here that the available bandwidth is the same for the MC and the WiFi AP, and that they both operate on the same spectrum, e.g., 2.4 or 5 GHz [23].

Parameter	Description
M	the number of MeNBs,
W	the number of WiFi APs,
N	the number of users,
σ^2	the noise variance,
b_i	the demand of user i . $b_i = 1$ when there exists a demand, and 0 otherwise,
a_{ik}	user i 's action defined by the user decision to connect to RAN k . $a_{ik} = 1$ when the user chooses MC k , and 0 when the user chooses WiFi AP k ,
h_{ik}	the downlink channel from MeNB k to user i ,
s_i	the channel state of user i . $s_i = 1$ if the channel is good, and $s_i = 0$ otherwise,
β_i	the probability that $b_i = 1$,
\mathbf{P}	the policy profile matrix.

TABLE I
DESCRIPTION OF THE VARIOUS PARAMETERS.

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) [24]. It is a vector of strategies (referred to hereafter and interchangeably as actions) $\mathbf{p}^{NE} = p_1^{NE}, \dots, p_N^{NE}$, one for each player, such that no player has incentive to unilaterally change his strategy, i.e., $u_n(p_n, \mathbf{p}_{-n}^{NE}) \geq u_n(p_n, \mathbf{p}_{-n}^{NE})$ for every action $p_n \neq p_n^{NE}$, where the $-n$ subscript on vector \mathbf{p} stands for “except user n ”, i.e., $\mathbf{p}_{-n} = \{p_1, \dots, p_{n-1}, p_{n+1}, \dots, p_N\}$. 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 $\mathbf{p}^{\epsilon NE} = p_1^{\epsilon NE}, \dots, p_N^{\epsilon NE}$ is an ϵ -Nash equilibrium³. 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 a) limiting the interference between the users by dividing them into the smallest possible number of layers, within which users cannot interfere, b) 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

³There are two different ways to define an ϵ -Nash equilibrium used in the literature. A more commonly used definition (see [25]) states that a vector \mathbf{p} is an ϵ -NE if it satisfies $u_n(p_n^{\epsilon NE}, \mathbf{p}_{-n}^{\epsilon NE}) + \epsilon \geq u_n(p_n, \mathbf{p}_{-n}^{\epsilon NE})$. In algorithmic game theory both definitions (additive and multiplicative) are used, depending on properties of the class of games under consideration, e.g. in case of congestion games [26] the multiplicative definition is commonly applied. It is not hard to see that in general if the payoffs of each user are in an interval $[0, U_{\max}]$, then any multiplicative ϵ -NE is an additive $U_{\max}\epsilon$ -NE.

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 two of our main algorithms. We start with a relatively simple algorithm designed for the case of a sparse network ($M \gg N$). A small value $\delta \in (0, 1)$ and an optional parameter $H > 0$ (if we do not want to use it, we may set it to 1) are the parameters of the algorithm.

Algorithm 1. MERE: Max-min uSEr oRdERing algorithm

Each user i computes $\Psi_i = \max \left\{ \max_{k \leq M} \log_2 \left(1 + \frac{ph_{ik}}{\sigma^2} \right), \max_{l \in \mathcal{W}_i} D_l \right\}$ and $\rho_{ik} = \frac{\log_2 \left(1 + \frac{ph_{ik}}{\sigma^2} \right)}{\Psi_j}$ 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 $\underline{\alpha} = 0$, $\bar{\alpha} = 1$, $\alpha^* = 0$, $\nu = 0$ and $\pi^* = [1 \dots N]$.

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

- 1) The MeNB computes $\bar{\alpha} - \underline{\alpha}$. If $\bar{\alpha} - \underline{\alpha} < \delta$ or $\underline{\alpha} > H$, then it stops, putting $\alpha^* = \underline{\alpha}$ and, if $\nu = 0$ also $\pi^* = \pi$. Otherwise it takes $\alpha^* = \frac{\bar{\alpha} + \underline{\alpha}}{2}$ 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 MeNB⁴.
- 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 $\bar{\alpha} = \alpha^*$ and returns to point 1).
- 4) The MeNB puts $\pi^* = \pi$, $\underline{\alpha} = \alpha^*$, $\nu = 1$ and returns to point 1).

For $i = 1, \dots, N$ user $\pi^*(i)$ chooses the network with the highest utility that is not already chosen by some other player.

To understand the sense of MERE algorithm, first note that the fraction ρ_{ik} appearing there can be interpreted as a measure of disutility⁵ of player i from choosing MeNB k or WiFi $k - M$ instead of his best network. Since the algorithm is designed for the sparse network case, it is natural to assume that no two different players can be connected to the same network, so the utilities are always of the form $\log_2 \left(1 + \frac{ph_{ik}}{\sigma^2} \right)$ or D_l .

⁴If 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.

⁵By disutility here and in the sequel we mean the decrease in the utility of a user measured as the ratio of his current utility to the biggest one he could receive under the same channel conditions if there was no interference at all.

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-case⁶ 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 MERE 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 were a leader). α^* found by MERE is the minimal value (computed with a δ toleration) for which such an ordering is possible.

MERE can be generalized to the case of a dense network in the way presented below. Here the computations made are distributed among all MeNBs and all users. A small value $\delta \in (0, 1)$ and optional parameters $\gamma_M, \gamma_W, H > 0$ (if we do not want to use them, we can always set H, γ_M and γ_W to 1)⁷ are the parameters of the algorithm.

Algorithm 2. PIXEL: oPtimal layer divisIon with maX-min user ordEring aLgorithm

Phase A:

Each user $i, i = 1, \dots, N$, 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 $(K^k(1), \dots, K^k(N_k)), (H^k(1), \dots, H^k(N_k))$ 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 $N_k > K^k(l_{\nu-1}^k + 1) + l_{\nu-1}^k$. Then, it sets $m_k = \nu$ and $l_{m_k}^k = N_k$, and creates lists $\mathcal{L}_1^k = (\pi^k(l_0^k + 1), \dots, \pi^k(l_1^k)), \dots, \mathcal{L}_{m_k}^k = (\pi^k(l_{m_k-1}^k + 1), \dots, \pi^k(l_{m_k}^k))$.

Phase B: (done simultaneously by each MeNB)

- B.1) Each MeNB k sets $\underline{\alpha}_1^k = 0, \dots, \underline{\alpha}_{m_k}^k = 0, \bar{\alpha}_1^k = 1, \dots, \bar{\alpha}_{m_k}^k = 1, \alpha_1^{*k} = 0, \dots, \alpha_{m_k}^{*k} = 0$ and $\pi_k^* = \pi^k$.
- B.2) It computes $\bar{H}_1^k = \mu \sum_{s \neq 1} \max\{H^k(l_{s-1}^k + 1), \dots, H^k(l_s^k)\}, \dots, \bar{H}_{m_k}^k = \mu \sum_{s \neq m_k} \max\{H^k(l_{s-1}^k + 1), \dots, H^k(l_s^k)\}$ and $\bar{m}_k = \gamma_W M m_k$, and sends (\bar{H}_s^k, \bar{m}_k) to each user on list \mathcal{L}_s^k 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 $j \in \mathcal{L}_s^k$ computes $\bar{\Psi}_j = \max \left\{ \max_{l \in \mathcal{M}_j} \log_2 \left(1 + \frac{p h_{jl}}{\sigma^2 + p \bar{H}_s^k} \right), \max_{l \in \mathcal{W}_j} \frac{D_l}{\bar{m}_k} \right\}$ and $\rho_{jl}, l = 1, \dots, M + W$, as follows:

$$\rho_{jl} = \frac{\log_2 \left(1 + \frac{p h_{jl}}{\sigma^2 + p \bar{H}_s^k} \right)}{\bar{\Psi}_j} \text{ if } l \leq M \text{ and } \rho_{jl} = \frac{D_l - M}{\bar{m}_k \bar{\Psi}_j} \text{ if } l > M \text{ and } l - M \in \mathcal{W}_j \text{ with } \rho_{jl} = 0 \text{ otherwise.}$$

