

Learning-Based Joint Power and Channel Assignment for Hyper Dense 5G Networks

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Abstract—Next generation mobile networks will face the unprecedented demand for higher data rates. To satisfy this demand, the dense deployment of heterogeneous wireless networks (HetNets) is a promising solution. One of the major challenges in dense HetNets is to dynamically allocate the resources such as power and channel so that the energy efficiency and throughput of the network improve. One of the important techniques for improving the energy efficiency of the base station (BS) is BS ON-OFF switching which allows the BS to turn off some of its components in lower load situations. On the other side, due to the proximity of BSs in the dense HetNets, co-channel interference (CCI) becomes a critical problem and significantly impacts the performance of the network. In this paper, we propose a dynamic channel assignment based on a learning algorithm (DCA-LA). Moreover, we combine DCA-LA with a BS ON-OFF switching algorithm in order to improve the energy efficiency of the system. In particular, the proposed DCA-LA/ON-OFF switching algorithm is self-organizing and performs in a fully distributed manner. Simulation results indicate that our proposed algorithm balances load among BSs and yields better performance in terms of average energy consumption, average load, average utility per BS and average rate per user, compared to the baseline algorithms.

Index Terms—Heterogeneous Networks; Energy Efficiency; Co-Channel Interference; Learning Algorithm.

I. INTRODUCTION

The anticipated explosive growth in traffic demands envisaged for next generation wireless networks and driven by media-hungry devices (e.g. smart phones and tablets) implies an increasing future energy consumption. In order to support this rapid evolution, new architectures are required. The deployment of heterogeneous wireless networks (HetNets) is a promising approach to address some key challenges in improving the energy and spectral efficiency [1], [2]. Typically, these networks consist of macro base stations (MBSs) overlaid with various classes of low power and low cost nodes such as micro and pico, also called small cell base stations (SBSs) and relay base stations (BSs) [3]. In HetNet, a significant improvement in spectral efficiency can be achieved through an

improved frequency reuse factor [4]. Moreover, these networks can inherently improve the energy efficiency of the system due to the reduced distance between the user and the BS.

On the other hand, BSs' traffic loads dynamically vary in time and space domain. The energy efficiency in the HetNets can be significantly improved by BS ON-OFF switching method and through adjusting BS's transmission power. Cell breathing is another method in which the cell size is adaptively adjusted according to the traffic load conditions [5]. Therefore, the network can be well adapted to spatial and temporal traffic fluctuations.

In [6], an opportunistic ON-OFF switching technique based on a game-theoretic model for the non-cooperative behavior of BSs in a HetNet scenario is proposed. This technique utilizes a distributed learning algorithm for solving the game. For sleeping cell users, a user association scheme based on BSs with maximum mean channel access probability is developed in [7]. This scheme can adapt to the network conditions such as traffic load and scheduling criteria at the active BSs. In [8], a quality of service (QoS)-aware user association scheme based on the cell zooming method is proposed. The network performance problem is modeled based on the graph and optimization theory. Later, for solving the optimization problem, a heuristic iteration algorithm is applied.

However, the dense deployment of HetNets brings some challenges such as co-channel interference (CCI) because of proximity of BSs. As a result, it may significantly degrade the overall performance of the network. Therefore, to enhance the performance of these networks, it is necessary to manage and control the interference. Some challenges in HetNets such as interference management, power control, user association and resource allocation are reviewed in [9]. Since the number of channels allocated to the network is limited, efficient assignment of channels among BSs is an important issue. Several studies have addressed channel assignment problem in wireless networks and suggest some algorithms to mitigate the CCI. Some dynamic channel assignment (DCA) schemes for cellular networks are investigated in [10]–[12]. In [13], an interference-aware channel segregation algorithm is proposed. Several literatures have suggested the channel assignment approaches based on heuristic algorithms such as tabu search, genetic and simulated annealing [14]–[16].

In this paper, we propose a dynamic channel assignment

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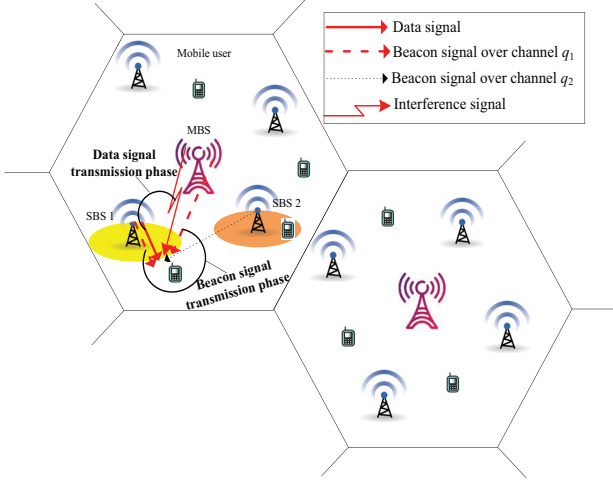


Fig. 1. A typical example of two-tier HetNet.

