Rethinking Offload: How to Intelligently Combine WiFi and Small Cells?

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***Abstract*—As future small cell base stations (SCBSs) are set to be multi-mode capable (i.e., transmitting on both licensed and unlicensed bands), a cost-effective integration of both technologies coping with peak data demands is crucial. Using tools from reinforcement learning, a distributed *cross-system* traffic steering framework is proposed whereby SCBSs leverage WiFi, to *autonomously* optimize their *long-term* performance over the licensed spectrum band, as a function of the traffic load and users' heterogeneous Quality of Service (QoS) requirements. The proposed traffic steering solution is validated in a Long-Term Evolution (LTE) simulator augmented with WiFi hotspots. Remarkably, it is shown that the proposed *cross-system* learning-based approach outperforms several benchmark algorithms and traffic steering policies, with gains reaching up to 200% when using a traffic-aware scheduler as compared to the classical proportional fair (PF) scheduler.**

I. Introduction

In order to cope with *peak* data traffic demands, operators are compelled to find new ways to boost their network capacity, provide better coverage, and ease network congestion. By 2016, mobile operators will face the so-called "pain-point" situations in which demand will outweigh capacity, thus calling for innovative and proactive solutions [1], [2], [3]. Since small cells are becoming multi-mode (operating on both licensed and unlicensed bands), leveraging the *already existing* WiFi component can help alleviate network congestion, smartly offload traffic, and achieve cell splitting gains [3].

The idea of integrating WiFi and small cells holds the promise of helping operators solve the capacity crunch problem, exacerbated by network *densification*. Indeed, WiFi technology has limits that small cells can capitalize on, such as in cases of high traffic congestion and load, in which a large number of WiFi users compete in shared but uncontrolled spectrum, yielding dramatically poor throughputs. This caveat is further exacerbated when other devices (laptops, tablets and dongles) transmit on the same unlicensed band. In contrast, a better managed small cell operation transmitting over licensed spectrum yields better performance gains.

In this article[1], we propose a self-organizing traffic offloading framework, through which small cells (seamlessly) steer their traffic between 3G and WiFi radio access technologies (RATs), as a function of (heterogeneous) users' traffic requirements, network load, and interference levels. Inspired from reinforcement learning (RL) theory [4], we build upon our earlier work in [5], by exploring the case where small cells *simultaneously* transmit on the licensed and unlicensed/WiFi bands serving an arbitrary number of users. In a nutshell, leveraging the free but potentially congested WiFi band, small cells engage in a *long-term* self-organizing process by learning their optimal transmission configuration over both licensed/unlicensed bands. The basic idea revolves around offloading traffic to WiFi suitable for delay-tolerant applications, whereas delay-stringent applications (video, streaming, etc) are steered towards the licensed spectrum with QoS guarantees. Furthermore, due to load coupling between 3G and WiFi, the cross-system learning procedure is jointly carried out on 3G and WiFi, in which the learning procedure on WiFi happens on a faster time-scale than on 3G. Besides, and as will be shown, endowing the cross-system learning framework with a traffic-aware scheduler leads to significant gains, outperforming several traffic steering and offloading policies.

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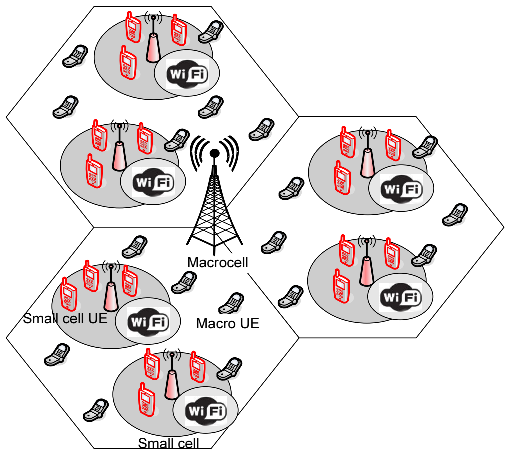

Fig. 1. An illustration of the inter Radio Access Technology Integration.

