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

Atefeh Hajijamali Arani | Abolfazl Mehbodnia | Mohammad Javad Omidi | Fumiyuki Adachi

1 Department of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan, Iran
2 Research Organization of Electrical Communication, Tohoku University, Sendai, Japan

Correspondence
Mohammad Javad Omidi, Department of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan 84156-83111, Iran.
Email: omidi@cc.iut.ac.ir

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, i.e., 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. From the network operator perspective, energy costs constitute a significant portion of operational expenditures. 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.

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. 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.

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. 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.
Ren and Tao 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 al where a distributed learning algorithm was applied to solve the game. In the work of Zhang et al, 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 works do not consider channel allocation among BSs and assume that all BSs operate on the same frequency band. Suárez et al 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 (i.e., power and channel) allocation. In practice and depending on the hardware, there are only a limited number of power levels available at the transmitters. Therefore, we assume that the transmission power at BSs is limited to a predetermined and finite number of discrete level sets. 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.

To save energy in BSs, a BS ON/OFF switching approach based on the game theoretic framework, proposed by Samarakoon et al, 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. 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 $B$, where tiers 1 and 2 represent the set of MBSs $B_M$ and the set of SBSs $B_S$, 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](image-url)
scheme, i.e., 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 $\Delta_M$ and $\Delta_S$ 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 $P_{\text{Max}}^M$ and $P_{\text{Max}}^S$, 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. Therefore, each MBS $m \in M$ and each SBS $s \in S$ can select their transmit power from the sets of $S_M = \{0, \frac{1}{2\Delta_M-1}P_{\text{Max}}^M, \ldots, \frac{\Delta_M-1}{2\Delta_M-1}P_{\text{Max}}^M\}$ and $S_S = \{0, \frac{1}{2\Delta_S-1}P_{\text{Max}}^S, \ldots, \frac{\Delta_S-1}{2\Delta_S-1}P_{\text{Max}}^S\}$, respectively. For example, for $\Delta_S = 2$, each SBS $s \in S$ 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) $B_{\text{ON}} \subseteq B$, where $B_{\text{ON}} = \{b | P_b \neq 0, b \in B\}$, and the set of BSs operating in OFF mode $B_{\text{OFF}} \subseteq B$, where $B_{\text{OFF}} = \{b | P_b = 0, b \in B\}$.

The set of UEs is denoted by $K$, and they are uniformly distributed in the network. The total bandwidth $\omega$ is divided into $\lfloor Q \rfloor$ orthogonal channels with bandwidth $\omega/\lfloor Q \rfloor$, where $Q$ is the set of channels. We assume that the flows arrive into the system with mean arrival rate $\lambda$ and mean packet size $1/\mu$ 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 $q_b \in Q$ is given by

$$\gamma_{b,k} = \sum_{b \in B_{\text{ON}} \setminus b} \frac{P_b g_{b,k}}{L_b} \frac{g_{b,k}}{\omega} \frac{1}{(q_b - q_b)} + \sigma^2,$$

where $L_b$ denotes the load of BS $b$. Let $\sigma^2$ be the additive white Gaussian noise power at the receiver of the UE. Here, function $\mathbb{I}_{\{\text{event}\}}$ 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 $b \in B_{\text{ON}}$ is given by

$$R_{b,k} = \frac{\omega}{\lfloor Q \rfloor} \log_2(1 + \gamma_{b,k}).$$

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

$$L_b = \sum_{k \in K} a_{b,k} l_{b,k},$$

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 $\frac{\lambda}{1 - L_b}$. Therefore, the total number of flows in the system is equal to $\sum_{b \in B_{\text{ON}}} \frac{L_b}{1 - L_b}$, which is proportional to the expected delay. Thus, with a low system load on average, the UEs experience less delay.