based on learning algorithm (DCA-LA). Furthermore, we investigate jointly the DCA-LA, user association and BSs with the ability of ON-OFF switching in a two-tier HetNet. We divide the problem into two stages, i.e., cascaded user association and BS operation problem. The BS operation problem comprises of channel assignment and ON-OFF switching problem. We focus on downlink transmission with several channels. Each channel can be used simultaneously at different cells. The channels are sufficiently separated, so that there is no interference among them. Moreover, BSs periodically advertise their estimated loads through beacon signals, similar to [6]. To achieve the distributed implementation, game theory is a rich tool to study interaction between agents. Therefore, we use a game-theoretic approach for formulation of our problems. For solving the problems, we use a regret based learning algorithm. For BS operation problem, BSs learn their power levels and channels by minimizing their regrets for not having selected other power levels and available channels. The combination of DCA-LA with BSs ON-OFF switching (DCA-LA/ON-OFF switching) simultaneously improves the energy efficiency as well as the spectral efficiency. Moreover, it balances load among BSs through offloading users associated with highly loaded BSs to lightly loaded BSs. Please note that the algorithms are executed in a fully distributed manner, without the need of any signaling exchange between BSs.

The remainder of this paper is structured as follows. In Section II, we introduce our system model over a two-tier HetNet and BS's power consumption model. Section III describes the problem formulation including user association and BS operation problem. Furthermore, the proposed joint power and channel allocation algorithm based on no-regret learning approach is provided. The simulation results are presented in Section IV, and finally conclusions are drawn in Section V.

II. SYSTEM MODEL

A. Notations

The regular and boldface symbols represent scalars and matrices, respectively. $|\mathcal{A}|$ denotes the number of elements in the set \mathcal{A} . $\mathbf{X} = \{x_{i,j}\}_{M \times N}$ represents matrix \mathbf{X} with dimension

M -by- N and the set of elements $x_{i,j}$ which $i = 1, \dots, M$ and $j = 1, \dots, N$. The function $\delta_{(condition)}$ denotes the indicator function which equals 1 if *condition* is true and 0 otherwise.

B. Deployment Scenario

We consider a two-tier HetNet with a set of BS \mathcal{B} including a set of MBSs \mathcal{B}_M overlaid with a set of SBSs \mathcal{B}_S , i.e. $\mathcal{B} = \mathcal{B}_M \cup \mathcal{B}_S$. For each hexagonal coverage area, the MBS is located at the center of area and SBSs are uniformly located within the coverage of MBSs. The set of active mobile users uniformly distributed is denoted by \mathcal{K} . Moreover, we assume a single antenna for each user and BS. Fig.1 represents an example of a network realization.

We assume that the total bandwidth W is divided into several orthogonal channels with bandwidth $W/|Q|$ and a central frequency called the carrier frequency where $Q = \{1, \dots, |Q|\}$ is the set of available channels, with $|Q| < |\mathcal{B}|$. Moreover, the MBSs and SBSs can operate in the same channel. Orthogonal frequency division multiplexing (OFDM) symbols are grouped into a collection of physical resource blocks (RBs). We consider the same finite number of available RBs R for all BSs which distribute among their associated users. To avoid interference between uplink and downlink transmission, each user $k \in \mathcal{K}$ transmits and receives over orthogonal channels. For the sake of simplicity, we only consider downlink transmission, i.e. from BSs to users. Moreover, we assume that an open access scheme for all users in the system, i.e. the users are allowed to associate with BSs in any tier, but each user is associated with at most one BS at each time.

Let $P_{m,r}^M(t)$ and $P_{s,r}^S(t)$ be the transmitted power of MBS $m \in \mathcal{B}_M$ and SBS $s \in \mathcal{B}_S$ in RB $r \in R$ at time t , respectively. We denote by $q_{m,r}$ and $q_{s,r}$ the channel which MBS m and SBS s are transmitting over them, respectively. The signal-to-interference-and-noise-ratio (SINR) at the receiver of macro cell user equipment (MUE) $k \in \mathcal{K}$ associated with MBS $m \in \mathcal{B}_M$ transmitting over channel $q_{m,r} \in Q$ and allocated in RB $r \in R$ at time t is defined by (1). In (1), $g_{m,k}^M(t)$ (or $g_{s,k}^S(t)$) denotes the total channel gain including path loss and lognormal shadow fading between MBS m (or SBS s) and user k at time t . Since the time scale for measuring the total channel gain is much larger than the time scale of fast fading, we do not consider fast fading. Let σ^2 be the additive white Gaussian noise (AWGN) power per RB at the receiver of users and assumed to be constant for all users. I_{MBS} and I_{SBS} indicate the interference caused by the MBSs and SBSs. The SINR at the receiver of small cell user equipment (SUE) $k \in \mathcal{K}$ associated with SBS $s \in \mathcal{B}_S$ transmitting over channel $q_{s,r} \in Q$ and allocated in RB $r \in R$ at time t is defined by (2).

