A Dynamic Resources Allocation Based on Learning Algorithm for Dense HetNets

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***Abstract*—One of the key challenges in dense heterogeneous wireless networks (HetNets) is to dynamically allocate the resources such as power and channel in order to improve the energy efficiency and throughput of the network. In this paper, we propose a dynamic channel assignment based on a learning algorithm. Moreover, we combine it with a BS ON-OFF switching algorithm in order to improve the energy efficiency of the system. Especially, our proposed algorithm performs in a fully distributed way. Simulation results show that our proposed algorithm yields better performance in terms of average energy consumption and throughput compared to the baseline algorithms.**

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

I. Introduction

The anticipated explosive growth in traffic demands in next generation wireless networks drives a significant growth in energy consumption of the wireless networks. Heterogeneous wireless networks (HetNets) consisting of macro base stations (MBSs), small cell base stations (SBSs) and relay nodes can be a promising approach to improve the energy and spectral efficiency of the system [1]–[3]. On the other hand, due to users mobility and bursty nature of data and video applications, the traffic load of wireless networks dynamically varies in time and space domain [4].

Several literatures have investigated energy efficiency problem in low load situations and suggested some solutions such as BSs ON-OFF switching and cell breathing to assist in the reduction of energy consumption in the networks. In [5], an opportunistic ON-OFF switching technique based on a non-cooperative game-theoretic model is proposed. For solving the proposed game, a distributed learning algorithm is applied. In [6], a basic switching off BSs with considering the time varying characteristic of the traffic profile is proposed. In [7], authors proposed a centralized sleep/wakeup scheme for a two-tier HetNet composed of macro and femto BSs. In [4], centralized and distributed cell zooming algorithms based on the traffic load, user requirements and channel conditions are proposed.

The research results presented in this material have been achieved by ”Towards Energy-Efficient Hyper-Dense Wireless Networks with Trillions of Devices”, the Commissioned Research of National Institute of Information and Communications Technology (NICT), JAPAN and KDDI foundation research grant, ”Energy-Efficient Radio Resource Management for Next Generation Wireless Network”

However, in the dense deployment of HetNets, because of proximity of BSs, co-channel interference (CCI) problem becomes a critical problem and significantly impacts on the performance of the network. Therefore, efficient assignment and sharing of channels among BSs is an important issue. In [8], an interference-aware channel segregation algorithm is proposed. Several studies have suggested the channel assignment approaches based on heuristic algorithms such as tabu search and genetic algorithm [9], [10].

In this paper, we propose a dynamic channel assignment 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. Moreover, BSs periodically advertise their estimated loads through beacon signals, similar to [5]. To achieve the distributed implementation, we use a game-theoretic approach for formulation of our problems. For solving the problems, we use a regret based learning algorithm. 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. Please note that the algorithms are executed in a fully distributed manner, without the need of any signalling exchange between BSs.

The reminder of this paper is structured as follows. In Section II, we introduce our system model and BS's power consumption model. Section III describes the problem formulation and provides the proposed joint power and channel allocation algorithm based on no-regret learning approach. The simulation results are presented in Section IV, and finally conclusions are drawn in Section V.

II. System Model

A. 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. $\mathcal{B} = \mathcal{B}_M \cup \mathcal{B}_S$. The MBS is located at the center of area and SBSs are uniformly located within the coverage of MBSs.

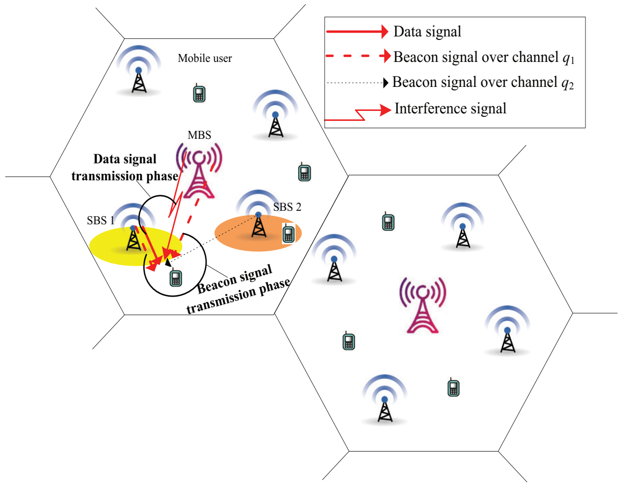

Fig. 1. A typical example of two-tier HetNet.