### 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 $b \in B$ periodically broadcasts its estimated load by a beacon signal. At each time $t$, UE $k$ is associated with and served by BS $b_k(t)$ in accordance with the following equation:

$$b_k(t) = \arg \max_{b \in B_{\text{ON}}} \frac{\log_{10} \left( P_b(t) g_{b_k(t)}(1 - \widehat{l}_b(t)) \right)}{10 \log_{10}(10)},$$

where $P_b(t)$ is the transmit power of BS $b$ at time $t$. $g_{b_k(t)}$ is the total channel gain from BS $b_k(t)$ to UE $k$. $\widehat{l}_b(t)$ is the estimated load of BS $b$ at time $t$. The average number of flows at BS $b$ is given by $\frac{\lambda}{1 - L_b}$. Therefore, the total number of flows in the system is equal to $\sum_{b \in B_{\text{ON}}} \frac{L_b}{1 - L_b}$, which is proportional to the expected delay.
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 follows\(^{20}\):

\[
\hat{L}_b(t) = \left(1 - \left(\frac{1}{\lambda}\right)^\alpha\right) \hat{L}_b(t-1) + \left(\frac{1}{\lambda}\right)^\alpha L_b(t-1),
\]

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 \( b \in B \) calculates the average CCI power over each channel \( q \in Q \) in accordance with the following equation\(^{21}\):

\[
\tilde{I}_{b,q}(t) = (1 - \lambda)I_{b,q}(t) + \lambda \tilde{I}_{b,q}(t-1),
\]

where \( \lambda \) 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 follows\(^{20}\):

\[
P_b^\text{Total} = \begin{cases} 
P_b^\text{OFF} + \frac{1}{\eta_b^\text{PA}} P_b, & \text{if} \ b \in B_{\text{ON}} \\ 
P_b^\text{ON}, & \text{if} \ b \notin B_{\text{ON}}, \end{cases}
\]

with

\[
\Lambda_b = (1 - \lambda_b^\text{DC}) (1 - \lambda_b^\text{MS}) (1 - \lambda_b^\text{Cool}) (1 - \lambda_b^\text{Feed}),
\]

where \( P_b^\text{OFF} \) is the fixed power consumption for BS \( b \), \( \eta_b^\text{PA} \) indicates the power amplifier efficiency of BS \( b \). For BS \( b \), \( \Lambda_b \) captures the losses in the DC-DC power supply (\( \lambda_b^\text{DC} \)), main supply (\( \lambda_b^\text{MS} \)), cooling system (\( \lambda_b^\text{Cool} \)), and feeder (\( \lambda_b^\text{Feed} \)).\(^{22}\) Given the described model, we aim at improving the EE of the network and balancing load among the BSs. Thus, for each BS \( b \in B \), 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 follows\(^{20}\):

\[
\pi_b = \omega_b^\text{Benefit} \frac{|A_b|}{|K|} - \frac{\omega_b^\text{Cost}}{\omega_b^\text{Cost} + \omega_b^\text{Benefit}} \left( \frac{P_b^\text{Total}}{\eta_b^\text{PA} \Lambda_b} \right),
\]

where

\[
P_b^\text{TXMax} = \frac{1}{\eta_b^\text{PA}} P_b^\text{Max},
\]

and \( \omega_b^\text{Benefit}, \omega_b^\text{Cost}, \) and \( \omega_b^\text{Total} \) 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:

\[
\max_{(P_b)} \sum_{b \in B} \pi_b \\
\text{subject to} \quad P_m \leq P_M^\text{Max}, \quad P_s \leq P_S^\text{Max}, \forall m \in B_M, \forall s \in B_S, \\
q_b \in Q, \forall b \in B, \\
a_{b,k} \in \{0, 1\}, \forall b \in B, \forall k \in K, \\
\sum_{b \in B} a_{b,k} \leq 1, \forall k \in K, \\
L_b \in [0, 1], \forall b \in B.
\]

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 \(G = (\mathcal{B}, \{\mathcal{S}_b\}_{b \in \mathcal{B}}, \{\pi_b\}_{b \in \mathcal{B}})\), where \(\mathcal{B}\) is the set of BSs as the players. \(\mathcal{S}_b\) represents the strategy set of player \(b\), in which \(\mathcal{S}_b\) is equivalent to \(\mathcal{S}_M\) and \(\mathcal{S}_S\) for the MBSs and the SBSs, respectively. The utility function of player \(b\) is denoted by \(\pi_b\) defined in Equation 9. A strategy profile is composed of the strategy of all players denoted by \(s = (s_1, \ldots, s_{|\mathcal{B}|}) \in \mathcal{S}_1 \times \cdots \times \mathcal{S}_{|\mathcal{B}|}\), where \(s_b\) is a strategy of player \(b\).