From Shannon's capacity formula, the achievable transmission rate of user k from BS b in RB r at time t in bit/sec/Hz is given by

$$R_{k,r}(t) = \frac{W}{|Q|} \log_2(1 + \text{SINR}_{b,k,r}(t)) \quad (3)$$

We assume that new flows arrive into the system according to an inhomogeneous Poisson point process (PPP) with the arrival rate $\lambda_k(t)$ and mean packet size $1/\mu_k(t)$ for user k at

$$\text{SINR}_{m,k,r}(t) = \frac{P_{m,r}^M(t) g_{m,k}^M(t)}{\underbrace{\sum_{\hat{m} \in \mathcal{B}_M, \hat{m} \neq m} P_{\hat{m},r}^M(t) g_{\hat{m},k}^M(t) \delta_{(q_{m,r}=q_{\hat{m},r})}}_{I_{MBS}} + \underbrace{\sum_{\hat{s} \in \mathcal{B}_S} P_{\hat{s},r}^S(t) g_{\hat{s},k}^S(t) \delta_{(q_{m,r}=q_{\hat{s},r})}}_{I_{SBS}} + \sigma^2} \quad (1)$$

$$\text{SINR}_{s,k,r}(t) = \frac{P_{s,r}^S(t) g_{s,k}^S(t)}{\underbrace{\sum_{\hat{m} \in \mathcal{B}_M} P_{\hat{m},r}^M(t) g_{\hat{m},k}^M(t) \delta_{(q_{s,r}=q_{\hat{m},r})}}_{I_{MBS}} + \underbrace{\sum_{\hat{s} \in \mathcal{B}_S, \hat{s} \neq s} P_{\hat{s},r}^S(t) g_{\hat{s},k}^S(t) \delta_{(q_{s,r}=q_{\hat{s},r})}}_{I_{SBS}} + \sigma^2} \quad (2)$$

time t . Therefore, the load density of BS b at time t is defined as $l_b(t) = \left\{ \frac{\lambda_k(t)}{\mu_k(t) R_{k,r}(t)} \mid k \in A_b^{t,r} \right\}$ and the load of BS b at time t is expressed by

$$L_b(t) = \sum_{k \in A_b^{t,r}} l_b(t) \quad (4)$$

where $A_b^{t,r}$ denotes the set of user associated with BS b in RB r at time t defined in Section III.

C. Power Consumption Model

In HetNets, the amount of power consumed by various types of BSs is different. The total power consumed by a BS consists of the transmission power and power consumed by the components of the BS. The main power consuming components of a BS are including power amplifier, radio frequency module, cooling system, baseband unit, DC-DC power supply and main supply. Therefore, the total power consumed by the BSs in the network at time t can be expressed as

$$P_{Network}(t) = \sum_{b \in \mathcal{B}} \sum_{r \in \mathcal{R}} P_{b,r}^{Total}(t) \quad (5)$$

where

$$P_{b,r}^{Total}(t) = P_b^{OFF} + \frac{P_{b,r}^j(t)}{\eta_b^{PA} \Lambda (1 - \lambda_b^{Feed})}, \quad j \in \{M, S\} \quad (6)$$

with

$$P_b^{OFF} = \frac{P_b^{RF} + P_b^{BB}}{\Lambda} \quad (7)$$

and

$$\Lambda = (1 - \lambda_b^{DC}) (1 - \lambda_b^{MS}) (1 - \lambda_b^{Cool}) \quad (8)$$

where $P_{b,r}^{Total}(t)$ and P_b^{OFF} are the total power consumption and the power consumption in OFF mode by BS b in RB r at time t , respectively. P_b^{RF} and P_b^{BB} denote the power of the radio frequency module and the total power of baseband engine consumed by BS b , respectively. η_b^{PA} indicates the power amplifier efficiency of BS b . λ_b^{Feed} , λ_b^{DC} , λ_b^{MS} and λ_b^{Cool} represent losses which are incurred by feeder, DC-DC power supply, main supply and cooling system, respectively. We assume that all parameters except $P_{b,r}^j(t)$ for BSs in any tier are constant over time.

III. PROBLEM FORMULATION

In this section, we present the problem formulation for jointly optimizing the power and channel allocation among BSs. Our goal is to develop a no-regret learning approach to solve the problem formulation presented in this section. At each time t , the HetNet can be configured as the transmission power levels vector, $\mathbf{P}_r(t)$, the channels vector, $\mathbf{Q}_r(t)$, and the association matrix between the users and BSs, $\mathbf{A}^{t,r}$, as follows

$$\begin{aligned} \mathbf{P}_r(t) &= \{P_{b,r}^j(t)\}_{|\mathcal{B}| \times 1}, \quad r \in \mathcal{R}, \quad b \in \mathcal{B}, \quad j \in \{M, S\} \\ \mathbf{Q}_r(t) &= \{q_{b,r}(t)\}_{|\mathcal{B}| \times 1}, \quad \mathbf{A}^{t,r} = \{a_{b,k}^{t,r}\}_{|\mathcal{B}| \times |\mathcal{K}|} \end{aligned} \quad (9)$$