The set of active mobile users uniformly distributed is denoted by $\mathcal{K}$. Fig.1 represents an example of a network realization. Moreover, we assume that the total bandwidth W is divided into several orthogonal channels with bandwidth $W/|\mathcal{Q}|$ where $\mathcal{Q} = \{1, \ldots, |\mathcal{Q}|\}$ is the set of available channels, with $|\mathcal{Q}| < |\mathcal{B}|$. 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. For the sake of simplicity, we only consider downlink transmission, i.e. from BSs to users.

Let $P_{b,r}(t)$ be the transmitted power of BS $b \in \mathcal{B}$ in RB $r \in R$ at time t. We denote by $q_{b,r}$ the channel which BS b are transmitting over it. The signal-to-interference-and-noise-ratio (SINR) at the receiver of user $k \in \mathcal{K}$ associated with BS $b \in \mathcal{B}$ transmitting over channel $q_{b,r} \in \mathcal{Q}$ and allocated in RB $r \in R$ at time t is defined by

$$SINR_{b,k,r}(t) = \frac{P_{b,r}(t)\ g_{b,k}(t)}{\sum_{\acute{b}\in\mathcal{B},\ \acute{b}\neq b} P_{\acute{b},r}(t) g_{\acute{b},k}(t)\ \delta_{(q_{b,r}=q_{\acute{b},r})} + \sigma^2} \tag{1}$$

where $g_{b,k}(t)$ denotes the total channel gain including path loss and lognormal shadow fading between BS b and user k at time t. Let σ^2 be the power spectral density (PSD) of additive white Gaussian noise (AWGN) per RB at the receiver of users. 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

$$R_{k,r}(t) = \frac{W}{|\mathcal{Q}|}\log_2(1 + SINR_{b,k,r}(t)) \tag{2}$$

We assume that new flows arrive into the system with the arrival rate $\lambda_k(t)$ and the traffic sizes which are independently distributed with mean $1/\mu_k(t)$ for user k at time t. Therefor, the load density of BS b at time t is defined as $l_b(t) = \left\{ \frac{\lambda_k(t)}{\mu_k(t)R_{k,r}(t)} \middle| k \in A_b^{t,r} \right\}$ and the load of BS b at time t is expressed by

$$L_b(t) = \sum_{k\in A_b^{t,r}} l_b(t) \tag{3}$$

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

B. Power Consumption Model

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

$$P_{Network}(t) = \sum_{b\in B}\sum_{r\in R} P_{b,r}^{Total}(t) \tag{4}$$

where

$$P_{b,r}^{Total}(t) = P_b^{OFF} + \frac{P_{b,r}(t)}{\eta_b^{PA}\Lambda(1-\lambda_b^{Feed})} \tag{5}$$

with

$$P_b^{OFF} = \frac{P_b^{RF} + P_b^{BB}}{\Lambda} \tag{6}$$

and

$$\Lambda = \left(1-\lambda_b^{DC}\right)\left(1-\lambda_b^{MS}\right)\left(1-\lambda_b^{Cool}\right) \tag{7}$$

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.

III. Problem formulation

At each time t, the HetNet can be configured as the transmission powers vector, $\mathbf{P}_r(t)$, the transmission channels vector, $\mathbf{Q}_r(t)$ and the association matrix between the users and BSs, $\mathbf{A}^{t,r}$, as follows

$$\begin{aligned} &\mathbf{P}_r(t) = \{P_{b,r}(t)\}_{|\mathcal{B}|\times 1}, \quad r\in R,\ b\in\mathcal{B}, \\ &\mathbf{Q}_r(t) = \{q_{b,r}(t)\}_{|\mathcal{B}|\times 1}, \quad \mathbf{A}^{t,r} = \left\{a_{b,k}^{t,r}\right\}_{|\mathcal{B}|\times|\mathcal{K}|} \end{aligned} \tag{8}$$