- B.4) Then, for each $s \in \{1, \dots, m_k\}$ MeNB k sets $\nu = 0$ and the following steps are repeated until the loop is interrupted in point B.4.1):

- B.4.1) MeNB k computes $\bar{\alpha}_s^k - \underline{\alpha}_s^k$. If $\bar{\alpha}_s^k - \underline{\alpha}_s^k < \delta$ or $\underline{\alpha}_s^k > H$, then it stops the loop, putting $\alpha_s^{*k} = \underline{\alpha}_s^k$ and, if $\nu = 0$, also $\pi_k^*(l_{s-1}^k + 1, \dots, l_s^k) = \bar{\pi}$. Otherwise it takes $\alpha_s^{*k} = \frac{\bar{\alpha}_s^k + \underline{\alpha}_s^k}{2}$ and announces α_s^{*k} to the users on list \mathcal{L}_s^k .
- B.4.2) Each user $j \in \mathcal{L}_s^k$ computes $K_j = |\{l : \rho_{jl} \geq \alpha_s^{*k}\}|$ and sends it back to MeNB k .
- B.4.3) MeNB k sorts pairs (K_j, j) where $j \in \mathcal{L}_s^k$ using its first coordinate in an increasing order obtaining vectors \bar{K} and $\bar{\pi}$. If $\bar{K}(l) < l$ for some $l \leq l_s^k - l_{s-1}^k$ it puts $\bar{\alpha} = \alpha_s^{*k}$ and returns to point B.4.1).
- B.4.4) MeNB k puts $\pi_k^*(l_{s-1}^k + 1, \dots, l_s^k) = \bar{\pi}, \underline{\alpha} = \alpha_s^{*k}, \nu = 1$ 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 $\pi_k^*(l_s^k + 1), \dots, \pi_k^*(i - 1)$, where s is such that $l_s^k < i \leq l_{s+1}^k$.

Before we try to explain the sense of PIXEL, we should note that in principle all the computations made in MERE are now repeated in Phases B and C of the algorithm. The introduction of Phase A is the consequence of the fact that here 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 should 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 MERE 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 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 PIXEL 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 MERE and PIXEL are used to allocate them to networks, as well as some other useful

⁶Worst-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 similar.

⁷The meaning and optimal selection of these parameters will be further discussed after Proposition 1.

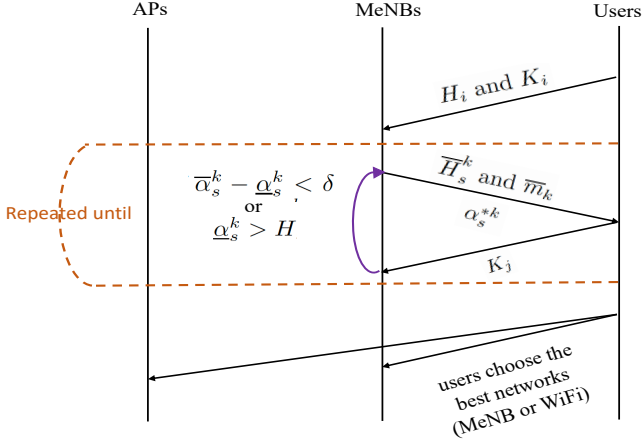


Fig. 2. Schematic diagram showing the set of parameters/values communicated among MeNBs, APs and UEs, and the set of steps implemented at MeNBs, APs and UEs for PIXEL.

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:

$$\alpha^* = \min_{k \leq M, s \leq m_k} \alpha_s^{*k}, \quad \bar{H} = \sum_{k=1}^M \sum_{s=1}^{m_k} \max_{i \in \mathcal{L}_s^k} H_i,$$

$$\bar{\lambda} = \min_{l \leq M, s \leq m_l} \frac{\bar{m}_l (\sigma^2 + p\bar{H})}{\sum_{k=1}^M m_k (\sigma^2 + p\bar{H}_s^l)},$$

$$\underline{\lambda} = \min_{l \leq M, s \leq m_l} \frac{\sum_{k=1}^M m_k (\sigma^2 + p\bar{H}_s^l)}{\bar{m}_l (\sigma^2 + p\bar{H})},$$

$$\lambda = \min\{\bar{\lambda}, \underline{\lambda}\}, \quad \theta = \min \left\{ \frac{1}{1 + \frac{p}{\sigma^2} \bar{H}}, \frac{1}{\sum_{k=1}^M m_k} \right\}.$$

Suppose⁸ that $\bar{H}_s^k \leq \bar{H}$ for every $k \leq M$ and $s \leq m_k$. Then, the choice of network selections done by PIXEL 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 optimum⁹.

The proof of this proposition is given in the appendix.

In Proposition 1 we try to break down the dependence on the utility of users in PIXEL into three separate factors described by coefficients α^* , θ and λ . They are all dependent on the numbers of users and channels available, as well as the quality of these channels, and parts of the algorithm are designed

to optimize these values. λ^* describes the dependence of users' disutility on the assignment of users to channels under assumption that the number of interfering users on any given channel is bounded above by $\sum_{k=1}^M m_k$ (m_k being the bound for the interfering channels assigned by MeNB k). Our first algorithm, MERE, is designed to optimize this parameter, and it is repeated as Phase B in PIXEL. The magnitude of parameter α^* is mainly dependent on the number of opportunities available to each user. It should thus improve as the number of MeNBs and WiFi APs available to an average user increases and should not depend in any meaningful way on the number of users in the system. The coefficient θ on the other hand estimates the disutility caused by the interference from the other users. It mainly depends on the total number $\sum_{k=1}^M m_k$ of layers interfering with each other which is minimized in Phase A of PIXEL. The minimization done there is done for a given number of MeNBs and WiFi APs available. As a consequence, θ will crucially depend on the number of users in the system, decreasing as its number increases. Finally, λ is meant to estimate the ratio between the average interference perceived by a single user and the biggest one. It is a kind of disutility which cannot be handled by the algorithm, as it could only be taken into account, if the optimization was done by an entity with full knowledge of the channel conditions of all the users and the coverage areas of each MeNB and WiFi AP. This is not the case in our algorithm. More specifically, the magnitude of λ mainly depends on the choices of the parameters γ_M , γ_W and on the range in which the values of \bar{H}_s^k differ in different layers. If the first two are equal to 1, $\bar{m}_k = M m_k$ is a natural estimate of the value of $\sum_{l=1}^M m_l$ based on the limited information available to MeNB k . Similarly, \bar{H}_s^k can be viewed as an estimate of \bar{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 and the quality of estimates \bar{H}_s^k will be limited, whence λ can be smaller. The reason why we will take γ_M and γ_W into account is the intuitive meaning of these parameters. Note that when γ_M and γ_W appear in PIXEL, \bar{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 AP. 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 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 PIXEL, 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

⁸For γ_M significantly smaller than 1, which will be our natural choice of this parameter, it should be naturally satisfied.

⁹The social optimum is a vector of strategies which maximizes the sum of utilities of all the players.

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.

Next, we present two results describing the properties of MERE. The first one follows directly from Proposition 1.

Corollary 1. *Suppose N , \mathcal{M}_i and \mathcal{W}_i , $i = 1, \dots, N$ 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 MERE 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 MERE.

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

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

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

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 MERE, 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 PIXEL, although writing any inequalities that could serve as counterparts of Equation (3) is problematic.

As we can see comparing the statements of Proposition 1 and Corollary 1, the quality of MERE depends only on the value α^* , while that of PIXEL on the product $\alpha^* \lambda \theta$. This is an important difference, as typically the value of θ (related to Phase A of the algorithm) is much smaller than that of α^* (related to Phase B), so the impact of Phase B on the quality of the users' throughputs will be relatively small when compared to that of Phase A. In practice, it can be even smaller, as the ordering made in Phase C takes into account an estimate of the *average* interference perceived by the users rather than the real interference, which is often far from the average. This suggests that we may obtain a performance not far from that of PIXEL if we keep Phase A and Phase C, but replace Phase B with a random ordering of users. This is done in the algorithm below.