where $q_{b,r}(t)$ is the channel which BS b transmits over it in RB r at time t . Let a binary single element $a_{b,k}^{t,r}$ in matrix $\mathbf{A}^{t,r}$ represents the association relation between user k and BS b such that $a_{b,k}^{t,r} = 1$ indicates user k is associated with BS b at time t otherwise $a_{b,k}^{t,r} = 0$. For each BS $b \in \mathcal{B}$, we define a utility function which is a difference between its benefit and cost. The benefit corresponds with the fraction of users associated with it. The cost function for each BS is including its total energy consumption and load. The weighted benefit function $n_b^r(t)$ and cost function $c_b^r(t)$ for BS b in RB r at time t can be expressed as [17]

$$n_b^r(t) = \omega_b^n \frac{|A_b^{t,r}|}{|\mathcal{K}|} \quad (10)$$

$$c_b^r(t) = \omega_b^l L_b(t) + \omega_b^p P_{b,r}^{Total}(t) \quad (11)$$

where

$$A_b^{t,r} = \left\{ k \mid k \in \mathcal{K} \text{ and } a_{b,k}^{t,r} = 1 \right\} \quad (12)$$

where ω_b^n , ω_b^l and ω_b^p denote the weight parameters which indicate the impact of subscription benefit, load and energy on the utility function for each BS $b \in \mathcal{B}$, respectively. $A_b^{t,r}$ denotes the set of users associated with BS b in RB r at time t . Hence, we define the utility function of BS b in RB r at time t as

$$\begin{aligned} \pi_b^r(t) &= n_b^r(t) - c_b^r(t) = \\ &= \omega_b^n \frac{|A_b^{t,r}|}{|\mathcal{K}|} - (\omega_b^l L_b(t) + \omega_b^p P_{b,r}^{Total}(t)) \end{aligned} \quad (13)$$

The overall goal is to maximize the total system utility.

$$\begin{aligned} & \max_{\{\mathbf{P}_r(t)\}, \{\mathbf{Q}_r(t)\}, \{\mathbf{A}^{t,r}\}} \sum_{\forall b \in \mathcal{B}} \sum_{\forall r \in \mathcal{R}} \pi_b^r(t) \\ \text{subject to} & \quad 0 \leq L_b(t) \leq 1, \forall b \in \mathcal{B} \\ & \quad \sum_{r \in \mathcal{R}} P_{b,r}^j(t) \leq P_b^{Max} \\ & \quad q_{b,r}(t) \in \mathcal{Q}, j \in \{M, S\}, \forall b \in \mathcal{B} \end{aligned} \quad (14)$$

where P_b^{Max} denotes the maximum transmit power of BS b . Since BS operation and user association mechanisms have a highly complex relation to each other, solving the above problem is very challenging. In (14), we decompose the optimization problem into two problems, i.e., user association problem and BS operation problem.

A. User Association Problem

In this subsection, given the set of BSs, we define the user's association rule. At each time, the set of dropped users at previous time, \mathcal{D} , the set of users belonging to BSs switched to OFF mode, \mathcal{O} , and the set of new users joined to the network, \mathcal{N} , should perform new association processes in order to assign to new BSs. We assume that each BS $b \in \mathcal{B}$ broadcasts its estimated load through a beacon signal in the downlink transmission. Moreover, each user $k \in \mathcal{K}$ is associated with at most one BS at each time t , i.e. $\max_{b \in \mathcal{B}} a_{b,k}^{t,r} = 1$.

At time t , user k is associated with BS b_k^* based on the BSs' estimated load and received power at its location according to rule (15). In (15), β_b denotes the cell range expansion bias used by SBS $b \in \mathcal{B}_S$ in order to effectively expand its coverage area. By convention, MBSs have a bias 1(0 dB) [18]. Let $\hat{L}_b(t)$ indicates the estimated load of BS $b \in \mathcal{B}$ at time t and is obtained according to:

$$\hat{L}_b(t) = \left(1 - \left(\frac{1}{t}\right)^\alpha\right) \hat{L}_b(t-1) + \left(\frac{1}{t}\right)^\alpha L_b(t-1) \quad (16)$$

where $\alpha > 0$ is learning rate exponent for the load estimation.

B. BS Operation Problem: Joint Power and Channel Assignment

In this subsection, we focus on BS operation problem including power and channel assignment. The achievable throughput of a BS depends on its and other BSs operations due to the interference. Therefore, we utilize game theory as a useful tool to study the strategic behavior of BSs. We apply the following non-cooperative game. The normal form of game is expressed as $\mathcal{G} = \langle \mathcal{B}, \mathcal{S}_{b \in \mathcal{B}}(s_{-b}), \{\pi_b^r\}_{b \in \mathcal{B}} \rangle$, where \mathcal{B} represents the set of BSs as players, $\mathcal{S}_{b \in \mathcal{B}}(s_{-b})$ is the strategy set of player b composed of transmission power and channel, s_{-b} is the strategies of all players other than player b , and π_b^r is the utility function of player b defined in (13). Each player $b \in \mathcal{B}$ aims at maximizing its utility function. Then, a no-regret learning approach is used to solve the BS operation problem in order to select power and channel and consequently obtain ϵ -coarse correlated equilibrium. We note that the set of correlated equilibria is nonempty, closed and convex in every finite game. The algorithm is a probabilistic