To solve the game and, consequently, obtain \(\epsilon\)-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. \(\epsilon\)-coarse correlated equilibrium**

A mixed strategy profile \(\Gamma_s\), where \(s \in \mathcal{S}_1 \times \cdots \times \mathcal{S}_{|\mathcal{B}|}\) is an \(\epsilon\)-coarse correlated equilibrium for game \(G\) if and only if, for all \(b \in \mathcal{B}\), \(s'_b \in \mathcal{S}_b\), we have

\[
\sum_{s \in \mathcal{S}} \Gamma_s \pi_b(s'_b, s_{-b}) \leq \sum_{s \in \mathcal{S}} \Gamma_s \pi_b(s) + \epsilon,
\]

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 \(s_b \in \mathcal{S}_b\), the regret of player \(b\) is defined as follows:

\[
R_{b,s_b}(t) = \max \left\{ \frac{1}{t} \sum_{\tau \leq t} \pi_b(s_b, s_{-b}(\tau)) - \hat{\pi}_b(\tau), 0 \right\},
\]

where \(\pi_b(\tau)\) is the time average of player \(b\)'s payoff. Then, the probability assigned with each strategy \(s_b \in \mathcal{S}_b\) is updated as follows:

\[
P_{b,s_b}(t + 1) := \begin{cases} \frac{1}{\rho} \pi_{b,s_b}(t), & \forall s_b \neq s_b(t) \\ 1 - \sum_{\forall s_b \neq s_b(t)} P_{b,s_b}(t + 1), & s_b = s_b(t), \end{cases}
\]

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 follows:

\[
\hat{W}(t) = \hat{W}(t - 1) + \Theta(t) \left( W(t) - \hat{W}(t - 1) \right),
\]

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, \(\Theta(t)\) 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 \(s_b \in \mathcal{S}_b\) as follows:

\[
\hat{\pi}_{b,s_b}(t) = \hat{\pi}_{b,s_b}(t - 1) + \left( \frac{1}{\rho_t} \right) \mathbb{1}_{\{s_b(t) = s_b\}} \left( \pi_b(t) - \hat{\pi}_{b,s_b}(t) \right),
\]

\[
\hat{R}_{b,s_b}(t) = \hat{R}_{b,s_b}(t - 1) + \left( \frac{1}{\rho_t} \right) \left( \hat{\pi}_{b,s_b}(t) - \pi_b(t) - \hat{R}_{b,s_b}(t - 1) \right),
\]

\[
P_{b,s_b}(t) = P_{b,s_b}(t - 1) + \left( \frac{1}{\rho_t} \right) \left( G_{b,s_b}(t) - P_{b,s_b}(t - 1) \right),
\]

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

\[
G_{b,s_b}(\hat{R}_b(t)) = \frac{\exp \left( \frac{1}{\nu_b} \hat{R}_{b,s_b}(t) \right)}{\sum_{\forall s_b \in \mathcal{S}_b} \exp \left( \frac{1}{\nu_b} \hat{R}_{b,s_b}(t) \right)},
\]
where $\frac{1}{\theta_b} > 0$ denotes the temperature parameter for player $b$. For converging the approach, all learning rate exponents $\zeta = \{\kappa, \zeta, \nu\}$ are chosen according to the following conditions:

$$\lim_{t \to \infty} t \sum_{n=1}^{t} \frac{1}{n^\zeta} = +\infty$$

(20)

and

$$\lim_{t \to \infty} t \sum_{n=1}^{t} \left(\frac{1}{n^\zeta}\right)^2 < +\infty.$$  

(21)