A. Related work

In [2], the authors compare the system performance when using cell range expansion based and WiFi offloading solutions. Small Cell Forum [6] recently discussed Femto-WiFi integration to provide dual air-interface support for co-located cell coverage locations. Therein, a comprehensive study of use cases, scenarios and challenges of integrated Femto-WiFi networks are presented. In [7], a quantitative study on the performance of 3G mobile data offloading through WiFi networks is studied. In [8], the authors propose a framework for 3G traffic offloading incentivizing mobile users with high delay tolerance to offload their traffic to WiFi. In [9], the authors look at the economical aspects of WiFi offloading. In [10], the authors characterize the coexistence of closed-access femtocells with other unlicensed band users[2]. Nevertheless, while interesting, none of these works deal with the dynamics of small cells and WiFi offloading, nor do they explore the degree of freedom of long-term scheduling.

This paper is organized as follows. In Section II, both system and game models are presented. Section III describes the cross-system learning framework carried out by small cells to learn their optimal transmission strategies, and smartly offload traffic. The distributed traffic steering algorithm coupled with the traffic-aware scheduler are described in Section IV. Finally, numerical results are presented in Section V, and Section VI concludes the paper.

II. System Model

A. Network Model

Let us consider $M = 1$ macrocell base station (MBS) operating over a set $\mathcal{S} = \{1, \ldots, S\}$ of S frequency bands. Consider a set $\mathcal{K} = \{1, \ldots, K\}$ of K SCBSs underlaying the macrocell. Each SCBS is dual-mode and transmits over both licensed and unlicensed bands to serve its UEs (see Fig. 1). Let $p_j^{(s)}$ denote the downlink transmit power of SCBS j on subband (SB) s and $|h_{i,j}^{(s)}|^2$ the channel gain between the SCBS and its associated UE in subband $s \in \mathcal{S}$. $\mathrm{N}_0^{(s)^2}$ is the variance of the additive white Gaussian noise (AWGN) at receiver k, assumed to be constant over all subbands. Let $p_{k,\max}$ with $k \in \mathcal{K}$ be the maximum transmit power of SCBS k. For all $k \in \mathcal{K}$, let the S-dimensional vector $\boldsymbol{p}_k(t) = \left(p_k^{(1)}(t), ..., p_k^{(S)}(t)\right)$ denote the power allocation (PA) vector of SCBS $k \in \mathcal{K}$ at time t. Here, $p_k^{(s)}(t)$ is the transmit power of SCBS k over subband s at time t. All SCBSs are assumed to transmit over the licensed and unlicensed spectrum band at each time t with a given power level not exceeding $p_{k,\max}$. Let $L_k \in \mathcal{N}$ be the number of discrete power levels of SCBS k and denote by $\boldsymbol{q}_k^{(\ell,s)}$ its ℓ-th transmit power level when used over channel s, with $(\ell, s) \in \mathcal{L}_k \times \mathcal{S}$, with $\mathcal{L}_k = \{1, \ldots, L_K\}$. Denote also by $\boldsymbol{q}_k^{(0,0)}$, with $k \in \mathcal{K}$, the S-dimensional null vector, i.e., $\boldsymbol{q}^{(0,0)} = (0, \ldots, 0) \in \mathcal{R}^S$. Thus, SCBS k has $N_k = L_k \cdot S + 1$ possible PA vectors and for all $t \in \mathcal{N}$, $\boldsymbol{p}_k(t) \in \mathcal{A}_k$, where:

$$\mathcal{A}_k = \boldsymbol{q}^{(0,0)} \cup \left\{\boldsymbol{q}_k^{(\ell,s)} : (\ell, s) \in \mathcal{L} \times \mathcal{S}\right\}. \tag{1}$$

The signal-to-interference-plus-noise-ratio (SINR) for SCBS $k \in \mathcal{K}$ serving its user equipments $k_i \in \{1, \ldots K_i\}$ is:

$$\mathrm{SINR}_{k_i}^{(s)} = \frac{|h_{k_i,k_i}^{(s)}|^2 p_{k_i}^{(s)}}{{\sigma_k^{(s)}}^2 + \underbrace{|h_{k_i,0}^{(s)}|^2 p_0^{(s)}}_{\text{MBS}} + \underbrace{\sum_{j \in \mathcal{K}\setminus\{k\}} |h_{k_i,j}^{(s)}|^2 p_j^{(s)}}_{\text{SCBS}}}. \tag{2}$$