learning procedure in which each strategy is played with non-zero probability and based on a regret measure. This type of learning algorithms has a good potential to learn mixed strategy equilibria. In our proposed algorithm, the BSs learn their environment and optimize their performances by modifying their transmission power levels and channels. Moreover, they impact the performance of other neighboring BSs, by minimizing their regrets for not having selected other strategies. The proposed algorithm is particularly useful because it does not need to exchange information in the network. In the following section, the learning procedure is described and then we divide the problem into two sub-problems, ON-OFF switching and channel assignment sub-problem. Let $I_{b,s_b}^r(t)$, $\hat{I}_{b,s_b}^r(t)$ and $\hat{\pi}_{b,s_b}^r(t)$ denote the average CCI power, the average CCI power estimation and the utility estimation for strategy $s_b \in \mathcal{S}_b$ in RB r at time t , respectively. We define $W_{b,s_b}^r(t) := \delta_{(\epsilon=0)} \pi_{b,s_b}^r(t) - \delta_{(\epsilon=1)} I_{b,s_b}^r(t)$ and $\widehat{W}_{b,s_b}^r(t) := \delta_{(\epsilon=0)} \hat{\pi}_{b,s_b}^r(t) - \delta_{(\epsilon=1)} \hat{I}_{b,s_b}^r(t)$, where ϵ is the indicator parameter in which $\epsilon = 0$ the problem focuses on power assignment sub-problem while $\epsilon = 1$ the problem reduces to the channel assignment sub-problem. For each value $\epsilon \in \{0, 1\}$, the regret estimation vector $\hat{\mathbf{r}}_{b,r}^\epsilon(t+1) = \left\{ \hat{r}_{b,s_b,r}^\epsilon(t+1) \right\}_{|\mathcal{S}_b| \times 1}$ and probability distribution vector $\mathcal{P}_{b,r}^\epsilon(t+1) = \left\{ \mathcal{P}_{b,s_b,r}^\epsilon(t+1) \right\}_{|\mathcal{S}_b| \times 1}$ are updated as follows [6]:

$$\begin{aligned} \hat{r}_{b,s_b,r}^\epsilon(t+1) &= \left(1 - \left(\frac{1}{t+1}\right)^\zeta\right) \hat{r}_{b,s_b,r}^\epsilon(t) \\ &+ \left(\frac{1}{t+1}\right)^\zeta \left(\widehat{W}_{b,s_b}^r(t+1) - W_{b,s_b}^r(t+1)\right) \end{aligned} \quad (17)$$

$$\begin{aligned} \mathcal{P}_{b,s_b,r}^\epsilon(t+1) &= \left(1 - \left(\frac{1}{t+1}\right)^\nu\right) \mathcal{P}_{b,s_b,r}^\epsilon(t) \\ &+ \left(\frac{1}{t+1}\right)^\nu G_{b,s_b}(\hat{\mathbf{r}}_{b,r}^\epsilon(t+1)) \end{aligned} \quad (18)$$

where $\zeta > 0$ and $\nu > 0$ denote the learning rate exponent for regret and probability, respectively. Here, $\mathbf{G}_b = \{G_{b,s_b}\}_{|\mathcal{S}_b| \times 1}$ is the Boltzmann-Gibbs distribution vector defined as follow:

$$G_{b,s_b}(\hat{\mathbf{r}}_{b,r}^\epsilon(t+1)) = \frac{\exp\left(\frac{1}{\theta_b} \hat{r}_{b,s_b,r}^\epsilon(t+1)\right)}{\sum_{\forall \acute{s}_b \in \mathcal{S}_b} \exp\left(\frac{1}{\theta_b} \hat{r}_{b,\acute{s}_b,r}^\epsilon(t+1)\right)} \quad (19)$$

for all $\acute{s}_b \in \mathcal{S}_b$, where $\frac{1}{\theta_b} > 0$ denotes the temperature parameter for player b . Now, we divide the problem into two sub-problems, ON-OFF switching sub-problem and channel assignment sub-problem.

C. Sub-Problem 1: ON-OFF Switching

For a given channel vector $\mathbf{Q}_r(t)$, the MBSs and SBSs select their transmission power levels from the set of $\{0, P_b^{Max} | b \in \mathcal{B}_M\}$ and $\{0, 1/3P_b^{Max}, 2/3P_b^{Max}, P_b^{Max} | b \in \mathcal{B}_S\}$, respectively. For solving the sub-problem, we set $\epsilon = 0$. Therefore, we

$$b_k^*(t) = \underset{b \in \mathcal{B}, j \in \{M, S\}}{\operatorname{argmax}} \left\{ P_{b,r}^j(t) (\beta_b \delta_{(b \in \mathcal{B}_S)} + 1 \delta_{(b \in \mathcal{B}_M)}) g_{b,k}^j(t) (1 - \hat{L}_b(t)) \right\} \quad (15)$$

have $W_{b,s_b}^r(t) := \pi_{b,s_b}^r(t)$ and $\widehat{W}_{b,s_b}^r(t) := \hat{\pi}_{b,s_b}^r(t)$. At each time t , each BS $b \in \mathcal{B}$ updates its utility estimation according to [6]

$$\begin{aligned} \hat{\pi}_{b,s_b}^r(t+1) &= \left(1 - \delta_{(s_b(t+1)=s_b(t))} \left(\frac{1}{t+1} \right)^\kappa \right) \hat{\pi}_{b,s_b}^r(t) \\ &\quad + \delta_{(s_b(t+1)=s_b(t))} \left(\frac{1}{t+1} \right)^\kappa \pi_{b,s_b}^r(t+1) \end{aligned} \quad (20)$$

where κ denotes the learning rate exponent for utility estimation. Then, each BS $b \in \mathcal{B}$ updates the regret estimation and the probability distribution vector for $\epsilon = 0$ according to (17) and (18), respectively.

