



RESEARCH ARTICLE

Distributed ON/OFF switching and dynamic channel allocation: Decreasing complexity and improving energy efficiency

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Abstract

Heterogeneous network (HetNet) has emerged as a promising and viable approach to deliver higher-rate data services. In HetNets, switching OFF base stations (BSs) is known as an effective solution to reduce the energy consumption of networks and thus enables the “greener” networks concept. In this paper, we investigate the impact of the number of energy-saving modes for BSs on improving energy efficiency. We assume that BSs are able to switch among several modes, ie, different transmission power levels. We apply a no-regret learning algorithm to choose the BS's operation mode while modeling the BS's operation under dynamic traffic with a Markov process. As a result, we face a trade-off between energy savings and computational complexity. Furthermore, we use a distributed channel allocation algorithm based on the average cochannel interference power. Simulation results show that energy consumption reduces with increased number of modes. However, increasing the number of modes beyond a certain limit will not have a significant effect on energy efficiency.

1 | INTRODUCTION

The phenomenal explosive growth in data traffic demands driven by smartphones and tablets is inevitably made possible at the expense of dramatically increasing the energy consumption of wireless networks. This will directly result in the increase of carbon footprint and particularly environmental problems.¹ From the network operator perspective, energy costs constitute a significant portion of operational expenditures.² Accordingly, there is a growing consensus on the need for revolutionary approaches, including development and deployment of new network architectures and networking technologies to improve the energy efficiency (EE) of the networks.³

Since base stations (BSs) are network elements with the highest energy consumption, this paper focuses on reducing the energy consumption of BSs. Heterogeneous networks (HetNets), composed of macrocell BSs (MBSs) overlaid with small-cell BSs (SBSs), have emerged as a promising approach to enhance both spectral efficiency and EE. Therefore, cellular networks are gravitating toward increased heterogeneity and density.⁴ On the other hand, BSs' traffic load fluctuates in the time and space domains, whereas the current networks are designed to operate only based on peak traffic load.⁵

In recent years, BS ON/OFF switching, alternatively termed as sleep mode, approaches are considered as effective solutions for reducing the energy consumption of the networks.⁶ In BS ON/OFF switching approaches, BSs are able to switch to low power consumption modes in light traffic load conditions. These approaches do not require changes to the current networks' architecture and the upgrade of equipments. Therefore, it is easier to test and implement them, and thus, implementation costs are low.⁷

Ren and Tao⁸ proposed a sleep mechanism for MBSs to offload user equipments (UEs) to SBSs or neighboring MBSs while the SBSs are always ON. A game theoretic approach for switching OFF BSs was proposed by Samarakoon et al⁹ where a distributed learning algorithm was applied to solve the game. In the work of Zhang et al,¹⁰ an energy-efficient sleep-mode activation scheme for SBSs was developed. The proposed activation scheme is controlled by the core network, in which the sleeping SBS with the best channel condition for the active UE is activated. However, the aforementioned works⁸⁻¹⁰ do not consider channel allocation among BSs and assume that all BSs operate on the same frequency band. Suárez et al¹¹ proposed a BS switching-OFF approach with hybrid energy sources. In this approach, a set of metrics is used to select the BS neighbors for offloading the traffic.

Moreover, switching between ON and OFF modes by BSs results in a new UE association problem. Accordingly, if some BSs are switched to OFF mode, their associated UEs need to migrate to other BSs. Thus, the UE association problem should be considered jointly with a resource management problem.

In this paper, we take into account a joint UE association and self-organizing mechanism to assign the UEs to the BSs and perform dynamic resource (ie, power and channel) allocation. In practice and depending on the hardware, there are only a limited number of power levels available at the transmitters.¹² Therefore, we assume that the transmission power at BSs is limited to a predetermined and finite number of discrete level sets.¹³ Several important advantages for solving problems by assuming discrete power level sets compared with continuous sets include reducing the complexity and simplifying the design of transmitters.¹⁴

To save energy in BSs, a BS ON/OFF switching approach based on the game theoretic framework, proposed by Samarakoon et al,⁹ is applied, which uses a distributed no-regret learning algorithm to solve the game. We try to study ON/OFF switching mechanism from a different perspective. In this respect, we investigate the effect of the number of transmit power levels (hereinafter referred to as BS's operation modes) on energy consumption of the BSs. With increasing the number of modes, EE improves at the cost of increasing computational complexity. However, by increasing the number of modes beyond a certain point, our mechanism does not provide significant EE gain. Moreover, the convergence of the algorithm can be established via stochastic approximation theory.¹⁵ We note that the ON/OFF switching mechanism enables us to solve the problem in polynomial time instead of exponential time. As for the channel allocation problem, the BSs utilize a distributed channel allocation scheme based on average cochannel interference (CCI) power. Therefore, the BSs choose their operation modes and channels independently and autonomously without the need to exchange any information among them.

The rest of this paper is organized as follows. In Section 2, we present our system model followed by the definition of BS load for a 2-tier HetNet. In Section 3, we describe the joint UE association and self-organizing resource allocation mechanism. Section 4 presents simulation results and discussions. Conclusions are drawn in Section 5.