Each SCBS k is interested in optimizing its (long-term) utility metric (i.e., small cell throughput) in both licensed and unlicensed spectrum:

$$u_k(\boldsymbol{p}_k, \boldsymbol{p}_{-k}) = \mathbb{E}\Big[\sum_{s=1}^{S} \sum_{k_i=1}^{K_i} \log_2\left(1 + \mathrm{SINR}_{k_i}^{(s)}\right)\Big], \tag{3}$$

B. Game Model

Due to the coupling in transmission strategies, the joint interference management and traffic offloading problem is modeled as a normal-form game $\mathcal{G} = \Big(\mathcal{K}, \{\mathcal{A}_k\}_{k \in \mathcal{K}}, \{u_k\}_{k \in \mathcal{K}}\Big)$. Here, $\mathcal{K}$ represents the set of SCBSs (i.e., players) in the network and for all $k \in \mathcal{K}$, the set of actions of SCBS k is the set of subbands and power allocation vectors $\mathcal{A}_k$ described in (1). We denote by $\mathcal{A} = \mathcal{A}_1 \times ... \times \mathcal{A}_K$ the action set and $u_k : \mathcal{A}_k \to \mathbb{R}^+$ is the payoff function of SCBS k.

At each time t, each SCBS k chooses its action from the finite set $\mathcal{A}_k$ following a probability distribution $\boldsymbol{\pi}_k(t) = \Big(\pi_{k,\boldsymbol{q}_k^{(0,0)}}(t), \pi_{k,\boldsymbol{q}_k^{(1,1)}}(t), ..., \pi_{k,\boldsymbol{q}_k^{(L_k,S_k)}}(t)\Big)$ where $\pi_{k,\boldsymbol{q}_k^{(l_k,s_k)}}$ is the probability that SCBS k plays action $q_k^{(l_k,s_k)}$ at time t, i.e.,

$$\pi_{k,q_k^{(l_k,s_k)}} = \Pr\left(\boldsymbol{p}_k(t) = q_k^{(l_k,s_k)}\right). \tag{4}$$

where $(l_k, s_k) \in \{1, ..., L_K\} \times \mathcal{S} \cup \{(0, 0)\}$.

III. Cross-System Learning Framework for Self-Organizing Radios

A. Rationale

The inter-RAT integration mandates a framework that allows SCBSs to optimize their transmission over the licensed band, by smartly offloading traffic to the WiFi network. For this purpose, we propose a novel framework for self-organizing radios, coined *cross-system learning*. In this framework, SCBSs judiciously steer their traffic over both the licensed and unlicensed spectrum, by learning over time how to select suitable subbands and corresponding power levels in licensed and unlicensed bands. In what follows, we first describe the *cross-system learning* procedure followed by the proactive scheduling mechanism. This scheduling mechanism is traffic-aware and takes into account users' QoS requirements, e.g. throughput and latency.

B. Subband Selection

Driven by the fact that every SCBS needs to learn its long-term utility metric, by transmitting on both licensed and unlicensed bands, we extend our recently proposed learning procedure [5] in two ways: (i) unlike [5], an SCBS serves an arbitrary number of UEs, (ii) unlike the standard proportional fair scheduling, every SCBS schedules its UEs in a proactive manner, by taking into account the instantaneous channel conditions, congestion levels and file sizes. For this purpose,

[2]In this work, the authors focus on a single band (worst case scenario). In addition, femtocells and WiFi hotspots are placed in different houses, and hence do not interfere significantly with each other.

a behavioral rule is defined in which SCBSs strike a balance between minimizing their long-term regret of choosing actions which yield lower regrets than those yielding higher regrets, but in any case always letting a *non-zero* probability of playing any of the actions. This behavioral rule is akin to the exploration-exploitation paradigm [4].