D. Sub-Problem 2: Channel Assignment

In this subsection, we focus on channel assignment sub-problem and propose a novel channel assignment algorithm based on no-regret learning approach, called DCA-LA. In particular, DCA-LA functions in a distributed manner. Thus, no central controller is needed. The performance of DCA-LA is compared with two channel assignment algorithms, i.e., an interference-aware dynamic channel selection (IADCS) algorithm and a hybrid IADCS joint with a BS sleep mode algorithm [13]. In IADCS algorithm, each BS transmits with its maximum power and evaluates average CCI power over each channel and finally selects the channel with minimum average CCI.

• Proposed Dynamic Channel Assignment Based on Learning Algorithm

In IADCS algorithm, at each time, the BS selects the channel with minimum average CCI. In dense HetNets scenarios due to proximity of BSs, they experience almost the same average CCI. Therefore, there is a high possibility that neighboring BSs select the same channel at the same time. In this regard, we propose a learning algorithm for channel assignment problem in which each BS assigns higher probability to the channel with more regret and a non-zero probability is assigned to each channel. It will reduce the chance of two adjacent cells selecting the same channel. Each player is interested in minimizing its average regret over time. For solving the sub-problem, we set $\epsilon = 1$. Therefore, we have $W_{b,s_b}^r(t) := -I_{b,s_b}^r(t)$ and $\widehat{W}_{b,s_b}^r(t) := -\hat{I}_{b,s_b}^r(t)$. With the power selected discussed in the ON-OFF switching sub-problem, each BS $b \in \mathcal{B}$ updates the average CCI vector $\hat{I}_b^r(t+1) = \left\{ \hat{I}_{b,q}^r(t+1) \right\}_{|\mathcal{Q}| \times 1}$ for each channel $q \in \mathcal{Q}$ according to [13]

$$\begin{aligned} \hat{I}_{b,q}^r(t+1) &= \left(1 - \left(\frac{1}{t+1} \right)^\phi \right) \hat{I}_{b,q}^r(t) \\ &\quad + \left(\frac{1}{t+1} \right)^\phi I_{b,q}^r(t+1) \end{aligned} \quad (21)$$

where ϕ and $I_{b,q}^r(t+1)$ denote the learning rate exponent for average interference estimation and average CCI power over channel q in RB r at time $t+1$, respectively. Later, each player $b \in \mathcal{B}$ randomizes over the set of available channels according to a mixed strategy $\mathcal{P}_{b,r}^1(t+1) = \left\{ \mathcal{P}_{b,q,r}^1(t+1) \right\}_{|\mathcal{Q}| \times 1}$. The elements of the vector $\mathcal{P}_{b,r}^1(t+1)$ are proportional to regrets for not having selected other channels. The regret estimation vector $\hat{\mathbf{r}}_{b,r}^1(t+1) = \left\{ \hat{r}_{b,q,r}^1(t+1) \right\}_{|\mathcal{Q}| \times 1}$ and probability distribution vector $\mathcal{P}_{b,r}^1(t+1)$ are updated according to (17) and (18), respectively. The pseudo code for our proposed algorithm is summarized in Algorithm 1.

Algorithm 1 : Proposed algorithm.