Algorithm 3. ADROIT: optimAl layer Division with Random user Ordering alORITHm

Phase A:

Each user i , $i = 1, \dots, N$, 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 $(K^k(1), \dots, K^k(N_k))$, $(H^k(1), \dots, H^k(N_k))$ 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 $N_k > K^k(l_{\nu-1}^k + 1) + l_{\nu-1}^k$. Then, it sets $m_k = \nu$ and $l_{m_k}^k = N_k$, and creates lists $\mathcal{L}_1^k = (\pi^k(l_0^k + 1), \dots, \pi^k(l_1^k)), \dots, \mathcal{L}_{m_k}^k = (\pi^k(l_{m_k-1}^k + 1), \dots, \pi^k(l_{m_k}^k))$.*

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

- B.1) *Each MeNB k computes $\bar{H}_1^k = \mu \sum_{s \neq 1} \max\{H^k(l_{s-1}^k + 1), \dots, H^k(l_s^k)\}, \dots, \bar{H}_{m_k}^k = \mu \sum_{s \neq m_k} \max\{H^k(l_{s-1}^k + 1), \dots, H^k(l_s^k)\}$ and $\bar{m}_k = \gamma_{\mathcal{W}} M m_k$, and sends (\bar{H}_s^k, \bar{m}_k) to each user on list \mathcal{L}_s^k for $s = 1, \dots, m_k$, where*

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

- B.2) *Each user $j \in \mathcal{L}_s^k$ computes $\bar{\Psi}_j = \max \left\{ \max_{l \in \mathcal{M}_j} \log_2 \left(1 + \frac{ph_{jl}}{\sigma^2 + p \bar{H}_s^k} \right), \max_{l \in \mathcal{W}_j} \frac{D_l}{\bar{m}_k} \right\}$ and ρ_{jl} , $l = 1, \dots, M + W$, as follows:*

$$\rho_{jl} = \frac{\log_2 \left(1 + \frac{ph_{jl}}{\sigma^2 + p \bar{H}_s^k} \right)}{\bar{\Psi}_j} \text{ if } l \leq M \text{ and } \rho_{jl} = \frac{D_l - M}{\bar{m}_k \bar{\Psi}_j} \text{ if } l > M \text{ and } l - M \in \mathcal{W}_j \text{ with } \rho_{jl} = 0 \text{ otherwise.}$$

- B.3) *Then, for each $s \in \{1, \dots, m_k\}$ MeNB k computes a random permutation $\bar{\pi}$ of the vector $\pi^k(l_{s-1}^k + 1, \dots, l_s^k)$ and puts $\pi_k^*(l_{s-1}^k + 1, \dots, l_s^k) = \bar{\pi}$.*

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 $\pi_k^*(l_s^k + 1), \dots, \pi_k^*(i - 1)$, where s is such that $l_s^k < i \leq l_{s+1}^k$.*

Theoretically, the performance measures of ADROIT can be characterized by Proposition 1 with α^* taken as $\min_{i,k: \rho_{ik} > 0} \rho_{ik}$, which is usually much smaller than α^* defined in Proposition 1. In practice, the performance of the two algorithms (as we will see in our numerical experiments) will be similar. ADROIT will also have two additional advantages. Firstly, it will require both less computation and less communication between MeNBs and users. Secondly, it will be immune to strategic lies of the users. This last issue will be addressed in more detail in the Section VI.

Next, we look at an even simpler algorithm which we will call hereafter as Best CQI. The idea behind this algorithm is to simply choose the network with the biggest CQI among all networks available. Comparing WiFi and MeNB networks is done by proper scaling of the data available for them used in PIXEL. This does not change the main characteristics of the algorithm: it is very easy to implement and immune to any kind of manipulation. At the same time, its performance shall be relatively poor, as it does not take interference (which is done in Phase C) into account.

Algorithm 4. Best CQI (Best CQI)

Do the same than in PIXEL Algorithm till Phase B.3. Then, remove Phase B.4 and, in Phase C, each user $j \in \mathcal{L}_s^k$ connects to the network l (MeNB l or WiFi AP $l - M$) with the highest ρ_{jl} for $l = 1, \dots, M + W$, regardless of the fact that this network has been already chosen or not.

IV. OFFLOADING

In this section, we will ask how macro cells can manipulate the outcome of the algorithm in order to push users to connect to WiFi APs whenever they are within their range. As nearly all the computations are done on the macro cell side, it is rather natural that their ability to steer the algorithms towards some chosen outcome is much bigger. We believe that one specific case when MCs will not be interested in the optimal assignment of networks will be when the load is so high that they will want to offload the users to WiFi. Our solution is inspired by the notion of Cell Selection Bias (CSB) proposed by LTE standards. It turns out that it can be done quite easily using the following algorithm:

Algorithm 5. Offloading (OFF):

In Phase B.1 of PIXEL Algorithm, compute for $s = 1, \dots, m_k$ $\bar{m}_k = \gamma_W M m_k$ and $\bar{H}_s^k = \frac{\max_{i \in \mathcal{L}_s^k} H_i}{2^\eta - 1}$, where $\eta = \frac{\min_{l \in \mathcal{W}} D_l}{\bar{m}_k}$ and send (\bar{m}_k, \bar{H}_s^k) to each user on list \mathcal{L}_s^k .

It turns out that using this small modification of PIXEL will result in steering large number of users to WiFi, as every user "seeing" a WiFi AP in his range will choose to connect to it.

Proposition 3. *If all the MeNBs use Algorithm 5, all the users with any WiFi available in Phase C of PIXEL (or ADROIT) will choose to connect to some WiFi.*

The proof of this proposition is given in the appendix. OFF algorithm is meant to make any nonzero ρ_{jl} for WiFi (in Phase B.3 of PIXEL) bigger than those for macro. This makes users connect to WiFi provided that they are within the range of a WiFi AP which has not been chosen by another user higher in the hierarchy in the layer. As we will see later in simulation results, this situation becomes even more interesting when a user is not concerned with offloading and thus gains a lot by staying alone on the macro cell.

V. LYING VS. TRUTHFUL REPORTING

So far, we have assumed that all the users give true information about their channel qualities. Now, let us suppose that each of them tries to improve his utility by giving fake information designed to misguide PIXEL or OFF. In fact, the MeNB depends crucially on truthful reporting of their channel states by the mobiles. For example, in the frequency-division duplex system, the MeNB has no direct information on the channel gains, but transmits downlink pilots, and relies on the mobiles' reported values of gains on these pilots for scheduling. A cooperative mobile will truthfully report this information to the MeNB. A non-cooperative mobile will however send a signal that is likely to induce the scheduler to behave in a manner beneficial to the mobile. A non-cooperative mobile may misrepresent its signal to the MeNB

so as to maximize his throughput. It was shown in [19] that the MeNB becomes successful in eliciting the truthful signals from the mobiles only when it uses additional information (signal statistics). Non-truthful reporting results in unfair allocations.

Let us focus on the case where $N \ll M$. In that case, PIXEL can be reduced to a simpler Algorithm MERE, which is easier to analyze. It can be easily shown in our case that indeed, whenever all the users except user i tell the truth about their channel conditions, user i can maximize his utility by using the following algorithm:

Algorithm 6. Lying:

Step 1: Declare that you have only one network with $\rho_{ik} > \alpha^$ whenever asked in Part 2) of MERE, PIXEL or OFF.*

Step 2: Connect to the network giving you the highest utility.

By doing Step 1, he will decrease α^* significantly (beyond what is necessary), but at the same time he will be given the possibility of choosing his network first in the second part of the algorithm, which will result in utility Ψ_i for him¹⁰. This is a big problem also because in case two or more users apply similar strategy, the algorithm will not finish until $\alpha^* = 0$, which will result in a random assignment of networks. This is however not a problem related exclusively to MERE, but to any good network assignment algorithm relying on measurements made by users. This is stated formally in the following proposition.

Proposition 4. *Suppose assumptions of Corollary 1 are satisfied and that some network-assigning algorithm basing its decisions on channel quality information provided by the users always assigns them to networks giving player i , $i = 1, \dots, N$, the utility of more than $\bar{\alpha}^* \Psi_i$, where $\bar{\alpha}^*$ is the limit of α^* obtained in MERE as $\delta \rightarrow 0$. Then, there exists a situation when some player can improve his utility by declaring false channel quality information.*

The proof of this proposition is given in the appendix.