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 [11]

$$n_b^r(t) = \omega_b^n \frac{\left|A_b^{t,r}\right|}{|\mathcal{K}|} \tag{9}$$

$$c_b^r(t) = \omega_b^l L_b(t) + \omega_b^p P_{b,r}^{Total}(t) \tag{10}$$

where

$$A_b^{t,r} = \left\{ k \,\middle|\, k\in\ \mathcal{K}\ and\ a_{b,k}^{t,r} = 1 \right\} \tag{11}$$

where ω_b^n, ω_b^l and ω_b^p denote the weight parameters. $A_b^{t,r}$ denotes the set of user 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

$$\begin{aligned}\pi_b^r(t) = & n_b^r(t) - c_b^r(t) = \\ & \omega_b^n \frac{\left|A_b^{t,r}\right|}{|\mathcal{K}|} - \left(\omega_b^l L_b(t) + \omega_b^p P_{b,r}^{Total}(t)\right)\end{aligned} \tag{12}$$

The overall goal is to maximize the total system utility.

$$\begin{aligned}\max_{\{\mathbf{P}_r(t)\},\,\{\mathbf{Q}_r(t)\},\,\{\mathbf{A}^{t,r}\}} \quad & \sum_{\forall b\in\mathcal{B}}\sum_{\forall r\in R} \pi_b^r(t) \\ \text{subject to} \quad & 0 \le L_b(t) \le 1,\ \forall b\in\mathcal{B} \\ & \sum_{r\in R} P_{b,r}(t) \le P_b^{Max} \\ & q_{b,r}(t) \in \mathcal{Q}, \forall b\in\mathcal{B}\end{aligned} \tag{13}$$

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. Thus we decompose the optimization problem into user association problem and BS operation problem.

A. User Association Problem

At each time, given the set of BSs, 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 process. We assume that each BS $b \in \mathcal{B}$ broadcasts its estimated load through a beacon signal in the downlink transmission. At time *t*, user k is associated with BS b_k^* according to rule (14). In (14), 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) [12]. The function $\delta_{(condition)}$ denotes the indicator function which equals 1 if *condition* is true and 0 otherwise. Let $\hat{L}_b(t)$ indicates the estimated load of BS $b \in \mathcal{B}$ at time *t* and is obtained according to:

$$\hat{L}_b(t) = \left(1 - \left(\frac{1}{t}\right)^{\alpha}\right)\hat{L}_b(t-1) + \left(\frac{1}{t}\right)^{\alpha} L_b(t-1) \tag{15}$$

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

B. BS Operation Problem: Joint Power and Channel Assignment

The achievable throughput of a BS depends on its and other BSs operation 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 $\mathcal{G} = \left\langle \mathcal{B}, \mathcal{S}_{b\in\mathcal{B}}(s_{-b}), \{\pi_b^r\}_{b\in\mathcal{B}}\right\rangle$, 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 (12). 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. In our proposed algorithm, the BSs learn their environment and optimize their performance by modifying their transmission powers and channels. 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 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 $\widehat{\mathbf{r}}_{b,r}^{\epsilon}(t+1) = \left\{\hat{r}_{b,s_b,r}^{\epsilon}(t+1)\right\}_{|\mathcal{S}_b|\times 1}$ and probability distribution vector $\boldsymbol{\mathcal{P}}_{b,r}^{\epsilon}(t+1) = \left\{\mathcal{P}_{b,s_b,r}^{\epsilon}(t+1)\right\}_{|\mathcal{S}_b|\times 1}$ are updated as follows [5]:

$$\begin{aligned}\hat{r}_{b,s_b,r}^{\epsilon}(t+1) = & \left(1 - \left(\frac{1}{t+1}\right)^{\zeta}\right)\hat{r}_{b,s_b,r}^{\epsilon}(t) \\ & + \left(\frac{1}{t+1}\right)^{\zeta}\left(\widehat{W}_{b,s_b}^r(t+1) - W_{b,s_b}^r(t+1)\right)\end{aligned} \tag{16}$$

$$\begin{aligned}\mathcal{P}_{b,s_b,r}^{\epsilon}(t+1) = & \left(1 - \left(\frac{1}{t+1}\right)^{\nu}\right)\mathcal{P}_{b,s_b,r}^{\epsilon}(t) \\ & + \left(\frac{1}{t+1}\right)^{\nu} G_{b,s_b}(\widehat{\mathbf{r}}_{b,r}^{\epsilon}(t+1))\end{aligned} \tag{17}$$