2 | SYSTEM MODEL

We consider the downlink of a 2-tier HetNet with the set of BSs \mathcal{B} , where tiers 1 and 2 represent the set of MBSs \mathcal{B}_M and the set of SBSs \mathcal{B}_S , respectively. As shown in Figure 1, in each hexagonal coverage area, an MBS is located at the center of the area and the SBSs are uniformly distributed in the coverage of the MBS. We assume that all BSs operate in open access

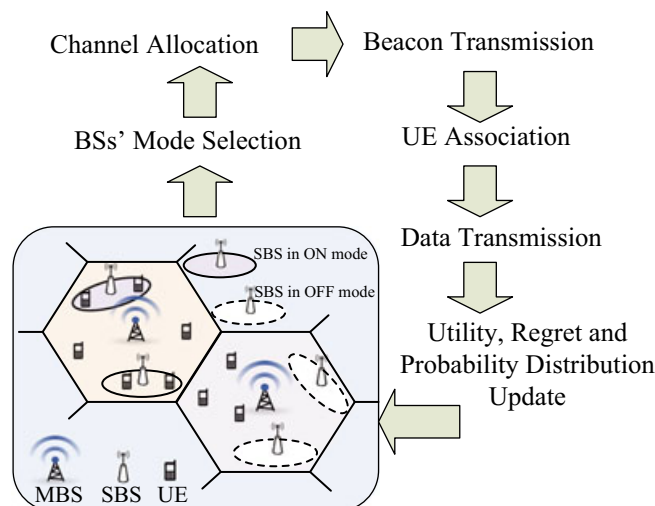


FIGURE 1 The joint user equipment association and resource management mechanism for a 2-tier heterogeneous network (HetNet)

scheme, ie, the UEs are allowed to associate to the BSs in any tier. During low traffic load conditions, the BSs can switch to energy-saving modes to save energy consumption. Let Δ_M and Δ_S be the numbers of MBS's operation modes and SBS's operation modes, respectively. Moreover, let P_b be the transmit power of BS b . The maximum transmit power values of the MBSs and the SBSs are denoted by P_M^{Max} and P_S^{Max} , respectively. Given the maximum transmit power and number of BS's operation modes, there are several possible choices for the quantization of power levels. Here, we consider the uniform type for the discrete power level sets.¹⁶ Therefore, each MBS $m \in \mathcal{B}_M$ and each SBS $s \in \mathcal{B}_S$ can select their transmit power from the sets of $\mathcal{S}_M = \{0, \frac{1}{\Delta_M-1}P_M^{\text{Max}}, \dots, \frac{\Delta_M-1}{\Delta_M-1}P_M^{\text{Max}}\}$ and $\mathcal{S}_S = \{0, \frac{1}{\Delta_S-1}P_S^{\text{Max}}, \dots, \frac{\Delta_S-1}{\Delta_S-1}P_S^{\text{Max}}\}$, respectively.

For example, for $\Delta_S = 2$, each SBS $s \in \mathcal{B}_S$ can select its transmit power from a set including 2 power levels: zero and maximum transmit power.

Accordingly, we define the set of BSs operating in ON mode (or active mode) $\mathcal{B}_{\text{ON}} \subseteq \mathcal{B}$, where $\mathcal{B}_{\text{ON}} = \{b | P_b \neq 0, b \in \mathcal{B}\}$, and the set of BSs operating in OFF mode $\mathcal{B}_{\text{OFF}} \subseteq \mathcal{B}$, where $\mathcal{B}_{\text{OFF}} = \{b | P_b = 0, b \in \mathcal{B}\}$.

The set of UEs is denoted by \mathcal{K} , and they are uniformly distributed in the network. The total bandwidth ω is divided into $|\mathcal{Q}|$ orthogonal channels with bandwidth $\omega/|\mathcal{Q}|$, where \mathcal{Q} is the set of channels. We assume that the flows arrive into the system with mean arrival rate λ_k and mean packet size $1/\mu_k$ at the location of UE k . Let $g_{b,k}$ be the total channel gain from BS b to UE k , including the path loss and log-normal shadow fading. Therefore, the signal-to-interference-and-noise ratio at the receiver of UE k from BS b transmitting over channel $q_b \in \mathcal{Q}$ is given by

$$\gamma_{b,k} = \frac{P_b g_{b,k}}{\underbrace{\sum_{b' \in \mathcal{B}_{\text{ON}} \setminus b} L_{b'} \frac{P_{b'}}{g_{b',k}} \mathbb{1}_{(q_b=q_{b'})}}_{\text{Interference}} + \sigma^2}, \quad (1)$$

where L_b denotes the load of BS b . Let σ^2 be the additive white Gaussian noise power at the receiver of the UE. Here, function $\mathbb{1}_{(event)}$ denotes the indicator function, which is equal to 1 if *event* is true and 0 otherwise. Using Shannon's formula, the achievable transmission rate of UE k from BS $b \in \mathcal{B}_{\text{ON}}$ is given by

$$R_{b,k} = \frac{\omega}{|\mathcal{Q}|} \log_2(1 + \gamma_{b,k}). \quad (2)$$

The fraction of time required to serve the traffic load from BS b to the location of UE k is defined as $l_{b,k} = \frac{\lambda_k}{\mu_k R_{b,k}}$. Thus, the total load of BS b can be represented as follows:

$$L_b = \sum_{k \in \mathcal{K}} a_{b,k} l_{b,k}, \quad (3)$$

Let $a_{b,k} \in \{0, 1\}$ represent the association relation between UE k and BS b such that $a_{b,k} = 1$ indicates that UE k is associated with BS b ; otherwise, $a_{b,k} = 0$. The average number of flows at BS b is given by $\frac{L_b}{1-L_b}$. Therefore, the total number of flows in the system is equal to $\sum_{b \in \mathcal{B}_{\text{ON}}} \frac{L_b}{1-L_b}$, which is proportional to the expected delay.^{17,18} Thus, with a low system load on average, the UEs experience less delay.¹⁹

3 | PROBLEM FORMULATION

In this paper, we primarily intend to improve the EE of the network by dynamically turning ON and OFF some BSs and associate the UEs to the BSs while ensuring the quality of service.