VI. IMMUNITY

While in practice Proposition 4 implies that any sensible network selection algorithm using channel quality signals provided by the users (including our algorithms MERE, PIXEL and OFF as well as algorithms that use more information than our ones) suffers from the same problem regarding truthful reporting of the channel quality information by the users when the network is sparse, we may try to mitigate the effect of this kind of behavior in our algorithms. Our suggestion here will be to introduce an additional parameter $L > 0$ (which we will call hereafter immunity parameter) into MERE (or Phase B of PIXEL) and start it with $\underline{\alpha} = L$ which will prevent α^* to drop below this value. In that way, in some cases, we will not obtain utility of at least $\alpha^* \Psi_i$ for every player i , but at this expense we will bound the profit of a player trying to outsmart the algorithm by reporting that he has only one good network available (because in case there are several players

¹⁰The same way of lying can be applied in Phase B.4 of PIXEL. However, in that case, the gain of the lying user is uncertain, as on his best channel he may suffer from greater interference – anyway we should expect that on the average this will be a profitable strategy in this case as well.

in such a situation, he will drop in hierarchy) and avoid the danger of a random assignment of networks in case there are several users attempting to lie about their channel conditions (the assignment will be random only among the lying users). As it is difficult to indicate an optimal choice of L from theoretical point of view, a good choice of this parameter will be further addressed in numerical results section. The efficiency of Algorithm 6 in case of a dense network, when only PIXEL can be used, will also be analyzed there.

Another possibility allowing to get rid of the problems with untruthful reporting of the CQIs is to use ADROIT instead of PIXEL. In that procedure, the phase B of PIXEL, where it is strategical to lie about the channel qualities, is replaced by a random ordering of users, which cannot be affected by themselves. As it will be seen in our simulations, this advantage of ADROIT will not be nullified by a significant loss in throughput – it will turn out that the main factor influencing the throughput will be interference, which is not affected by Phase B of PIXEL and ADROIT in any way.

VII. PERFORMANCE EVALUATION

The proposed algorithm is implemented in an LTE compliant system level simulator [27] in order to analyze its performance. Table I summarizes the system characteristics and simulation scenario's parameters. Here, we consider a deployment of 7 omni-directional macro cells as shown in Fig. 3.

As for MC deployment, general hexagonal structure with three sector MC is assumed, where the MeNB is located at the center of hexagonal structure and WiFi APs are overlaid on the MCs randomly and operated in the same frequency band as MeNBs. Users are scattered into MCs in the same way as WiFi APs. Table II depicts the system characteristics and global simulation parameters. For comparison purposes, we will further study the following two *traditional* association approaches¹¹:

- *Least load approach (LEAST)*: The network broadcasts the exact numbers of connected users on different networks. Any new user will then connect to the system with the least load. Note that this scheme is not realistic as the network operator will not divulge the exact number of connected users in each system and each position of the cell.
- *Peak rate maximization approach (PEAK)*: This is a simple association scheme where users do not have any information about the loads of the systems. They connect to the system offering them the best peak rate. Note that this peak rate can be known by measuring the quality of the receiving signal.

These three approaches will serve to demonstrate how much gain may be exploited through considering such solutions with respect to the proposed schemes.

¹¹From now on, for the sake of conciseness, we will use the term "PIXEL" to designate both Algorithm 1 and Algorithm 2.

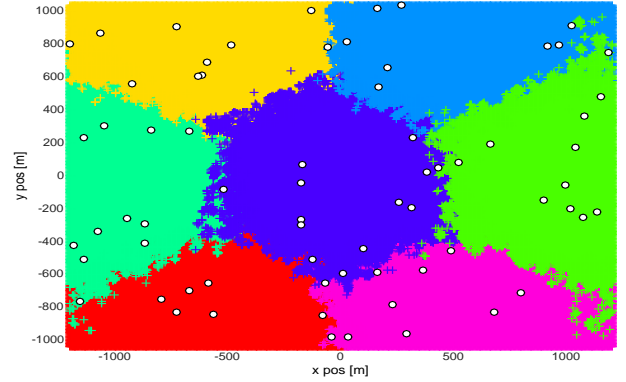


Fig. 3. The network layout with 7 MeNBs and UE positions.

A. Basic approach

Average utility: As we can see from Fig. 4, for all algorithms average utility decreases fast for small number of users, and then slows down at some level. We can also observe that PIXEL and ADROIT algorithm outperform all the other algorithms for a low number of users (till $N = 50$), whereas OFF is the best for a high number of users. PEAK and LEAST perform badly for both low and high N . This is natural, as the main idea of design of our algorithms is to minimize the interference between users, which is not done for traditional algorithms. Moreover, in the case of our algorithms, load balancing between networks implies that all the networks become more or less equally occupied at the same threshold (around 40 users). Note that, as the number of users goes large, the gap between the traditional algorithms and ours decreases, as for such a large number of users, all the cells become overloaded, resulting in all schemes tending towards almost the same average utility.

Load balancing: In order to get good intuition on the load balancing characteristics, we plot two pictures: In Fig. 5, we plot the load ratio defined as the ratio between the most loaded cell and the average cell load, and in Fig. 6, we plot the overall load balancing defined as the ratio between the load of WiFi APs and that of MeNBs. Obviously, we aim to have the lowest load ratio and an overall load balancing close to 1. We can see from Fig. 5 that BEST CQI performs badly, whereas LEAST's load ratio is in general smaller than that for the other algorithms till $N = 24$ users. Then, PEAK becomes the best, but, in return, fails to balance the load between WiFi and macro cells, as it is illustrated in Fig. 6. Indeed, with PEAK, most likely all users connect to macro cells (which can be seen from the zero overall load balancing), as it offers the best peak rate. On the other hand, the proposed algorithms perform pretty well in terms of load ratio when the number of users grows large (see Fig. 5), while OFF shows the best overall load balancing performances (see Fig. 6). To understand it, note that, in OFF algorithm, we force users to use WiFi APs rather than MeNBs, whenever a WiFi AP is in the range. More specifically, what we observe from Fig. 6 is that, with OFF, there is a general tendency to use WiFi more often. Then, for an increasing number of users, this tendency decreases, as WiFi becomes more and more occupied. When WiFi APs

TABLE II
SIMULATION ENVIRONMENT.

Network parameters	Number of MeNBs (M) Average cell radius Number of WiFi APs (W)	7 omnidirectional antenna 500 m 50
LTE parameters	Frequency band Bandwidth Number of PRBs	2.4 GHz 5 MHz 25
eNodeB and UE characteristics	Scheduler Transmission mode eNodeB TX Power UE distribution Total number of UEs Traffic profile	Proportional fair SISO 2x125mW over all the 5MHz bandwidth Uniform 100 Full buffer
Radio channel	Pathloss model Shadowing Fast fading	TS36.92 Log normal, 5 dB standard deviation ITU Pedestrian A

become congested as well, the overall load balancing decreases to 1 (from 40 users), which roughly means that macro cells and WiFi APs become equally loaded.

B. Lying vs. Truthful reporting

We know from Prop. 4 that it is individually beneficial not to tell the truth about own CQIs when asked by an MeNB if everyone else tells the truth. However, as there is an incentive to lie for all the users and the users do not coordinate their actions, in our next experiment we suppose that some fraction of users lies about their CQIs claiming that they only have one good channel.

Fig. 7 depicts, for the three proposed algorithms (PIXEL, ADROIT and OFF), the ratio between the number of users (liars/non-liars) who gain and the number of those who lose when there are liars as function of the number of users for a percentage of liars of $P = 20\%$. Fig. 8 depicts the same ratio as function of the percentage of liars for a total number of users of $N = 20$. First notice that ADROIT is the most immune to lying since there is no way to improve your utility by lying, because the lying happens in the phase of the algorithm which is missing from ADROIT (this is illustrated in Fig. 7 and Fig. 8 by the ratio equal to 1 regardless of P and N).