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 follows:

$$G_{b,s_b}\left(\widehat{\mathbf{r}}_{b,r}^{\epsilon}(t+1)\right) = \frac{exp\left(\frac{1}{\theta_b}\hat{r}_{b,s_b,r}^{\epsilon}(t+1)\right)}{\sum_{\forall \acute{s}_b\in\mathcal{S}_b} exp\left(\frac{1}{\theta_b}\hat{r}_{b,\acute{s}_b,r}^{\epsilon}(t+1)\right)} \tag{18}$$

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 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 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

$$b_k^*(t) = \arg\max_{b\in B} 10\log_{10}\left\{P_{b,r}\left(t\right)\left(\beta_b\delta_{(b\in\mathcal{B}_S)} + 1\delta_{(b\in\mathcal{B}_M)}\right)g_{b,k}(t)(1-\hat{L}_b(t))\right\} \tag{14}$$

to [5]

$$\hat{\pi}^r_{b,s_b}(t+1) = \left(1 - \delta_{(s_b(t+1)=s_b(t))}\left(\frac{1}{t+1}\right)^{\kappa}\right)\hat{\pi}^r_{b,s_b}(t) + \delta_{(s_b(t+1)=s_b(t))}\left(\frac{1}{t+1}\right)^{\kappa}\pi^r_{b,s_b}(t+1) \tag{19}$$

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 (16) and (17), 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. 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 [8]. In IADCS algorithm, each BS transmits with its maximum power and evaluates averages CCI power over each channel and finally selects the channel with minimum average CCI.

- **Proposed Dynamic Channel Assignment Based on Learning Algorithm**

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. For solving the sub-problem, we set $\epsilon = 1$. Therefore, we have $W^r_{b,s_b}(t) := -I^r_{b,s_b}(t)$ and $\widehat{W}^r_{b,s_b}(t) := -\hat{I}^r_{b,s_b}(t)$. With the power selected discussed in the ON-OFF switching sub-problem, each BS $b \in \mathcal{B}$ updates the average CCI vector $\widehat{\mathbf{I}}^r_b(t+1) = \left\{\hat{I}^r_{b,q}(t+1)\right\}_{|\mathcal{Q}|\times 1}$ for each channel $q \in \mathcal{Q}$ according to [8]

$$\hat{I}^r_{b,q}\left(t+1\right) = \left(1 - \left(\frac{1}{t+1}\right)^{\phi}\right)\hat{I}^r_{b,q}\left(t\right) + \left(\frac{1}{t+1}\right)^{\phi} I^r_{b,q}\left(t+1\right) \tag{20}$$

where ϕ and $I^r_{b,q}(t+1)$ 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 $\boldsymbol{\mathcal{P}}^1_{b,r}(t+1) = \left\{\mathcal{P}^1_{b,q,r}(t+1)\right\}_{|\mathcal{Q}|\times 1}$. The elements of the vector $\mathcal{P}^1_{b,r}(t+1)$ are proportional to regrets for not having selected other channels. The regret estimation vector $\hat{\mathbf{r}}^1_{b,r}(t+1) = \left\{\hat{r}^1_{b,q,r}(t+1)\right\}_{|\mathcal{Q}|\times 1}$ and probability distribution vector $\boldsymbol{\mathcal{P}}^1_{b,r}(t+1)$ are updated according to (16) and (17), respectively.

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		180 Kbps
θ_b		0.1
Weights ω_b^n , ω_b^l, ω_b^p		1, 0.5, 0.5
Learning rate exponent κ, ϕ, ζ, ν, α		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+37.6log$_{10}(d)$ d in Km	140.7+37.6log$_{10}(d)$ d in Km
Minimum distance	MBS-SBS: 75m MBS-User: 35m	SBS-SBS: 40m SBS-User: 10m

IV. SIMULATION RESULTS

We consider a single hexagonal cell served by one MBS and the set of SBSs with 4 available channels. 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 [8]. The main reason is that the proposed algorithm in [8] 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 [8] and IADCS algorithm, respectively.

Fig. 3 plots the average loads per BS *vs* different number of users, with 10 SBSs. As the number of users increases, the average loads 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 [8].