The considered behavioral assumption is that all small cells are interested in choosing a probability distribution $\boldsymbol{\pi}^* \in \triangle(\mathcal{A})$ that minimizes the regret, where the regret of SCBS k for not having played action $q_k^{(\ell_k,s_k)}$ from $n=1$ up to time t is calculated as follows:

$$r_{k,q_k^{(\ell,s)}}(t) = \frac{1}{t}\sum_{n=1}^{t} u_k\left(q_k^{(\ell,s)}, \boldsymbol{p}_{-k}(n)\right) - \tilde{u}_k(n), \quad (5)$$

$\tilde{u}_k(n)$ is the instantaneous utility observation of SCBS k at time n (or feedback). obtained by constantly changing its actions following a particular strategy π_k. Formally speaking, this behavioral rule can be modeled by the probability distribution $\beta_k(\boldsymbol{r}_k^+(t))$ satisfying:

$$\beta_k(\boldsymbol{r}_k^+(t)) \in \arg\min_{\boldsymbol{\pi}_k \in \triangle(\mathcal{A}_k)} \Big[\sum_{\boldsymbol{p}_k\in\mathcal{A}_k} \pi_{k,\boldsymbol{p}_k} r_{k,\boldsymbol{p}_k}(t) + \frac{1}{\kappa_k} H(\boldsymbol{\pi}_k)\Big], \quad (6)$$

where $\boldsymbol{r}_k^+(t) = \max(0, \boldsymbol{r}_k(t))$ denotes the vector of positive regrets, and H represents the Shannon entropy function of the mixed strategy. The *temperature* parameter $\kappa_k > 0$ represents the interest of SCBS k to choose other actions rather than those minimizing the regret in order to improve the estimations of the regret vectors (5). The unique solution to the right-hand-side of the continuous and strictly concave optimization problem in (6) is written as:

$$\beta_k(\boldsymbol{r}_k^+(t)) = \Big(\beta_{k,q_k^{(0,0)}}(\boldsymbol{r}_k^+(t)), \beta_{k,q_k^{(1,1)}}(\boldsymbol{r}_k^+(t)), ..., \beta_{k,q_k^{(L_k,A_k)}}(\boldsymbol{r}_k^+(t))\Big) \quad (7)$$

where $\forall k \in \mathcal{K}$ and for all $(l_k, s_k) \in \mathcal{L}_k \times \mathcal{S}$:

$$\beta_{k,q_k^{(l_k,s_k)}}(\boldsymbol{r}_k^+(t)) = \frac{\exp\left(\kappa_k r^+_{k,q_k^{(l_k,s_k)}}(t)\right)}{\sum_{\boldsymbol{p}_k\in\mathcal{A}_k} \exp\left(\kappa_k r^+_{k,\boldsymbol{p}_k}(t)\right)}, \quad (8)$$

where $\beta_{k,q_k^{(l_k,s_k)}}(\boldsymbol{r}_k^+(t)) > 0$ holds with strict inequality regardless of the regret vector $\boldsymbol{r}_k(t)$. Note that if $r_{k,q_k^{(l_k,s_k)}}(t) > 0$, SCBS $k \in \mathcal{K}$ would have obtained a higher average utility by playing action $q_k^{(\ell_k,s_k)}$ during all the previous stages. Thus, player k regrets for not having done it.

C. Long-Term Scheduling

After the SCBS acquires its subband, it schedules its UEs according to their QoS requirements by considering instantaneous channel conditions and completion time of each transmission. In short, the SCBSs carry out their (long-term) traffic aware scheduling procedure on the resource blocks of the selected subband (in the licensed spectrum), whereas in the unlicensed band, a subband is allocated to a given UE and for a fixed transmission time. By means of the cross-system learning procedure, the SCBS attempts to access the unlicensed band at random time instants through sensing, and selects the unlicensed subband whenever sensed idle for a fixed duration. Otherwise, the SCBS does not access the unlicensed band and waits for the next access opportunity. In what follows, we define three key parameters that describe the channel access procedure in the unlicensed band:

- **Attempt interval**: the period of the access opportunities, which is random for each SCBS.
- **Transmission duration**: the fixed duration during which an SCBS accesses the unlicensed band after a successful channel access attempt. Within this duration, SCBS allocates its selected subband to one UE, either based on a *coverage* or *load* policy. Under the coverage-based policy, the UE with maximum reference signal received power (RSRP) is selected. In the load-based policy, SCBSs strike a balance between LTE and WiFi networks. Here, UEs with non real-time sensitive traffic models (e.g., FTP) are steered towards the unlicensed band based on a set of thresholds.
- **Sensing duration**: the predefined time (1ms) duration during which the SCBS senses the unlicensed band.