PIXEL and OFF increase significantly the number of liars who gain. Yet, this happens only for a low number of users (see Fig. 7) and/or a low percentage of liars (see Fig. 8). This can be easily explained, as for a small number of users, the network resources may be assigned in such a way that no interference (or very little interference) is perceived by the players, even if some of the opponents lie about their CQIs. On the other hand, those who lie, may often cause their assignment to a more saturated MeNB, which, as we can see from our previous experiments, may lead to a decrease in their utility, even if they use the MeNB with the highest CQI. This is not very likely to happen for low N , so the number of liars who lose then is relatively small. For high N however, lying is not efficient anymore, as for a bigger number of layers, players have too little information about the interference to take it into account in their lying strategy, resulting in that they gain and lose almost equally often. Similarly, for a high value of P , it is much harder to gain by lying, as lying is designed to gain

over truth-tellers. If everyone (or a significant percentage) lies, the choices become random.

One of the key issues in wireless networks is guaranteeing fairness among users. The proposed algorithms are designed to maximize overall throughput. This is done by minimizing the interference, which in turn is done by a balanced use of all the cells (MC and WiFi). In order to increase fairness among users, in addition, in Phase B, we further balance the usage of all these networks, so that the throughput of the user with the lowest one is as big as possible. However, when it comes to lying, there may be a problem with sustaining fairness, especially for non-liars, which can be seen, at first glance, as "victims" of liars. Let us then focus on the performance of non-liars to study how they are impacted by liars in each of the proposed algorithms. We see from Fig. 7 that the number of non-liars losing is slightly less in OFF than in PIXEL. As the number of users increases, the ratio between the number of non-liars who gain and the number of non-liars who lose increases, which means that non-liars lose less, till reaching a ratio of 1 (almost at $N = 40$), which means that we have the same number of non-lying users who gain and lose. Notice also that the number of liars gaining is much more significant than the number of non-liars losing (a ratio of up to 7 times for PIXEL and 4 times for OFF for $N = 7$ users, decreasing to a ratio of 1.5 times for both PIXEL and OFF as N goes large), which suggests that for a moderate percentage of liars in the system, the performance of non-liars is relatively little affected by lying. Fig. 8 shows that for a bigger percentage of liars, non-liars become more affected, but even for $P = 90\%$ the ratio of non-liars who gain to those who lose is around 0.4 for PIXEL and 0.5 for OFF, which seems still acceptable.

In Figure 9, we plot the CDF of the ratio between the utility of liars and their utility when there are no liars. First, notice that the jump in 1 for OFF is smaller than for PIXEL. This means that the number of those who gain/lose significantly is bigger for PIXEL. In fact, both for OFF and PIXEL, around 80% of users gain/lose a little (this is what we can read from the jump of the CDF around 1), but the gap for OFF is around 5% smaller. Also notice that in OFF liars and non-liars lose less than in PIXEL. At the same time in OFF non-liars and liars gain less than in PIXEL (this can be read from the relative position of CDFs on the left and on the right from

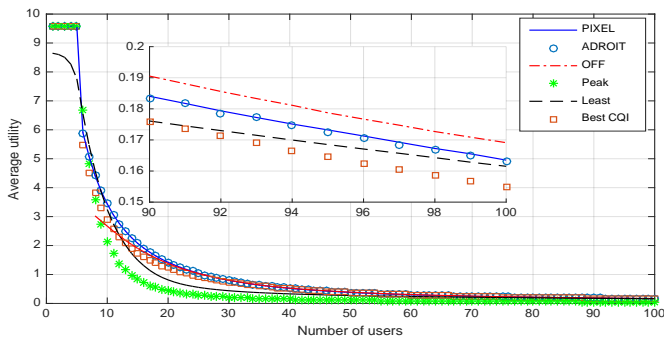


Fig. 4. The average utility.

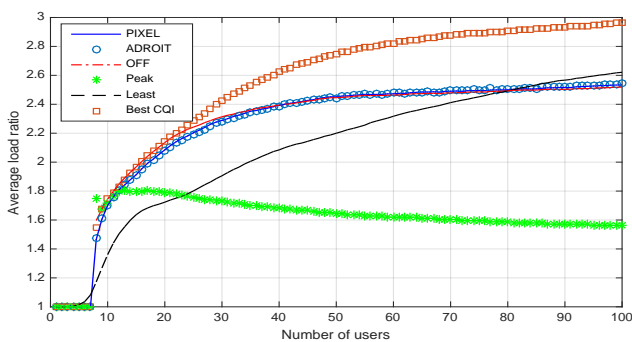


Fig. 5. The average load ratio.

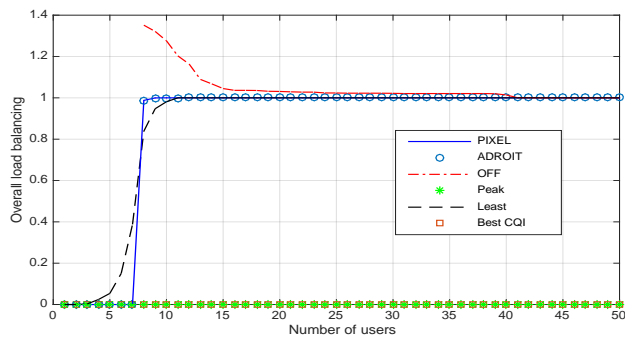
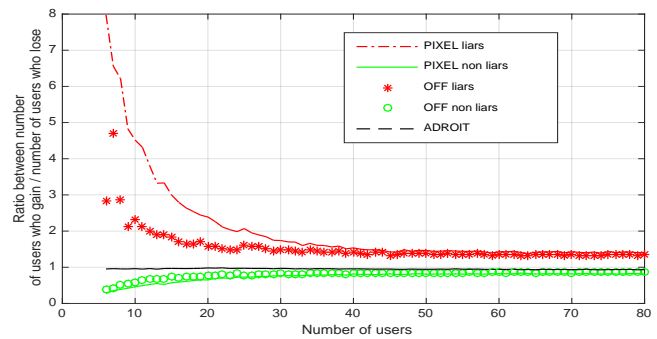
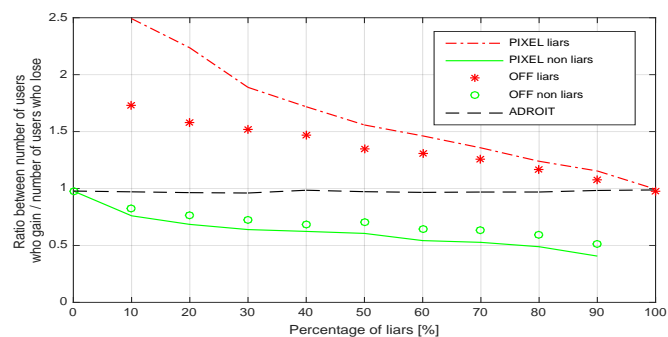
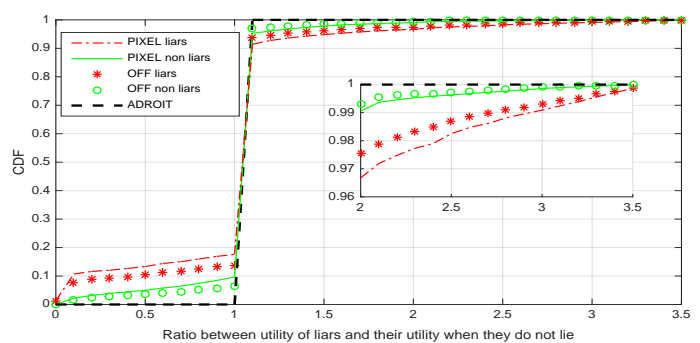


Fig. 6. The average load balancing.