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1: Input:  $\mathcal{D}, \mathcal{O}, \mathcal{N}, \widehat{W}_{b,s_b}^r(t), \hat{\mathbf{r}}_{b,r}^\epsilon(t), \mathcal{P}_{b,r}^\epsilon(t)$ 
2: Output:  $\mathbf{A}^t, \widehat{W}_{b,s_b}^r(t+1), \hat{\mathbf{r}}_{b,r}^\epsilon(t+1), \mathcal{P}_{b,r}^\epsilon(t+1)$ 
3: Initialization:  $\mathcal{B} = \{1, \dots, |\mathcal{B}|\}, \mathcal{K} = \{1, \dots, |\mathcal{K}|\}, \mathcal{S}_b = \{1, \dots, |\mathcal{S}_b|\}, \epsilon \in \{0, 1\}, t = 1$ 
4: while do
5:   for  $\forall r \in R$  do
6:     for  $\forall b \in \mathcal{B}$  and  $j \in \{M, S\}$  do
7:       Find  $s_b(t)$ 
8:       Advertise estimated load  $\hat{L}_b(t)$ 
9:     end for
10:    for  $\forall k \in \mathcal{K}$  do
11:      if  $(k \in \mathcal{D}) \vee (k \in \mathcal{O}) \vee (k \in \mathcal{N})$  then
12:        Find  $b_k^*(t)$ 
13:      end if
14:    end for
15:    Updating:  $\mathbf{A}^{t,r}$ 
16:    for  $\forall b \in \mathcal{B}$  do
17:      Calculations:  $L_b(t), \pi_{b,s_b}^r(t)$ 
18:    end for
19:    for  $\forall b \in \mathcal{B}$  do
20:      for  $\forall q \in \mathcal{Q}$  do
21:        Calculation:  $I_{b,q}^r(t)$ 
22:      end for
23:    end for
24:    for  $\forall \epsilon \in \{0, 1\}$  do
25:      for  $\forall b \in \mathcal{B}$  do
26:        Updating:  $\widehat{W}_{b,s_b}^r(t+1), \hat{\mathbf{r}}_{b,r}^\epsilon(t+1), \mathcal{P}_{b,r}^\epsilon(t+1)$ 
27:      end for
28:    end for
29:  end for
30:   $t \leftarrow t + 1,$ 
31: end while

```

IV. SIMULATION RESULTS

In this section, we provide the simulation results for three algorithms, i.e., IADCS algorithm, the joint ON-OFF switching and dynamic channel allocation algorithm proposed in [13]

TABLE I
SYSTEM-LEVEL SIMULATION PARAMETERS

| System Parameters | | |
|---|---------------------------------------|---------------------------------------|
| Parameter | Value | |
| Physical link type | Downlink | |
| Carrier frequency/ Channel bandwidth | 2 GHz/ 10 MHz | |
| Noise PSD | -174 dBm/Hz | |
| Traffic model | Full buffer | |
| Mean packet arrival rate | 1800 Kbps | |
| θ_b | 0.1 | |
| Weights $\omega_b^r, \omega_b^l, \omega_b^p$ | 1, 0.5, 0.5 | |
| Learning rate exponent $\kappa, \phi, \zeta, \nu, \alpha$ | 0.6, 0.6, 0.7, 0.8, 0.9 | |
| BSs Parameters | | |
| Parameter | MBS | PBS |
| Maximum power | 46 dBm | 30 dBm |
| Shadowing standard deviation | 8 dB | 10 dB |
| Radius cell | 250 m | 40 m |
| Distance-dependent path loss model | $128.1+37.6\log_{10}(d)$ d in Km | $140.7+37.6\log_{10}(d)$ d in Km |
| Minimum distance | MBS-SBS: 75m MBS-User: 35m | SBS-SBS: 40m SBS-User: 10m |

and our proposed DCA-LA/ON-OFF switching algorithm, using performance criteria such as average load per BS, average utility per BS, average energy consumption per BS and average rate per user. For our simulation, we consider a single hexagonal cell served by one MBS and the set of SBSs with 4 available channels, i.e. $|Q| = 4$. The communications are carried out in full buffer in accordance to the system parameters shown in Table I.

Fig. 2 shows average energy consumption per BS vs different number of SBSs for 30 active users. We can observe that, as the number of SBSs increases, the average energy consumption per BS decreases. Moreover, for a given number of SBSs, our proposed approach consumes less energy compared to the other approaches. However, the improvement over IADCS algorithm is more than the proposed algorithm in [13]. The main reason is that the proposed algorithm in [13] utilizes a sleep mode mechanism for unnecessary BSs whereas in IADCS algorithm, each BS transmits with its maximum power. For instance, at the number of SBSs 20, the proposed algorithm improves average energy consumption per BS about 4% and 32% over the proposed algorithm in [13] and IADCS algorithm, respectively.