Fig. 4 illustrates the average utility per BS *vs* different number of users, with 10 SBSs. Our proposed algorithm has better average utility per BS than the other approaches. For

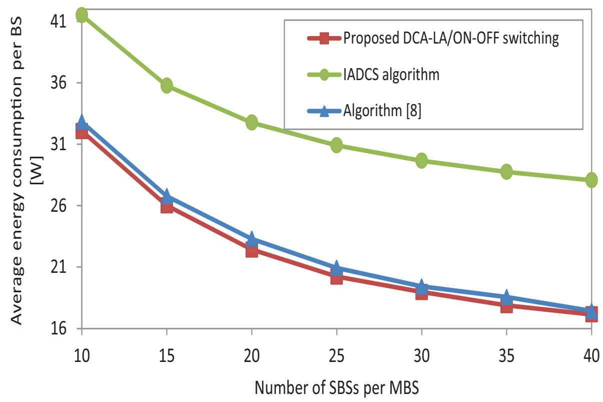

Fig. 2. Average energy consumption per BS *vs* the number of SBSs, given 30 users.

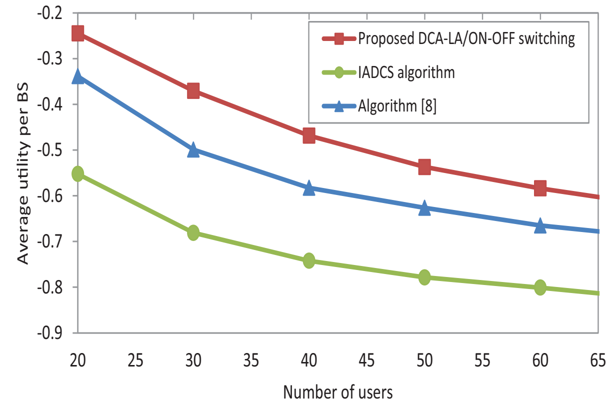

Fig. 4. Average utility per BS *vs* the number of users, given 10 SBSs.

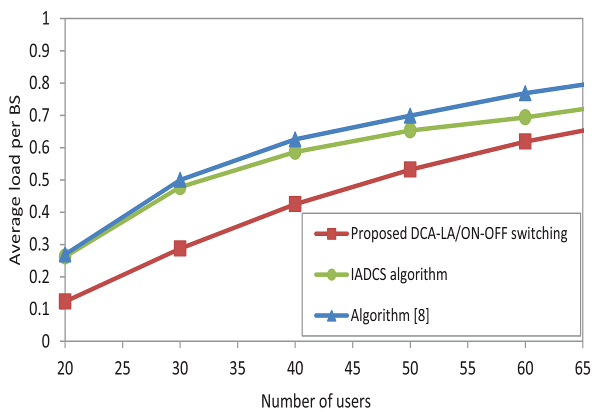

Fig. 3. Average load per BS *vs* the number of users, given 10 SBSs.

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 [8] 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 improving the energy efficiency. The proposed DCA-LA/ON-OFF switching algorithm is fully distributed and uses a game theoretic approach in which each BS selects its transmission channel and power. The proposed algorithm balances the load among BSs and therefore improves system throughput and consequently yields a better spectral efficiency. As a result, our proposed 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.

REFERENCES

[1] H. Boostanimehr and V. K. Bhargava, "Unified and distributed qos-driven cell association algorithms in heterogeneous networks," *Wireless Communications, IEEE Transactions on*, vol. 14, no. 3, pp. 1650–1662, 2015.

[2] S. Navaratnarajah, A. Saeed, M. Dianati, and M. A. Imran, "Energy efficiency in heterogeneous wireless access networks," *Wireless Communications, IEEE*, vol. 20, no. 5, pp. 37–43, 2013.

[3] H. Dahrouj, A. Douik, and O. Dhifallah, "Resource allocation in heterogeneous cloud radio access networks: advances and challenges," *Wireless Communications, IEEE*, vol. 22, no. 3, pp. 66–73, 2015.

[4] Z. Niu, Y. Wu, J. Gong, and Z. Yang, "Cell zooming for cost-efficient green cellular networks," *Communications Magazine, IEEE*, vol. 48, no. 11, pp. 74–79, 2010.