1). In general, for both PIXEL and OFF, it is shown that liars lose more than non-liars (for values on the x -axis lower than 1), and gain more than non-liars (for x -axis above 1). This means that liars affect their own utility (both for good and bad) a lot more than that of non-liars, and this phenomenon is even more pronounced when it comes to OFF. This confirms our previous assertions that the effect of lying on non-liars is insignificant, hence the proposed algorithms are fair. Another important phenomenon that we see on the CDFs is that the structure of gains and loses, both for liars and non-liars, is different. On the one hand, the number of those who lose (in

Fig. 7. The ratio between the number of users (liars/non-liars) who gain and the number of users who lose when there are liars for $P = 20\%$ of liars.Fig. 8. The ratio between the number of users (liars/non-liars) who gain and the number of users who lose when there are liars for $N = 20$ users.Fig. 9. The CDF in function of the ratio between the utility of liars (resp. non-liars) and their utility when there are no liars for $P = 20\%$ of liars and $N = 20$ users.

both groups) more than 10% is smaller than the number of those who gain more than 10% (we can read that from the values of the CDFs for the x -values equal to 0.9 and 1.1, respectively). On the other hand, both liars and non-liars who gain or lose will likely gain much more significantly than they lose. This is what we can read from the fact that a visible fraction of users gain at least additional 200% of their initial utility when lying occurs (the CDFs for x -value equal to 3 are still increasing), while the losses are limited by initial utility of the users (so they cannot exceed 100%).

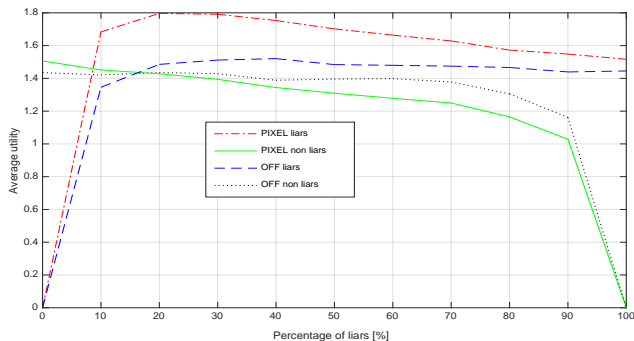


Fig. 10. The average utility of liars and non-liars in PIXEL and OFF for $N = 20$ users.

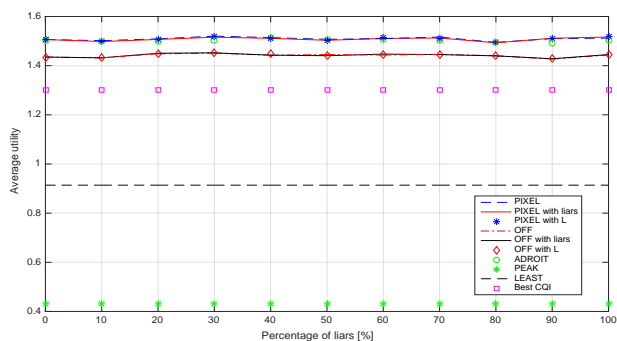


Fig. 11. The average utility of all algorithms for $N = 20$ users.

Fig. 10 shows, for both PIXEL and OFF, the average utility of liars and non-liars as function of the percentage of liars for a total number of users $N = 20$. It is clearly shown that PIXEL improves upon utility of lying users, mostly when the percentage of lying users is low, while OFF improves upon utility of non-lying users, mostly when the percentage of lying users is high. In general, Fig. 10 also shows that liars outperform non-liars in average utility. This is possibly expected, given that, as we have seen from Fig. 7 and Fig. 8, a higher number of liars gain. However, in view of Fig. 9 and our observations made there, the most significant factor here may be that the gains of those who take advantage of lying are often rather significant, which strongly affects the average utility. The complementary performance between liars and non-liars makes the overall average utility almost constant as function of the percentage of liars, as it is illustrated in Fig. 11. Moreover, it is shown there that PIXEL and ADROIT have the best average utility, slightly above OFF and BEST CQL. As N goes large, we will see later in Fig. 16 that OFF gives the best average utility.

To sum it up, what we have observed from these figures are two tendencies: first, lying with PIXEL and OFF improves significantly the average utility of users who lie with respect to their utility when they do not lie (see Fig. 10). Interestingly, overall average utilities for both algorithms are not affected by lying. The second tendency is that the increase in the percentage of users lying decreases its efficiency. As already

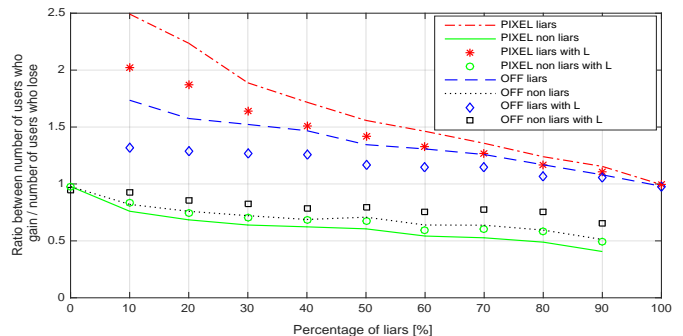


Fig. 12. The ratio between the number of users who gain and the number of users who lose when there are liars and non-liars in PIXEL and OFF for $N = 20$ and $L = 0.5$.

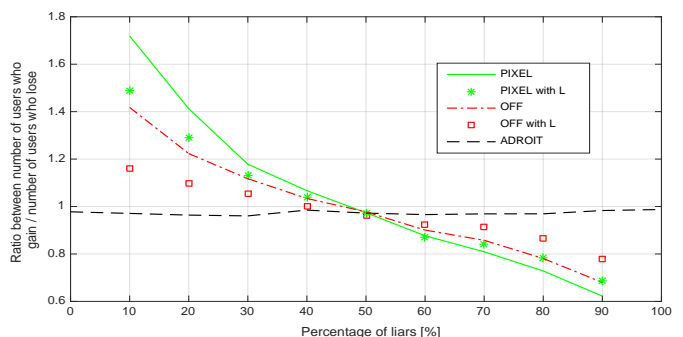


Fig. 13. The ratio between the number of users who gain and the number of users who lose when there are liars in PIXEL, OFF and ADROIT for $N = 20$ and $L = 0.5$.

mentioned, this can be explained easily when we understand what happens if a big number of players claims that they only have one good network. In that case, the assignment of networks (specifically among those who do not tell the truth) becomes increasingly arbitrary, decreasing not only the utilities of truth-tellers (as it may be the case if the percentage of non-truth-tellers is small), but also of those who do not tell the truth. However, a general observation is that it is always worth lying.

C. Immunity

So far, we have seen that both PIXEL and OFF are not immune to lies (although OFF is more immune to lies than PIXEL). In this part, we will try to make lies slightly less profitable for liars. Remember that the additional immunity parameter L is meant to decrease the gain of liars without heavily harming the throughput of those who tell the truth. We hope that this will further improve the overall system performance when there are liars. In the sequel, we revisit the previous analysis, in order to figure out how liars and non-liars will be impacted by L .

Fig. 12 shows, for both liars and non-liars in PIXEL and OFF, the ratio between the number of users who gain and the number of users who lose when there are liars as function of the percentage of liars for a number of users $N = 20$ and $L =$

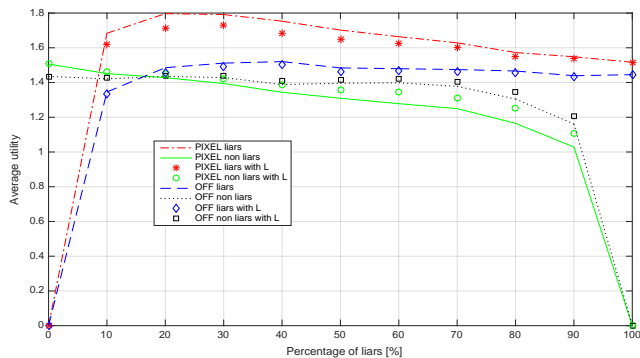


Fig. 14. The average utility of liars and non-liars in PIXEL and OFF for $N = 20$ and $L = 0.5$.

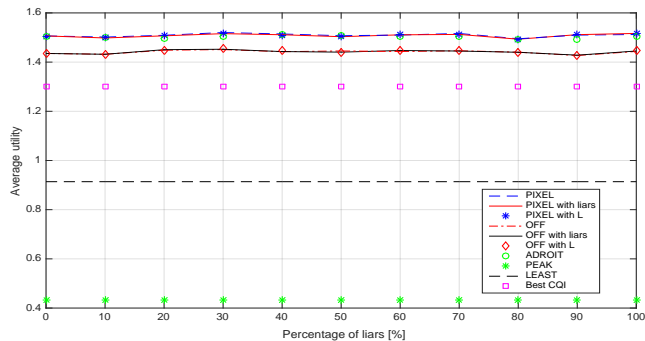


Fig. 15. The average utility of all algorithms for $N = 20$ and $L = 0.5$.