3.1 | UE association

Dynamic BS ON/OFF switching affects the UE association mechanism and, consequently, the BSs' loads. We assume that each BS $b \in \mathcal{B}$ periodically broadcasts its estimated load by a beacon signal.²⁰ At each time t , UE k is associated with and served by BS $b_k(t)$ in accordance with the following equation²⁰:

$$b_k(t) = \arg \max_{b \in \mathcal{B}_{\text{ON}}} 10 \log_{10} \left(P_b(t) g_{b,k}(t) (1 - \hat{L}_b(t)) \right), \quad (4)$$

where $P_b(t)g_{b,k}(t)$ is the received power from BS b at the location of UE k at time t . Here, $\hat{L}_b(t)$ is the estimated load of BS b at time t , and it is calculated as follows²⁰:

$$\hat{L}_b(t) = \left(1 - \left(\frac{1}{t}\right)^\alpha\right) \hat{L}_b(t-1) + \left(\frac{1}{t}\right)^\alpha L_b(t-1), \quad (5)$$

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

3.2 | Self-organizing resource allocation

3.2.1 | Channel allocation problem

Using first-order filtering, each BS $b \in \mathcal{B}$ calculates the average CCI power over each channel $q \in \mathcal{Q}$ in accordance with the following equation²¹:

$$\bar{I}_{b,q}(t) = (1 - \lambda)I_{b,q}(t) + \lambda \bar{I}_{b,q}(t-1), \quad (6)$$

where λ and $I_{b,q}(t)$ denote the forgetting factor and the received CCI power at BS b over channel q at time t , respectively. Then, each BS b selects the channel with minimum average CCI power from the set of channels.

3.2.2 | Energy-saving problem

We adopt a power consumption model that is proportional to the BS's operation mode. Therefore, the total power consumed by BS b can be expressed as follows²⁰:

$$P_b^{\text{Total}} = \begin{cases} P_b^{\text{OFF}} + \frac{1}{\eta_b^{\text{PA}} \Lambda_b} P_b, & \text{if } b \in \mathcal{B}_{\text{ON}} \\ P_b^{\text{OFF}}, & \text{if } b \notin \mathcal{B}_{\text{ON}}, \end{cases} \quad (7)$$

with

$$\Lambda_b = (1 - \lambda_b^{\text{DC}}) (1 - \lambda_b^{\text{MS}}) (1 - \lambda_b^{\text{Cool}}) (1 - \lambda_b^{\text{Feed}}), \quad (8)$$

where P_b^{OFF} is the fixed power consumption for BS b . η_b^{PA} indicates the power amplifier efficiency of BS b . For BS b , Λ_b captures the losses in the DC-DC power supply (λ_b^{DC}), main supply (λ_b^{MS}), cooling system (λ_b^{Cool}), and feeder (λ_b^{Feed}).²² Given the described model, we aim at improving the EE of the network and balancing load among the BSs. Thus, for each BS $b \in \mathcal{B}$, we define the utility function, which is the difference between the benefit function and the cost function. The benefit function corresponds to the fraction of UEs associated with the BSs. This term assesses the generated income. The cost function captures the BS's load and the total power consumption. Therefore, the utility function is defined as follows²⁰:

$$\pi_b = \underbrace{\omega_b^k \frac{|A_b|}{|\mathcal{K}|}}_{\text{Benefit}} - \underbrace{\left(\omega_b^l L_b + \omega_b^p \frac{P_b^{\text{Total}}}{P_b^{\text{OFF}} + P_b^{\text{TXMax}}} \right)}_{\text{Cost}}, \quad (9)$$

where

$$P_b^{\text{TXMax}} = \frac{1}{\eta_b^{\text{PA}} \Lambda_b} P_b^{\text{Max}}, \quad (10)$$

and ω_b^k , ω_b^l , and ω_b^p indicate the weight parameters of the benefit, load, and energy for BS b , respectively. Here, A_b and $|A_b|$ denote the set of UEs served by BS b and the cardinality of A_b , respectively. The energy-saving problem can be formulated as follows:

$$\begin{aligned} & \max_{\{P_b\}} \sum_{b \in \mathcal{B}} \pi_b \\ & \text{subject to} \quad P_m \leq P_m^{\text{Max}}, P_s \leq P_s^{\text{Max}}, \forall m \in \mathcal{B}_M, \forall s \in \mathcal{B}_S, \\ & \quad q_b \in \mathcal{Q}, \forall b \in \mathcal{B}, \\ & \quad a_{b,k} \in \{0, 1\}, \forall b \in \mathcal{B}, \forall k \in \mathcal{K}, \\ & \quad \sum_{b \in \mathcal{B}} a_{b,k} \leq 1, \forall k \in \mathcal{K}, \\ & \quad L_b \in [0, 1], \forall b \in \mathcal{B}. \end{aligned} \quad (11)$$

In the energy-saving problem (11), our goal is to choose the transmission power of the BSs, which defines the BSs' operation modes. However, finding an optimal solution for this problem requires global information collected by a centralized controller

and performing an exhaustive search over $(\Delta_M)^{|\mathcal{B}_M|} \times (\Delta_S)^{|\mathcal{B}_S|}$ combinations of BSs' modes. As a result, its computational complexity grows exponentially with the number of BSs, and the problem becomes intractable when $|\mathcal{B}|$ is large. In recent years, the game theory tool has received significant attention, which can be adopted to solve the problems in noncooperative scenarios.²³ The problem is formulated as a noncooperative game $\mathcal{G} = \langle \mathcal{B}, \{S_b\}_{b \in \mathcal{B}}, \{\pi_b\}_{b \in \mathcal{B}} \rangle$, where \mathcal{B} is the set of BSs as the players. S_b represents the strategy set of player b , in which S_b is equivalent to S_M and S_S for the MBSs and the SBSs, respectively. The utility function of player b is denoted by π_b defined in Equation 9. A strategy profile is composed of the strategy of all players denoted by $s = (s_1, \dots, s_{|\mathcal{B}|}) \in S_1 \times \dots \times S_{|\mathcal{B}|}$, where s_b is a strategy of player b .