In Fig. 3, we compare the average utility per BS vs different number of SBSs for 30 active users. We can see that, our proposed algorithm has the best utility among the other approaches. For instance, at the number of SBSs 15, it improves the average payoff per BS about 34% and 50% over the algorithm proposed in [13] and IADCS algorithm, respectively.

Fig. 4 compares the average rate per user vs different number of users for 10 SBSs. As the number of users increases, the average rate per user decreases. It is shown that the proposed DCA-LA/ON-OFF switching algorithm significantly outperforms the other algorithms. For instance, at the number of users 40, the average rate per user is improved around 16% and 41% as compared to the proposed algorithm in [13] and IADCS algorithm, respectively.

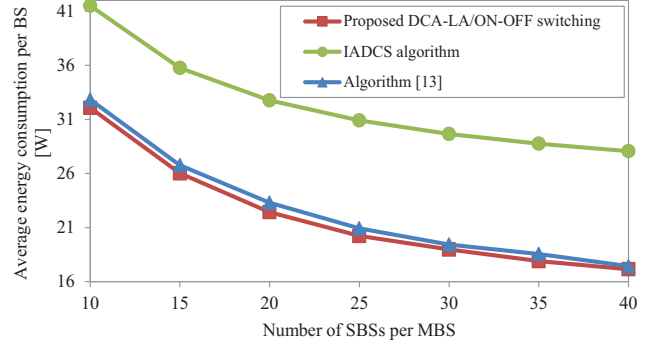


Fig. 2. Average energy consumption per BS vs the number of SBSs, given 30 users.

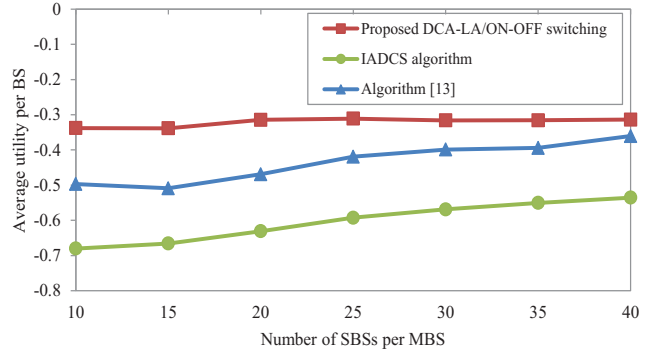


Fig. 3. Average utility per BS vs the number of SBSs, given 30 users.

Fig. 5 plots the average load per BS vs different number of users, with 10 SBSs. As the number of users increases, the average load per BS increases. We can observe that, our proposed DCA-LA/ON-OFF switching algorithm outperforms the other algorithms in term of average load per BS through offloading users associated with highly loaded BSs to lightly loaded BSs. For instance, at the number of users 40, the proposed algorithm improves the average load per BS about 33% over the proposed algorithm in [13].

Fig. 6 illustrates the average utility per BS vs different number of users, with 10 SBSs. As the number of users increases, the average utility per base station decreases. Our proposed algorithm has better average utility per BS than the other approaches. For instance, at the number of users 40, our proposed algorithm improves the average utility per BS about 20% and 37% over the proposed algorithm in [13] and IADCS algorithm, respectively.

V. CONCLUSION

In this paper, we proposed a dynamic channel assignment based on learning algorithm (DCA-LA). Later we combined this algorithm with BSs ON-OFF switching for jointly optimizing power and channel allocation. The proposed DCA-LA/ON-OFF switching algorithm is fully distributed and uses a game theoretic approach in which each BS selects its transmission power and channel based on a no-regret learning algorithm. The proposed algorithm balances the load among BSs and therefore improves system throughput and consequently yields a better spectral efficiency. As a result, our pro-

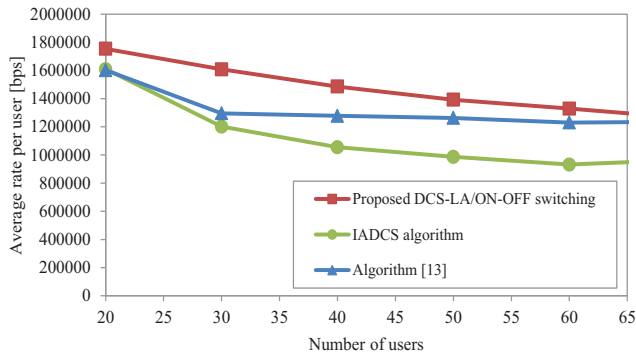


Fig. 4. Average rate per user vs the number of users, given 10 SBSs.

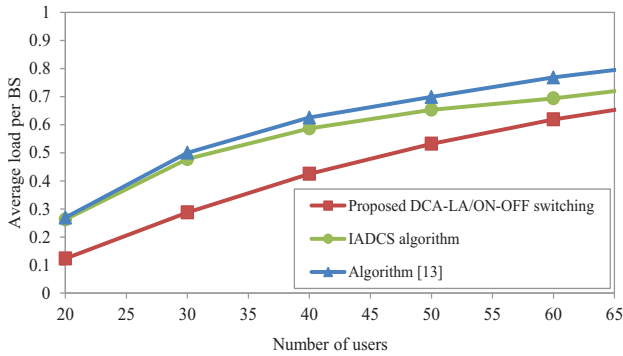


Fig. 5. Average load per BS vs the number of users, given 10 SBSs.

posed algorithm achieves both energy- and spectral- efficiency. Simulation results showed that, the proposed DCA-LA/ON-OFF switching algorithm provides a better performance over the baseline algorithms and significantly outperforms them in terms of average energy consumption, average load, average utility per BS and average rate per user.

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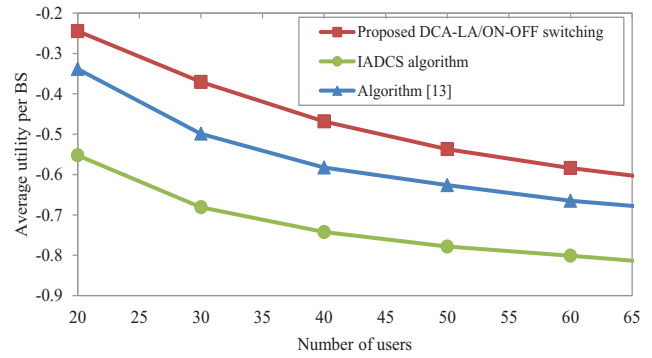


Fig. 6. Average utility per BS vs the number of users, given 10 SBSs.

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