0.5. We see that, using L decreases the number of liars who gain mostly for a low percentage of liars, while, for non-liars, L slightly increases the number of users who gain, mostly for a high percentage of liars. Moreover, the difference between liars and non-liars becomes smaller with L . Also notice that, in general, the immunity parameter L has more impact on PIXEL than on OFF.

Fig. 13 illustrates, for the three proposed algorithms, the same ratio with and without L . Particularly noteworthy is the slope of these curves: an immune algorithm would have a zero slope of the ratio curve (as it is the case for ADROIT which is perfectly immune to lies by design). As we can see in Fig. 13, introducing the immunity parameter L improves a lot PIXEL and OFF immunity to lies, and this is even more noticeable with OFF.

Fig. 14 depicts the average utility of liars and non-liars as function of the percentage of liars for both PIXEL and OFF with and without L , for $N = 20$ and $L = 0.5$. It is shown that, using L and for a low percentage of liars, liars gain less than without L . When the percentage of liars increases, it is normal that we have the same performance with and without L , as the network selection becomes random in this case (similar to the case without ordering). The performance of non-liars is complementary to that of liars: they gain significantly by introducing L for high percentage of liars, while for low percentage of liars they perform almost the same with and without L . Again, this “immunity” effect is even more significant for PIXEL than for OFF.

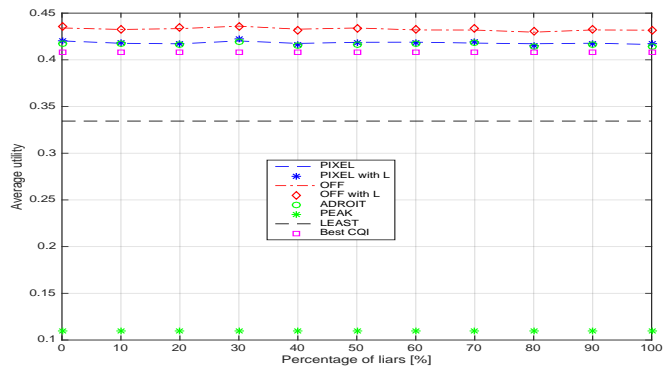


Fig. 16. The average utility of all algorithms for $N = 50$ and $L = 0.5$.

In Fig. 15 (resp. Fig. 16), we plot the average utility of all algorithms for $L = 0.5$ and $N = 20$ (resp. $N = 50$) and compare it to situation when parameter L is not used. Our first observation is that average utilities for all algorithms are not affected by introducing L and constant as functions of P . This is due to the complementary effect between liars and non-liars (as already shown in Fig. 11). Next, we notice that for a low number of users, PIXEL and ADROIT are the best algorithms. As the number of users increases, OFF becomes the best one. In order to have the complete picture, we plot in Fig. 17 the average utility of all algorithms as function of N for $P = 20\%$. When we look closely, for a bigger number of users, the average utilities of PIXEL, OFF and ADROIT become indeed hardly distinguishable, but with a slight advantage for OFF. This is because when lying players claim they have only one good channel, in practice it leads to bigger offloading, and OFF is beneficial for higher number of users.

To resume, PIXEL is the best in terms of utility (with ADROIT) for low N , but it is the least fair. Indeed, the fact that users gain and lose much more often than for OFF and ADROIT can be interpreted as a negative point, although there are much more users who gain with PIXEL. But again, we have to pay attention here because the number of users who gain/lose does not mean that they are far away from their utility in ADROIT or OFF. It is likely that users have a slight increase/decrease in utility (we can see it from Fig. 17, where ADROIT and OFF are very close to PIXEL). This suggests that, in general, ADROIT is the best because it gives (slightly) lower utility than OFF (mainly for high number of users), but it is fair (there is neither gain nor loss due to lies), immune to lies (in the sense that by design it is oblivious to lies) and simpler (there is no Phase B, as for PIXEL and OFF). That said, if one has to choose the best algorithm in an expected interference limited context, it would be OFF with the immunity parameter L , because it gives the best utility and load balancing performances, while all the other performance indicators are second best to ADROIT.

VIII. CONCLUSIONS AND DISCUSSION

While operators continue to rely on their macro cellular networks to improve capacity and user quality, it becomes crucial to find complementary alternatives in local-area scenarios by making further enhancements to LTE deployments,

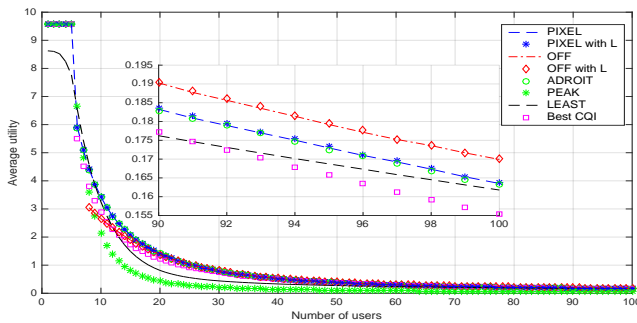


Fig. 17. The average utility of all algorithms for $P = 20\%$ and $L = 0.5$.

as well as creating better possibilities for the integration of LTE and WiFi deployments. In this paper we have proposed a load-aware network selection method in an integrated cellular WiFi system. Both analytical and system level simulation results have shown that the proposed scheme based on the network selection game achieves a good tradeoff between load balancing and 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. We have also proposed a simple procedure in which users have incentive to stick to truthful signaling. Furthermore, we have found here several key remarks that need particular attention: It has appeared that lying increases liars average utility, but the increase is only significant for a small percentage of liars. When the percentage of liars goes large, liars' average utility decreases as network assignment among liars becomes arbitrary rather than profitable. On the other hand, the decrease of utility of truth-tellers is not very significant for any percentage of liars, which confirms our claim that PIXEL and OFF are rather fair in the presence of liars. Noteworthy is the fact that adding the immunity parameter L decreases liars' profitability, while in return, it improves the throughput of those who tell the truth. In particular, we have shown that using L decreases the number of liars who gain mostly for a low percentage of liars, while, for non-liars, L slightly increases the number of users who gain, mostly for a high percentage of liars. Moreover, the difference between liars and non-liars becomes smaller with L . This will further incite lying users to stick to truthful reporting. Finally, ADROIT algorithm which is by design immune to lying, has also shown good performance in terms of load balancing, fairness and utility, while OFF algorithm (using the additional immunity parameter L) has proved to perform the best in an interference limited context.

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APPENDIX

A. Proof of Proposition 1

Proof:

First, see that Algorithm 1 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), $\bar{\alpha}_s^k - \underline{\alpha}_s^k$ decreases twice, thus at most after $\log_2(\delta^{-1})$ passages, $\bar{\alpha}_s^k - \underline{\alpha}_s^k < \delta$, 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 1 constantly decreases α_s^{*k} , the final value $\alpha_s^{*k} = 0$ and the final ordering π_k^* satisfy

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

where k_i denotes the network choice made by player j in part C.1) of Algorithm 2. 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 achieved 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 chosen arbitrarily 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

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

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

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

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 is not smaller than

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

where the first inequality follows from (4), while the second and the last one from the definitions of λ , 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

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

with the first inequality following from (4), the second from the concavity of the logarithm, while the last two from the definitions of $\bar{\lambda}$, 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 1 form an equilibrium in the game. Suppose they do not, that is – there exists a player i who can gain by deviating from 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 1 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

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

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 1 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

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

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

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

C. Proof of Proposition 3

Proof: Note that in Phase C of Algorithms 2 and 3 users choose networks based on the values of their ρ_{jl} . To prove the proposition it is thus enough to show that ρ_{jl} computed by user $j \in \mathcal{L}_s^k$ if he obtains the modified value of \bar{H}_s^k given by Algorithm 5 for any $l \leq M$ will be smaller than those computed for $l > M$.