To solve the game and, consequently, obtain ϵ -coarse correlated equilibrium, a classical regret matching algorithm is considered as an approach.²⁴ We note that, in every finite game, the set of correlated equilibria is nonempty, closed, and convex.

Definition 1. ϵ -coarse correlated equilibrium

A mixed strategy profile Γ_s where $s \in S_1 \times \dots \times S_{|\mathcal{B}|}$ is an ϵ -coarse correlated equilibrium for game \mathcal{G} if and only if, for all $b \in \mathcal{B}$, $s'_b \in S_b$, we have

$$\sum_{s \in S} \Gamma_s \pi_b(s'_b, s_{-b}) \leq \sum_{s \in S} \Gamma_s \pi_b(s) + \epsilon, \quad (12)$$

where s_{-b} denotes the strategy of players other than player b . In the classical regret matching approach, the probability of switching from the current strategy to another pure strategy is proportional to the regret relative to the current strategy. In this regard, for each strategy $s_b \in S_b$, the regret of player b is defined as follows²⁴:

$$R_{b,s_b}(t) = \max \left\{ \frac{1}{t} \sum_{\tau \leq t} \pi_b(s_b, s_{-b}(\tau)) - \bar{\pi}_b(\tau), 0 \right\}, \quad (13)$$

where $\bar{\pi}_b(\tau)$ is the time average of player b 's payoff. Then, the probability assigned with each strategy $s_b \in S_b$ is updated as follows²⁴:

$$P_{b,s_b}(t+1) := \begin{cases} \frac{1}{\rho} R_{b,s_b}(t), & \forall s_b \neq s_b(t) \\ 1 - \sum_{s_b \in S_b \setminus s_b(t)} P_{b,s_b}(t+1), & s_b = s_b(t), \end{cases} \quad (14)$$

where $s_b(t)$ is the strategy played at time t . However, the classical regret matching algorithm requires the knowledge of the other players such as strategies, payoff functions, and the history of play of the other players. As a result, it is not suitable for solving the problem in a distributed manner. Therefore, the following no-regret algorithm is used.^{9,15} The learning algorithm does not require to exchange information in the network and enables us to solve the problem in polynomial time. In learning algorithms, a general form that is used to express an update rule for a target function W is given as follows²⁵:

$$\hat{W}(t) = \hat{W}(t-1) + \vartheta(t) (W(t) - \hat{W}(t-1)), \quad (15)$$

where $\hat{W}(t)$ and $W(t)$ indicate the estimation for next iteration and the current value function at time t , respectively. The expression $W(t) - \hat{W}(t-1)$ is considered as an error in the estimation, which is reduced by taking a step toward the target. Here, $\vartheta(t)$ is a small positive fraction that influences the rate of learning, and it is reduced over time appropriately.

Accordingly, each BS $b \in \mathcal{B}$ updates its utility estimation $\hat{\pi}_{b,s_b}(t)$, regret estimation $\hat{R}_{b,s_b}(t)$, and probability distribution $P_{b,s_b}(t)$ for each $s_b \in S_b$ as follows⁹:

$$\hat{\pi}_{b,s_b}(t) = \hat{\pi}_{b,s_b}(t-1) + \left(\frac{1}{t^\kappa} \right) \mathbb{1}_{\{s_b(t)=s_b\}} (\pi_b(t) - \hat{\pi}_{b,s_b}(t)), \quad (16)$$

$$\hat{R}_{b,s_b}(t) = \hat{R}_{b,s_b}(t-1) + \left(\frac{1}{t^\zeta} \right) (\hat{\pi}_{b,s_b}(t) - \pi_b(t) - R_{b,s_b}(t-1)), \quad (17)$$

$$P_{b,s_b}(t) = P_{b,s_b}(t-1) + \left(\frac{1}{t^\nu} \right) (G_{b,s_b}(\hat{R}_b(t)) - P_{b,s_b}(t-1)), \quad (18)$$

where $\kappa, \zeta > 0$, and $\nu > 0$ denote the learning rate exponents. Let $\hat{R}_b(t) = [\hat{R}_{b,1}(t), \dots, \hat{R}_{b,|S_b|}(t)]$ represent the vector of regret estimation values. Here, $G_b(\hat{R}_b(t)) = [G_{b,1}(\hat{R}_b(t)), \dots, G_{b,|S_b|}(\hat{R}_b(t))]$ is the Boltzmann-Gibbs (BG) distribution vector defined as follows⁹:

$$G_{b,s_b}(\hat{R}_b(t)) = \frac{\exp\left(\frac{1}{\theta_b} \hat{R}_{b,s_b}(t)\right)}{\sum_{s_b \in S_b} \exp\left(\frac{1}{\theta_b} \hat{R}_{b,s_b}(t)\right)}, \quad (19)$$