[5] S. Samarakoon, M. Bennis, W. Saad, and M. Latva-aho, "Opportunistic sleep mode strategies in wireless small cell networks," in *Communications (ICC), 2014 IEEE International Conference on*. IEEE, 2014, pp. 2707–2712.

[6] E. Oh and B. Krishnamachari, "Energy savings through dynamic base station switching in cellular wireless access networks," in *Global Telecommunications Conference (GLOBECOM 2010), 2010 IEEE*. IEEE, 2010, pp. 1–5.

[7] L. Saker, S.-E. Elayoubi, R. Combes, and T. Chahed, "Optimal control of wake up mechanisms of femtocells in heterogeneous networks," *Selected Areas in Communications, IEEE Journal on*, vol. 30, no. 3, pp. 664–672, 2012.

[8] A. Mehbodniya, K. Temma, R. Sugai, W. Saad, I. Guvenc, and F. Adachi, "Energy-efficient dynamic spectrum access in wireless heterogeneous networks," in *Communication Workshop (ICCW), 2015 IEEE International Conference on*. IEEE, 2015, pp. 2775–2780.

[9] C. Y. Lee and H. G. Kang, "Cell planning with capacity expansion in mobile communications: A tabu search approach," *Vehicular Technology, IEEE Transactions on*, vol. 49, no. 5, pp. 1678–1691, 2000.

[10] S. C. Ghosh, B. P. Sinha, and N. Das, "Channel assignment using genetic algorithm based on geometric symmetry," *Vehicular Technology, IEEE Transactions on*, vol. 52, no. 4, pp. 860–875, 2003.

[11] A. Hajijamali Arani, M. J. Omidi, A. Mehbodniya, and F. Adachi, "A handoff algorithm based on estimated load for dense green 5g networks," in *Global Communications Conference (GLOBECOM), 2015 IEEE, Accepted*.

[12] J. Andrews, S. Singh, Q. Ye, X. Lin, and H. Dhillon, "An overview of load balancing in hetnets: Old myths and open problems," *Wireless Communications, IEEE*, vol. 21, no. 2, pp. 18–25, 2014.

[13] G. Wu, C. Yang, S. Li, and G. Y. Li, "Recent advances in energy-efficient networks and their application in 5g systems," *Wireless Communications, IEEE*, vol. 22, no. 2, pp. 145–151, 2015.

[14] R. Hu and Y. Qian, "An energy efficient and spectrum efficient wireless heterogeneous network framework for 5g systems," *Communications Magazine, IEEE*, vol. 52, no. 5, pp. 94–101, 2014.

[15] D. Feng, C. Jiang, G. Lim, L. J. Cimini, G. Feng, and G. Y. Li, "A survey of energy-efficient wireless communications," *Communications Surveys & Tutorials, IEEE*, vol. 15, no. 1, pp. 167–178, 2013.

[16] H. Tabassum, U. Siddique, E. Hossain, and M. J. Hossain, "Downlink performance of cellular systems with base station sleeping, user association, and scheduling," *Wireless Communications, IEEE Transactions on*, vol. 13, no. 10, pp. 5752–5767, 2014.

[17] G. F. Marias, D. Skyrianoglou, and L. Merakos, "A centralized approach to dynamic channel assignment in wireless atm lans," in *INFOCOM'99. Eighteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, vol. 2. IEEE, 1999, pp. 601–608.

[18] G. Cao and M. Singhal, "Distributed fault-tolerant channel allocation for cellular networks," *Selected Areas in Communications, IEEE Journal on*, vol. 18, no. 7, pp. 1326–1337, 2000.

[19] Y. Furuya and Y. Akaiwa, "Channel segregation, a distributed adaptive channel allocation scheme for mobile communication systems," *IEICE Transactions on Communications*, vol. 74, no. 6, pp. 1531–1537, 1991.

[20] Y. Zhu, T. Kang, T. Zhang, and Z. Zeng, "Qos-aware user association based on cell zooming for energy efficiency in cellular networks," in *Personal, Indoor and Mobile Radio Communications (PIMRC Workshops), 2013 IEEE 24th International Symposium on*. IEEE, 2013, pp. 6–10.