In general it is clear that for $l \leq M$

$$\rho_{jl} \leq \frac{1}{\bar{\Psi}_j} \log_2 \left(1 + \frac{pH_j}{\sigma^2 + p\bar{H}_s^k} \right) < \frac{1}{\bar{\Psi}_j} \log_2 \left(1 + \frac{pH_j}{p\bar{H}_s^k} \right).$$

Inputting the value of \bar{H}_s^k given by Algorithm 5 we obtain

$$\begin{aligned} & \frac{1}{\bar{\Psi}_j} \log_2 \left(1 + \frac{H_j}{\max_{i \in \mathcal{L}_s^k} H_i} \left(2^{\frac{\min_{l \in \mathcal{W}} D_l}{\bar{m}_k}} - 1 \right) \right) \\ & \leq \frac{1}{\bar{\Psi}_j} \log_2 \left(2^{\frac{\min_{l \in \mathcal{W}} D_l}{\bar{m}_k}} \right) = \frac{1}{\bar{\Psi}_j} \frac{\min_{l \in \mathcal{W}} D_l}{\bar{m}_k} \end{aligned}$$

which is the smallest value of ρ_{jl} for $l > M$. ■

D. Proof of Proposition 4

We precede the actual proof of Proposition 4 with one technical lemma.

Lemma 1. Let $\beta = \sqrt[4]{\frac{4}{3}}$. Then,

$$\log_2 \left(1 + 2^{(\beta^i - 1)\beta^{N-1}} - 2^{-\beta^N} \right) < \beta^{i-1}$$

for $i = 1, \dots, N$.

Proof: First note that

$$1 - 2^{-\beta^N} < 2 - 2^{\beta^{N-1}(\beta-1)} \quad (6)$$

as $2^{\beta^{N-1}(\beta-1)} - 2^{-\beta^N} = 2^{\frac{4}{3}-\beta^{N-1}} - 2^{-\frac{4}{3}} < 2^{\frac{1}{3}} - 2^{-\frac{4}{3}} \approx 0.863 < 1 = 2 - 1$. However, (6) is equivalent to

$$1 + 2^{\beta^{N-1}(\beta^1-1)} - 2^{-\beta^N} < 2^{\beta^{1-1}}$$

and further to

$$\log_2 \left(1 + 2^{\beta^{N-1}(\beta^1-1)} - 2^{-\beta^N} \right) < \beta^{1-1}$$

which is the thesis of the lemma for $i = 1$.

Further, consider the function $f(x) = 2^{\frac{x}{\beta}} - 2^{\beta^{N-1}(x-1)}$. We will show that it is increasing on interval $(1, \frac{4}{3})$.

$$\begin{aligned} f'(x) &= \ln 2 \left[\frac{1}{\beta} 2^{\frac{x}{\beta}} - \beta^{N-1} 2^{\beta^{N-1}(x-1)} \right] \\ &= \frac{\ln 2}{\beta} \left(2^{\frac{x}{\beta}} - \frac{4}{3} 2^{\beta^{N-1}(x-1)} \right). \end{aligned}$$

This is positive iff $2^{\frac{x}{\beta}} > \frac{4}{3} 2^{\beta^{N-1}(x-1)}$ which is equivalent to $\frac{x}{\beta} > \log_2 \left(\frac{4}{3} \right) + \beta^{N-1}(x-1)$ and further to $x > \beta \log_2 \left(\frac{4}{3} \right) + \frac{4}{3}(x-1)$ and $x < 4 - 3\beta \log_2 \left(\frac{4}{3} \right)$. The RHS of this inequality is not smaller than $4 - 4 \log_2 \left(\frac{4}{3} \right) \approx 2.3399 > x$ if x is taken from $(1, \frac{4}{3})$.

The fact that f is increasing on $(1, \frac{4}{3})$ implies that, for $i = 2, \dots, N$, we have by (6)

$$1 - 2^{-\beta^N} < 2 - 2^{\beta^{N-1}(\beta-1)} = f(\beta) < f(\beta^i) = 2^{\beta^{i-1}} - 2^{\beta^{N-1}(\beta^i-1)}.$$

This can be rewritten as

$$1 + 2^{\beta^{N-1}(\beta^i-1)} - 2^{-\beta^N} < 2^{\beta^{i-1}}$$

which is equivalent to the thesis of the lemma for $i = 2, \dots, N$. ■

Now we move to the main part of the proof of the proposition.

Proof: Suppose first that the CQIs for the players are as follows:

$$h_{ik} = \begin{cases} \frac{\sigma^2}{p} & \text{if } k = 1, \dots, M - i \\ \frac{\sigma^2}{p} \left(2^{\beta^{k+i+N-M-1}} - 1 \right) & \text{if } k = M - i + 1, \dots, M \end{cases}$$

while $D_l < 1$ for $l = 1, \dots, W$. Then, $\Psi_i = \beta^{N+i-1}$, always obtained on MeNB M . Moreover, for $i = 1, \dots, N$, user i has exactly i MeNBs $M - i + 1, \dots, M$ giving him the utility of at least β^N if there is no interference, while all other MeNBs and WiFi APs give him the utility of no more than 1. Thus, it is easy to see that $\bar{\alpha}^* = \beta^{-(N-1)}$ and the only network assignment such that each player is assigned to a different network which gives each player i the utility of at least $\bar{\alpha}^* \Psi_i$ connects user i to MeNB $M - i + 1$. On the other hand, if two users, i and j , were connected to the same MeNB $k \geq M - N + 1$ (connecting to any other MeNB or WiFi AP does not make sense, since it gives a utility lower than $\bar{\alpha}^* \Psi_i$ even if there is no interference) user i receives at most

$$\log_2 \left(1 + \frac{p \frac{\sigma^2}{p} (2^{\beta^{N+i-1}} - 1)}{\sigma^2 + p \frac{\sigma^2}{p} (2^{\beta^N} - 1)} \right) = \log_2 (1 + 2^{\beta^{N+i-1}-\beta^N} - 2^{-\beta^N}) < \log_2 (1 + 2^{\beta^{N-1}(\beta^i-1)} - 2^{-\beta^N})$$

which is by Lemma 1 smaller than $\beta^{i-1} < \beta^i = \Psi_i \bar{\alpha}^*$. A similar inequality is true for user j .

Next, suppose that the true channel quality data is

$$\tilde{h}_{Nk} = \begin{cases} \frac{\sigma^2}{p} & \text{if } k = 1, \dots, M - 1 \\ \frac{\sigma^2}{p} \left(2^{\beta^{2N-1}} - 1 \right) & \text{if } k = M \end{cases}$$

with $\tilde{h}_{ik} = h_{ik}$ for $i < N$ and $D_L < l$ for $l = 1, \dots, W$, as before. In this case, user N has one MeNB with channel conditions much better than on the others - $\Psi_i = \beta^{2N-1}$ is obtained on MeNB N with every other MeNB or WiFi AP giving him the utility of at most 1. As a result $\bar{\alpha}^* = \beta^{-N}$

and the only network assignment which gives each player i the utility of at least $\bar{\alpha}^* \Psi_i$ connects player N to MeNB M , players $i = 2, \dots, N-1$ to MeNBs $M-i+1$, while user 1 is assigned to any remaining MeNB. A reasoning similar to the one in the first case can be used to show that connecting two users i and j to the same MeNB will result in both of them receiving less than $\bar{\alpha}^* \Psi_i$ or $\bar{\alpha}^* m_j$, respectively.

Now, suppose that user N 's CQIs are in reality equal to h_{Nk} , $k = 1, \dots, M$. If he claims his real values of CQIs, any algorithm satisfying the assumptions of the proposition should connect him to MeNB $M-N+1$, which will give him the utility of $\log_2 \left(1 + \frac{p\beta^N}{\sigma^2} \right)$. If he lies about his CQIs telling that they are equal to \tilde{h}_{Nk} , $k = 1, \dots, M$, the algorithm must assign him to MeNB M , which gives him the utility of $\log_2 \left(1 + \frac{p\beta^{2N+1}}{\sigma^2} \right)$, so he benefits from lying. ■



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