The proposed traffic-aware scheduling algorithm incorporates users' traffic requirements and builds on the work in [13]. Notably, the scheduling decision is not only based on the instantaneous channel condition, but also on the completion time (delay), and users' service class. In detail, let $D_{k_i}(t)$ denote the scheduling metric of UE k_i serviced by SCBS i. The proactive scheduling algorithm encompasses the following two phases:

- **Phase I:** Within every small cell, all users are sorted in an ascending order as a function of their remaining file size $X_{k_i}(t)$ and the estimated average data rate $\overline{u}_{k_i}$ of UE k_i. The position of an UE k_i is denoted by $P_{k_i}(t)$, which reflects the priority of an UE according to its expected transmission completion time.
- **Phase II:** Depending on this position, the following cost metric $D_{k_i}(t)$ is calculated:

$$D_{k_i}(t) = \Big(P_{k_i}(t) - 1\Big) - \Big(M_k(t) - P_{k_i}(t) + 1\Big)\left(\frac{X_{k_i}(t)}{\overline{u}_{k_i}} - 1\right), \quad (9)$$

where $M_k(t)$ denotes the number of UEs served by SCBS k at time t, having data in their traffic queue. Finally, the scheduled UE k_i at time instant t is performed for each resource block based on:

$$k_i^* = \arg\min_{k_i} (D_{k_i}(t)) \quad (10)$$

In the simulations, we consider phase I as a benchmark scheduler in which resource block allocation is performed for each UE k_i according to its priority obtained by its position $P_{k_i}(t)$. This scheduler is known as Earliest Deadline First (EDF) [11].

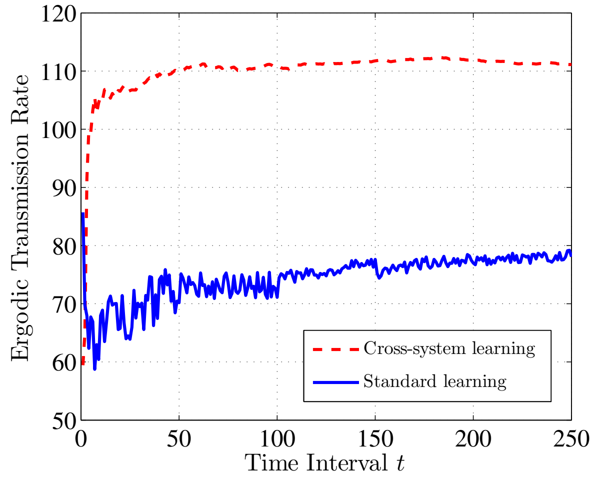

Fig. 2. Convergence of the proposed cross-system learning algorithm vs. standard independent learning.

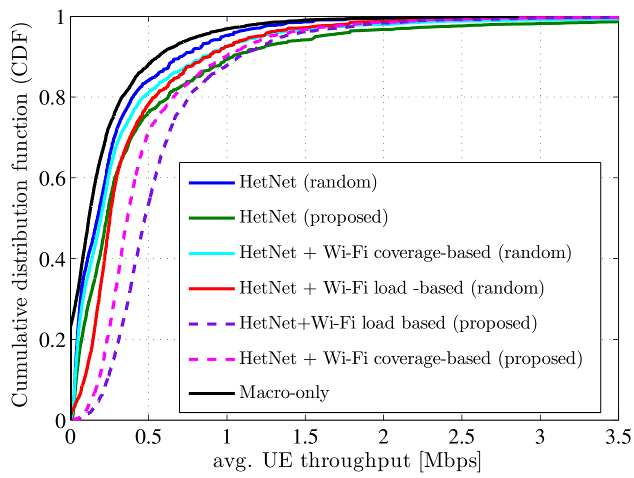

Fig. 3. Cumulative distribution function (CDF) of the average UE throughput for $N_{\text{UE}} = 30$ UEs.