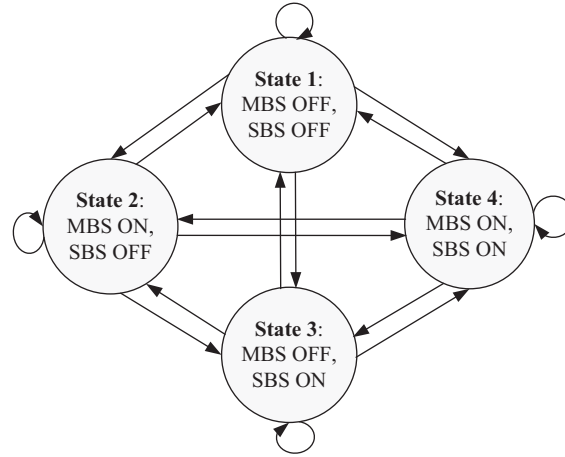


FIGURE 2 The Markov chain model for 1 macrocell base station and a small-cell base station with 2 operation modes

where $\frac{1}{\theta_b} > 0$ denotes the temperature parameter for player b . For converging the approach, all learning rate exponents $\varsigma = \{\kappa, \zeta, \nu\}$ are chosen according to the following conditions²⁵:

$$\lim_{t \rightarrow \infty} \sum_{n=1}^t \frac{1}{n^\varsigma} = +\infty \quad (20)$$

and

$$\lim_{t \rightarrow \infty} \sum_{n=1}^t \left(\frac{1}{n^\varsigma} \right)^2 < +\infty. \quad (21)$$

Therefore, we choose all learning rate exponents $\iota = \{\gamma, \zeta, \nu\} \in (0.5, 1)$. Furthermore, each BS b selects its strategy using a mapping function $f : \mathcal{P}_b = [\mathcal{P}_{b,1}, \dots, \mathcal{P}_{b,|S_b|}] \rightarrow s_b$, which maps the probability distribution to an element in its strategy set S_b .

Since transition from state $s(t)$ to $s(t+1)$ takes place when some BSs update their strategies according to their observations on $s(t)$, the transition depends only on the current configuration strategy profile. As a result, the energy-saving mechanism can be modeled as a Markov chain with the set of cliques \mathcal{B} , average regret as global energy, and finite configuration space $S_1 \times \dots \times S_{|B|}$. Using the aforementioned learning procedure, computational complexity becomes linear with the number of BSs. However, with the increasing number of modes, computational complexity increases. All state transitions for 1 MBS and an SBS with 2 operation modes are presented in Figure 2.

4 | SIMULATION RESULTS

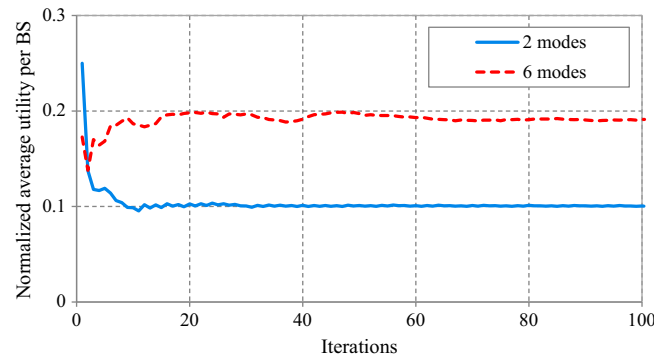
In this section, the joint UE association and resource allocation mechanism is validated by extensive simulations under various configurations. We consider a single hexagonal cell composed of 1 MBS with the maximum transmit power of 46 dBm and a set of SBSs. For the SBSs, the maximum transmit power P_S^{Max} is considered to be 30 dBm, unless we mention that it is set to be $P_S^{\text{Max}} = 20$ dBm. For the MBS, we consider 2 operation modes, ie, $\Delta_M = 2$, and the simulation results are provided under different values of SBSs' operation modes, unless we mention another policy that $\Delta_M > 2$ and $\Delta_S = 2$. The parameters used for the simulations are listed in Table 1.

The convergence behavior of the mechanism for $\Delta_S = 2$ and $\Delta_S = 6$ is shown in Figure 3. It plots the evolution of the normalized average utility per BS versus the number of iterations, where utility is computed from Equation 9. The utility of each BS is updated along with updating of the BS's operation mode at each iteration. The proposed mechanism with $\Delta_S = 2$ converges faster than $\Delta_S = 6$ since the mechanism with $\Delta_S = 2$ has less candidate solutions to update and thus requires less number of iterations to converge. Instead, the mechanism with $\Delta_S = 6$ yields better performance compared with the mechanism with $\Delta_S = 2$. Convergence is achieved in about 31 and 60 iterations for $\Delta_S = 2$ and $\Delta_S = 6$, respectively. Therefore, the trade-off between performance and convergence speed is controlled by the number of modes. Note that the more number of BS's modes represents the more extensive space search with slow convergence, whereas the less number of BS's modes represents the limited space search with fast convergence.

TABLE 1 System-level simulation parameters

System Parameters		
Parameter	Value	
Physical link type	Downlink	
Carrier frequency/total bandwidth	2 GHz/10 MHz	
Number of channels ($ Q $)	4	
Noise power	-174 dBm/Hz	
Mean packet arrival rate	1800 Kbps	
Weights $\omega_b^k, \omega_b^l, \omega_b^p$	1, 0.5, 0.5	
Learning rate exponent α	0.9	
Base Stations' Parameters		
Parameter	MBS	SBS
P_b^{OFF}	56.1001 W	4.6919 W
η_b^{PA}	31.1%	6.7%
DC-DC loss	7.5%	9%
Main supply loss	9%	11%
Cooling loss	10%	0%
Feeder loss	3 dB	0 dB
Shadowing standard deviation	8 dB	10 dB
Cell radius	250 m	40 m
Distance-dependent path loss model	$128.1 + 37.6 \log_{10}(d); d$ in km	$140.7 + 36.7 \log_{10}(d); d$ in km
Minimum distance	MBS-SBS: 75 m; MBS-UE: 35 m	SBS-SBS: 40 m; SBS-UE: 10 m

Abbreviations: MBS, macrocell base station; SBS, small-cell base station; UE, user equipment.