Therefore, we choose all learning rate exponents $\zeta = \{\gamma, \zeta, \nu\} \in (0.5, 1)$. Furthermore, each BS $b$ selects its strategy using a mapping function $f : P_b = [P_{b,1}, \ldots, P_{b,|S_b|}] \to s_b$, 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 $B$, average regret as global energy, and finite configuration space $S_1 \times \cdots \times S_{|B|}$. 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 $P_{\text{Max}}$ is considered to be 30 dBm, unless we mention that it is set to be $P_{\text{Max}}^S = 20$ 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

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical link type</td>
<td>Downlink</td>
</tr>
<tr>
<td>Carrier frequency/total bandwidth</td>
<td>2 GHz/10 MHz</td>
</tr>
<tr>
<td>Number of channels (</td>
<td>Q</td>
</tr>
<tr>
<td>Noise power</td>
<td>−174 dBm/Hz</td>
</tr>
<tr>
<td>Mean packet arrival rate</td>
<td>1800 Kbps</td>
</tr>
<tr>
<td>Weights ω_k b, ω_l b, ω_p b</td>
<td>1, 0.5, 0.5</td>
</tr>
<tr>
<td>Learning rate exponent α</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Base Stations’ Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>MBS</th>
<th>SBS</th>
</tr>
</thead>
<tbody>
<tr>
<td>p^OFF_b</td>
<td>56.1001 W</td>
<td>4.6919 W</td>
</tr>
<tr>
<td>η_b PA</td>
<td>31.1%</td>
<td>6.7%</td>
</tr>
<tr>
<td>DC-DC loss</td>
<td>7.5%</td>
<td>9%</td>
</tr>
<tr>
<td>Main supply loss</td>
<td>9%</td>
<td>11%</td>
</tr>
<tr>
<td>Cooling loss</td>
<td>10%</td>
<td>0%</td>
</tr>
<tr>
<td>Feeder loss</td>
<td>3 dB</td>
<td>0 dB</td>
</tr>
<tr>
<td>Shadowing standard deviation</td>
<td>8 dB</td>
<td>10 dB</td>
</tr>
<tr>
<td>Cell radius</td>
<td>250 m</td>
<td>40 m</td>
</tr>
<tr>
<td>Distance-dependent path loss model</td>
<td>128.1+37.6log_{10}(d); d in km</td>
<td>140.7+36.7log_{10}(d); d in km</td>
</tr>
<tr>
<td>Minimum distance</td>
<td>MBS-SBS: 75 m; MBS-UE: 35 m</td>
<td>SBS-SBS: 40 m; SBS-UE: 10 m</td>
</tr>
</tbody>
</table>

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 Δ_S = 4 and Δ_S = 6 are improved, respectively, up to 27% and 28%, as compared with Δ_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 Δ_S = 4 improves the average load per BS by about 11% over the mechanism with Δ_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) ($|\mathcal{S}| = 5, 10, \text{ and } 15$). SBSs, small-cell base stations

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

FIGURE 6  Normalized average utility per base station (BS) versus the number of small-cell BSs (SBSs) ($|\mathcal{S}| = 50 \text{ and } 100$). 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, \text{ and } 15 versus the number of UEs. As depicted in Figure 8, we can expect more significant energy conservation with the increase in $\Delta S$ 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
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 (...) denote $\Delta_M$ and $\Delta_S$, 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.
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 $s_b \in S_b$ is updated as $P_{b,s_b}(t) = G_{b,s_b}(\hat{\pi}_b(t))$. 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
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.

ACKNOWLEDGEMENTS

This research is supported by “Towards Energy-Efficient Hyper-Dense Wireless Networks with Trillions of Devices,” the Commissioned Research of the National Institute of Information and Communications Technology, Japan, and KDDI Foundation research grant “Energy-Efficient Radio Resource Management for Next Generation Wireless Network.”

ORCID

Atefeh Hajijamali Arani http://orcid.org/0000-0002-4177-3558
Mohammad Javad Omidi http://orcid.org/0000-0002-0249-3633
REFERENCES


How to cite this article: Hajijamali Arani A, Mehbodniya A, Omidi MJ, Adachi F. Distributed ON/OFF switching and dynamic channel allocation: Decreasing complexity and improving energy efficiency. Trans Emerging Tel Tech. 2017;28:e3222. https://doi.org/10.1002/ett.3222