IV. Simulation Results

In this section, we validate the proposed *cross-system learning* framework in an LTE-A simulator integrating WiFi capabilities. In detail, we consider a time and frequency selective multi-carrier WiFi with a mix of traffic distributions. The considered scenario comprises one macrocell consisting of three sectors underlaid with an arbitrary number of K open access small cells operating on both 3G and WiFi. SCBSs are uniformly distributed within each macro sector, while considering a minimum MBS-SCBS distance of 75 m. The path-loss models and other set-up parameters were selected according to the 3rd Generation Partnership Project (3GPP) recommendations for outdoor picocells (model 1) [12]. $N_{\text{UE}} = 30$ mobile UEs were dropped within each macro sector out of which $N_{\text{hotspot}} = \frac{2}{3}N_{\text{UE}}/K$ are randomly and uniformly dropped within a 40 m radius of each SCBS, while the remaining UEs are uniformly dropped within each macro sector. Each UE is assumed to be active, with a fixed traffic model from the beginning of the simulations while moving at a speed of 3 km/h. The traffic mix consists of different traffic models following the requirements of the Next Generation Mobile Networks (NGMN) [14].

The bandwidth in the licensed (resp. unlicensed) band is 5 MHz (resp. 20 MHz). The simulations are averaged over 500 transmission time intervals (TTIs). For sake of comparison, we consider the following cases:

- ***Macro-only**:* The macrocell is the only serving cell of all UEs using the PF scheduler by uniformly distributing its maximum transmission power over the whole bandwidth.
- ***HetNet**:* SCBSs are activated and transmit *only* on the licensed band. Here, both MBS and SCBSs serve their UEs in the licensed band. Uniform power distribution is assumed per subband.
- ***HetNet + WiFi (load-based)**:* each SCBS transmits on both licensed and unlicensed bands by selecting one subband on each licensed and unlicensed band. Access to the unlicensed band is performed based on the load as described in Section III.C. PF scheduling is performed on the licensed band.
- ***HetNet + WiFi (coverage-based)**:* Same as *HetNet + WiFi load-based* except that the access method on the (un)licensed band is based on the maximum reference signal received power criterion.

Fig. 2 plots the convergence behavior of the proposed cross-system learning algorithm in terms of the ergodic transmission rate. Here, we consider 10 UEs per macro sector, with 1.4 MHz bandwidth in the licensed band. In addition, we plot the *standard* RL algorithm [5], in which learning is carried out *independently* over both licensed and unlicensed bands. Quite remarkably, it is shown that the cross-system learning approach converges within less than 50 iterations, while the standard approach [4] needs several hundreds iterations to converge. Furthermore, the standard procedure exhibits an undesirable oscillating behavior (i.e., ping-pong effect between the licensed and unlicensed band).

Fig. 3 plots[3] the cumulative distribution function (CDF) of the average UE throughput for $N_{\text{UE}} = 30$ UEs. While, in the *macro-only* case, 25% of UEs obtain no rate, deploying small cells is shown to increase the performance; especially for cell-edge UEs. In particular, the proposed solution (HetNet+WiFi load-based) yields the best performance, outperforming the other benchmark solutions.

Fig. 4 plots the total cell throughput as a function of the deployed small cells. The proposed cross-system learning approach using the traffic-aware (TA) scheduler outperforms the traditional PF scheduler and earliest deadline first (EDF) scheduler, with gains reaching 200% when deploying 6 small cells. Additionally, Fig. 5 depicts the total cell throughput as a function of the number of UEs in the network. While the

[3]For sake of clarity, in the case of *random*, an SCBS selects randomly one subband and performs PF scheduling, whereas *proposed* refers to the regret-based subband selection with traffic-aware (TA) scheduling.