**FIGURE 3** Convergence of average utility per base station (BS) ($|B_S| = 5, |K| = 50$)

Now, we define the EE metric as the ratio between the average rate per UE and the average energy consumption per BS. This definition is reasonable since it can show the goal of an energy-saving mechanism. Figure 4 illustrates EE versus different numbers of UEs for 5, 10, and 15 SBSs. As the number of UEs increases, EE deteriorates. We can observe that, with increasing the number of modes from 2 to 4, EE improves. For instance, when the number of SBSs = 10, the EE values with $\Delta_S = 4$ and $\Delta_S = 6$ are improved, respectively, up to 27% and 28%, as compared with $\Delta_S = 2$. Moreover, with increasing the number of SBSs in the area, EE improves. This is due to the fact that the average UE's rate increases and the average energy consumption per BS decreases.

In order to evaluate the impact of the number of modes on the delay, we depict the average load per BS versus the number of UEs for = 5, 10, and 15 SBSs. In Figure 5, it is demonstrated that increasing the number of modes results in balancing the load among BSs and decreasing delay due to the relation of load and delay (see Section 2). As the number of UEs increases, the average load increases. Moreover, with increasing the number of SBSs, the average load per BS decreases. For instance, when the number of UEs = 50 and the number of SBSs = 10, the joint UE association and resource allocation mechanism with $\Delta_S = 4$ improves the average load per BS by about 11% over the mechanism with $\Delta_S = 2$.

Figure 6 compares the normalized average utility per BS versus different numbers of SBSs for the number of UEs = 50 and 100. As the number of SBSs in the area increases, the average energy consumption per BS and the average load per BS

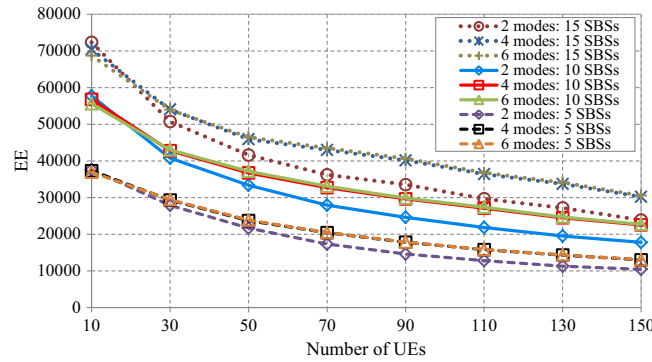


FIGURE 4 Energy efficiency (EE) versus the number of user equipments (UEs) ($|B_S| = 5, 10, \text{ and } 15$). SBSs, small-cell base stations

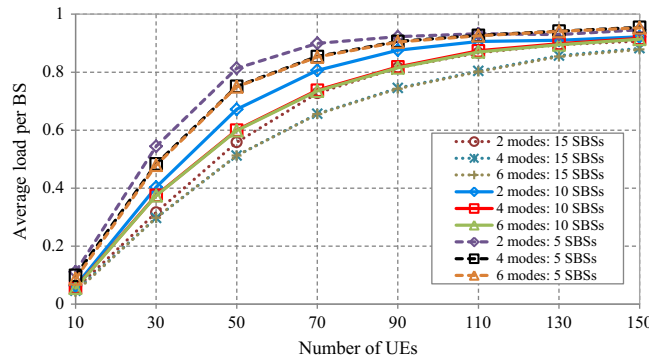


FIGURE 5 Average load per base station (BS) versus the number of user equipments (UEs) ($|B_S| = 5, 10, \text{ and } 15$). SBSs, small-cell BSs

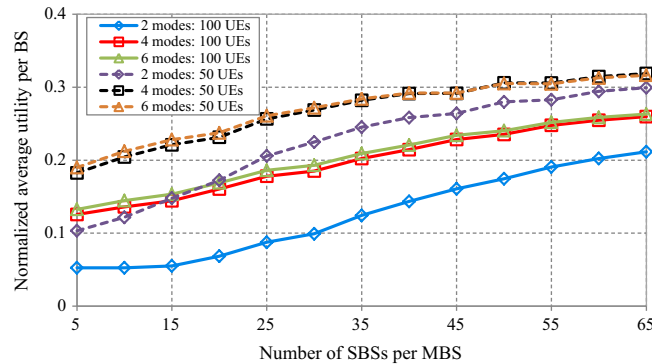


FIGURE 6 Normalized average utility per base station (BS) versus the number of small-cell BSs (SBSs) ($|K| = 50 \text{ and } 100$). MBS, macrocell BS; UEs, user equipments

decrease. Therefore, the average utility per BS increases. Moreover, with increasing the number of modes, the average utility per BS increases. For instance, at SBSs = 25 and UEs = 100, the mechanisms with $\Delta_S = 4$ and $\Delta_S = 6$ improve the average utility per BS, respectively, by about 22% and 24% over the mechanism with $\Delta_S = 2$.

Figure 7 illustrates the average number of ON playing modes with maximum transmit power versus the number of UEs. We consider 2 cases in which the maximum power values of SBSs are 20 and 30 dBm. We can observe that, when the number of modes increases, the average number of playing modes with maximum transmit power decreases, and thus, more BSs select energy-saving modes. The main reason is due to the load balancing property in the mechanism with the higher number of modes. Moreover, with decreasing the maximum transmit power of SBSs from 30 to 20 dBm, the average number of selecting modes with maximum power increases.