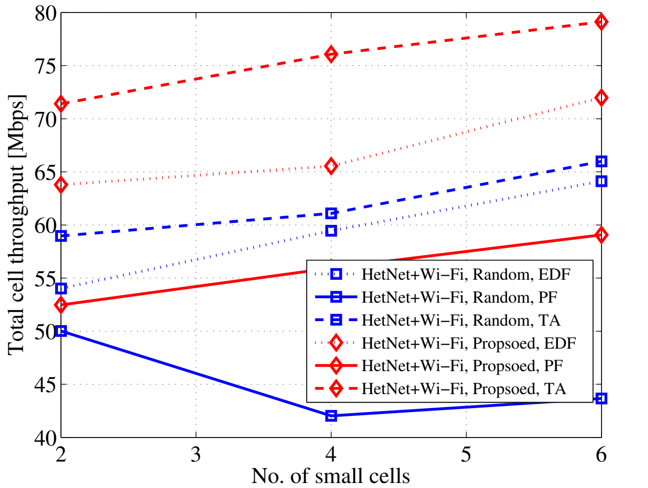

Fig. 4. Overall cell throughput versus the number of deployed small cells, for different scheduling algorithms.

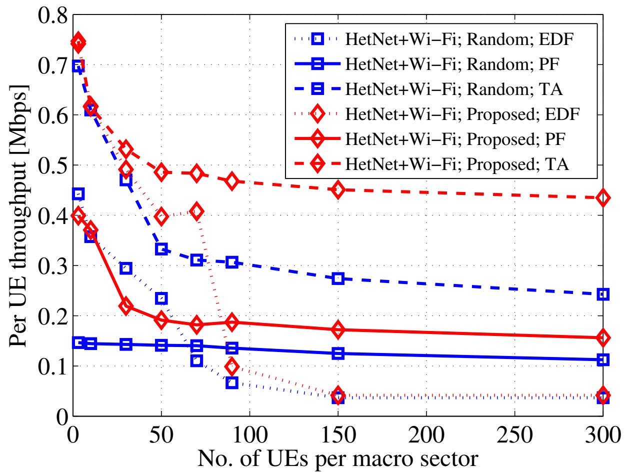

Fig. 6. per UE throughput as a function of the number of UEs.

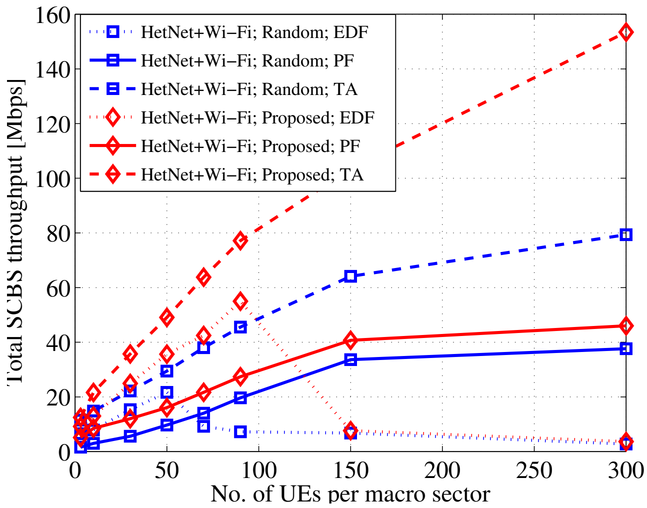

Fig. 5. Total cell throughput vs. number of users.

standard PF-based scheduler cannot cope with the increasing number of UEs, the proposed approach is able to steer users' traffic in an intelligent and dynamic manner over both licensed and unlicensed spectrum, and the gains are pronounced with 300 UEs. Finally, Fig. 6 plots the average UE throughput as a function of the number of users per sector, in which the proposed approach outperforms the benchmark algorithms with traditional schedulers, with 5X more gains as compared to the EDF with 300 UEs.

V. Conclusion

In this paper, the tight integration of 3G/LTE and WiFi networks has been investigated, where SCBSs transmit simultaneously on both licensed and unlicensed bands. We demonstrated that the proposed *cross-system* learning framework allows small cells to optimize their performance, by striking a balance between selecting actions yielding high regrets more often than those with low regret, while experimenting any of the other actions. The *cross-system* learning framework has been shown to exhibit significant improvements in terms of average UE throughput, especially in high load conditions. In future investigations, we will extend the current model to the case of high-mobility users and interplay between mobility, cell association, and interference management.

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