In Figure 8, we plot the average energy consumption achieved by the number of SBSs = 5, 10, and 15 versus the number of UEs. As depicted in Figure 8, we can expect more significant energy conservation with the increase in Δ_S from 2 to 4. In other words, the more BSs operate in energy-saving modes, larger energy savings can be expected. This mainly comes from choosing

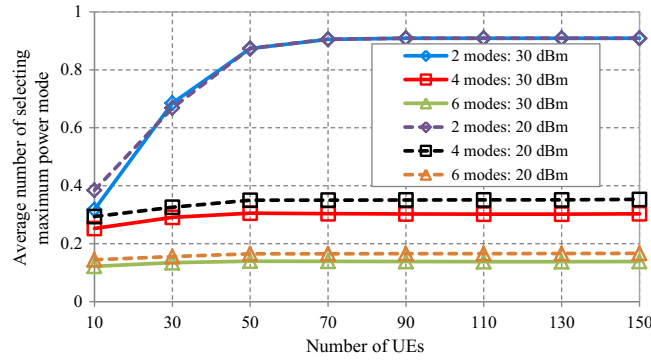


FIGURE 7 Average number of selecting maximum power mode versus the number of user equipments (UEs) ($|\mathcal{B}_S| = 10$, $P_S^{\text{Max}} = 20$ and 30 dBm)

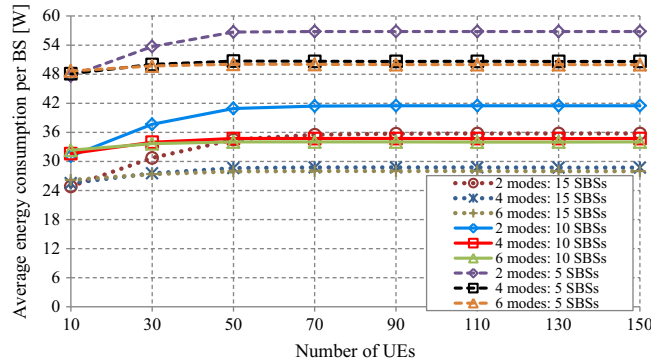


FIGURE 8 Average energy consumption per base station (BS) versus the number of user equipments (UEs) ($|\mathcal{B}_S| = 5, 10$, and 15). SBSs, small-cell BSs

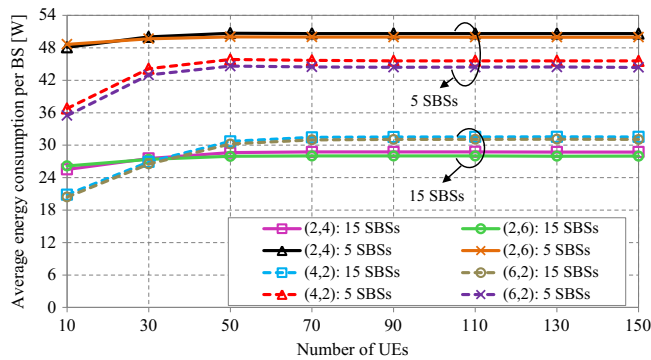


FIGURE 9 Average energy consumption per base station (BS) versus the number of user equipments (UEs) ($|\mathcal{B}_S| = 5$ and 15). The first and second elements of (Δ_M, Δ_S) denote Δ_M and Δ_S , respectively. SBSs, small-cell BSs

power levels less than the maximum power levels. However, the gap between the mechanisms with $\Delta_S = 4$ and $\Delta_S = 6$ is small, and it does not cause significant impact when $\Delta_S \geq 4$. Moreover, it can be seen that, with increasing the SBSs in the network, the average energy consumption per BS decreases.

In Figure 9, we investigate the policy that the MBS has several operation modes with $\Delta_M > 2$ whereas the SBSs have only 2 operation modes. In this regard, we consider 2 cases where the number of SBSs is equal to 5 and 15. In Figure 9, the first and second elements of (Δ_M, Δ_S) denote Δ_M and Δ_S , respectively. It can be noticed that, for the smaller number of SBSs, the power consumption of MBS is of more importance, and defining multiple power levels for the MBS results in increased energy savings. However, for the large number of SBSs, most of the power consumption is due to SBSs' activities, and defining more power levels for the SBSs increases energy savings.

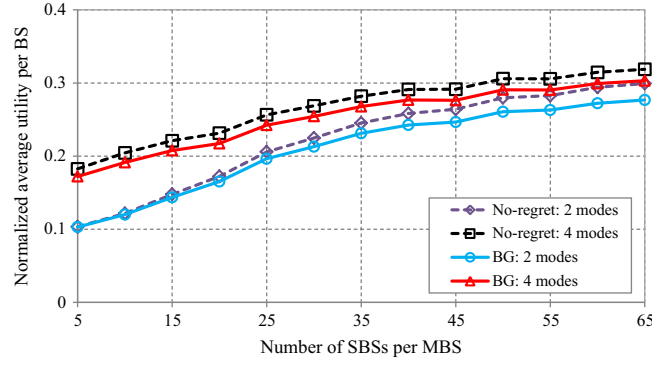


FIGURE 10 Normalized average utility per base station (BS) versus the number of small-cell BSs (SBSs) ($|\mathcal{K}| = 50$). BG, Boltzmann-Gibbs; MBS, macrocell BS

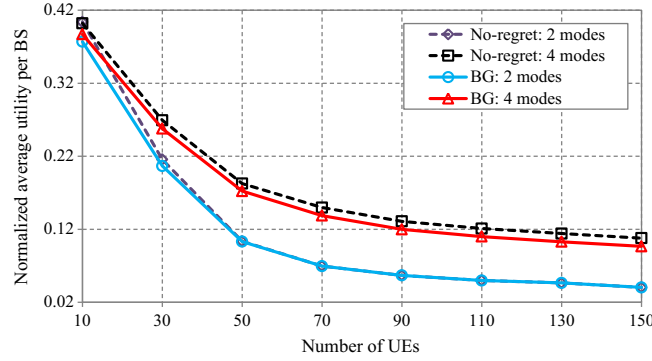


FIGURE 11 Normalized average utility per base station (BS) versus the number of user equipments (UEs) ($|\mathcal{B}_S| = 5$). BG, Boltzmann-Gibbs

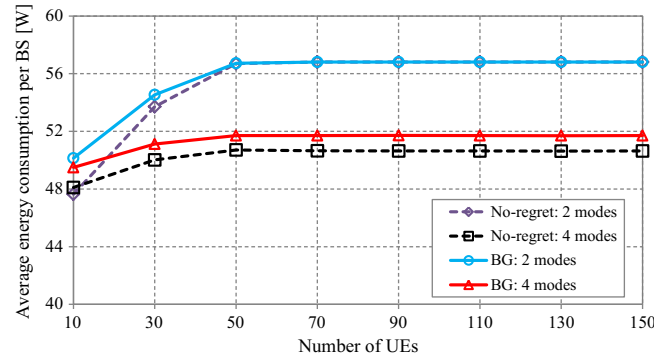


FIGURE 12 Average energy consumption per base station (BS) versus the number of user equipments (UEs) ($|\mathcal{B}_S| = 5$). BG, Boltzmann-Gibbs

Now, we compare the resource allocation mechanism based on the no-regret algorithm with a benchmark based on BG distribution. In this algorithm, the probability of selecting a strategy is calculated by BG distribution. Thus, the probability assigned with each strategy $s_b \in \mathcal{S}_b$ is updated as $\mathcal{P}_{b,s_b}(t) = G_{b,s_b}(\hat{\pi}_b(t))$.²⁶ To calculate $\hat{\pi}_b(t)$, we use Equation 16.

Figure 10 compares the normalized average utility per BS versus different numbers of SBSs for 50 UEs in the network. We can observe that the no-regret learning algorithm improves the average utility compared with the BG approach. In Figure 11, we have compared the normalized average utility per BS versus the number of UEs in the network given 5 SBSs. It can be seen that, with increased number of BS's modes, the gap between the no-regret mechanism and the BG approach becomes larger.

Figure 12 shows the average energy consumption per BS as the number of UEs varies for 5 SBSs. As the number of UEs increases, more BSs are working in ON mode and less BSs choose OFF mode. Therefore, for $\Delta_S = 2$, the no-regret and BG approaches have almost the same performance compared with $\Delta_S = 4$. For $\Delta_S = 4$, the no-regret approach consumes less energy compared with the BG approach. In Figure 13, we depict the average energy consumption per BS when increasing the

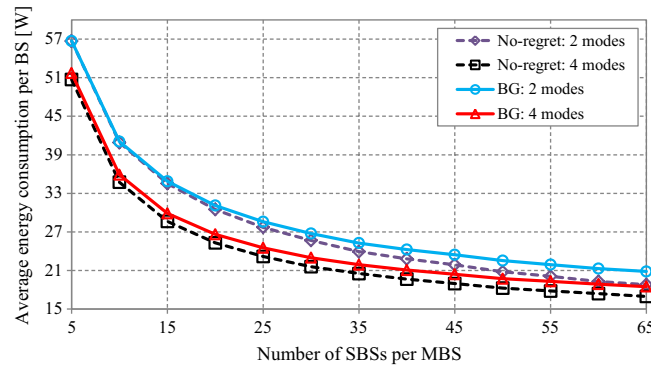


FIGURE 13 Average energy consumption per base station (BS) versus the number of small-cell BSs (SBSs) ($|\mathcal{K}| = 50$). BG, Boltzmann-Gibbs; MBS, macrocell BS

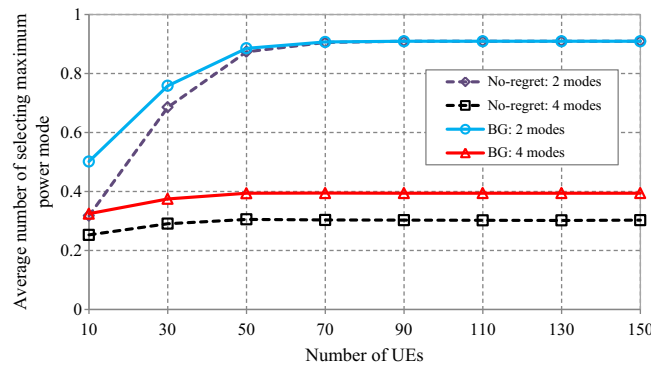


FIGURE 14 Average number of selecting maximum power mode versus the number of user equipments (UEs) ($|\mathcal{B}_S| = 10$). BG, Boltzmann-Gibbs

number of SBSs for 50 UEs. We observe that, with increased number of SBSs in the network, the average energy consumption per BS decreases. Moreover, the no-regret learning mechanism saves more energy compared with the BG approach.

Figure 14 illustrates the average number of ON playing modes with maximum transmit power versus the number of UEs for 10 SBSs. It can be seen that, for $\Delta_S = 2$, when the number of UEs is high ($|\mathcal{K}| > 70$), the no-regret and BG approaches have almost the same performance. This is due to the fact that BSs select the maximum transmit power and switch to OFF mode less frequently. However, for $\Delta_S = 4$, in the no-regret mechanism, BSs select their maximum transmit power levels less, and thus, more BSs select energy-saving modes, as compared with the BG approach.

5 | CONCLUSION

In this paper, we have investigated the impact of the number of BS's operation modes on a joint UE association and resource management mechanism in a 2-tier HetNet. In order to improve EE, we have deployed an energy-saving scheme by switching ON and OFF BSs, adaptive to traffic load fluctuations. The mechanism has been modeled as a Markov chain, in which increasing the number of modes increases computational complexity. However, it results in improving the EE of the network and balancing load among BSs.

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