A Distributed Sleep Mode and Bandwidth Allocation Algorithm for Improving Energy-Efficiency in Dense HetNet

Abolfazl Mehbodniya and Fumiyuki Adachi

Graduate School of Engineering, Department Communications Engineering,
Tohoku University
6-6-05 Aza-Aoba, Aramaki, Sendai 980-8579, Japan
Email: mehbod@mobile.ecei.tohoku.ac.jp adachi@ecei.tohoku.ac.jp

***Abstract*—Designing high-speed, energy-efficient heterogeneous wireless networks has recently emerged as a key research challenge. A novel approach for radio resource management at the base station (BS) level is introduced with the objective of improving the spectral-efficiency, while keeping the energy-efficiency (EE) at an acceptable level. In this paper, a hybrid opportunistic ON/OFF switching (OOFS) and dynamic channel allocation (DCA) mechanism is proposed. The problem is formulated as a non-cooperative game between the BSs who seek to decide on their transmission mode and channel allocation parameters. To solve this game, a two-step algorithm is proposed. At first, a mixed-strategy game is used, so the BSs may decide independently about their power management strategy. In the second step, the BS selects its downlink channel using a fully distributed channel segregation approach. In dense heterogeneous environments, the DCA algorithm shows a significant improvement in terms of BS throughput over OOFS algorithm, while keeping an acceptable EE level comparable to OOFS.**

***Index Terms*—Channel segregation, distributed design, dynamic channel allocation, energy-efficiency, ON/OFF Switching, sleep mode, spectral-efficiency.**

I. Introduction

Next generation wireless cellular systems, commonly referred as heterogeneous networks (HetNets) [1], are expected to rely on the large-scale and dense deployment of low-cost small cell base stations. While a dense deployment of HetNets can significantly boost the capacity and coverage of wireless networks, it also faces several challenges, such as network modeling, maintaining an energy-efficient operation [2], and handling radio resource management (RRM) with large number of connected user equipments (UEs). Indeed, energy efficiency (EE) has become a major research challenge in a variety of fields as the global awareness for reducing CO2 emissions has continuously increased in the past decade. In cellular networks, it is believed that at least 70% of energy is consumed at the base station (BS). As a result, it becomes vital to improve the EE of future BSs. Several approaches are proposed for this purpose such as adaptively moving the BSs into sleep mode based on the traffic conditions [3]. Due to issues related to cost, technical feasibility, and control traffic, development of distributed radio resource management (RRM) techniques is critical to maintain EE of the network.

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In the design of last four generations of wireless systems, most emphasis was on improving the spectral efficiency (SE) with less attention on EE. Recently, there have been some efforts in improving the EE of BSs. On one hand, most of these works target only the EE problem without considering the SE performance. SE is an important parameter specially for dense HetNet scenarios, in which large number of UEs should be guaranteed a minimum level of quality of service (QoS) and EE should not compromise the SE of the system. On the other hand, these works are mostly based on centralized RRM solutions.

In [4], a cell biasing technique is proposed for femtocells to improve the user association and resource utilization, which shows improvement in capacity and EE of the network through frequency reuse and subchannel power control. In [5], authors proposed an energy efficient user association and ON/OFF switching algorithm. They have formulated an optimization problem for user association which takes into account the energy efficiency as well. Later, a quantum particle swarm optimization (QPSO) is used to solve this user association problem. The aforementioned works succeed in improving the EE, however they are based on centralized solutions. In [6], an ON/OFF switching algorithm is proposed based on game theory, which decides about the transmission power level of each BS. For the UE association problem, they have proposed a cost function, which includes both the received signal strength (RSS) and the BSs' loads. Therefore, it can reduce overloading of the BSs. While [6] manages to significantly improve the average energy consumption of the BSs, its emphasis is only on EE considerations.

The main contribution of this paper is to propose a joint opportunistic ON/OFF switching (OOFS) & dynamic channel allocation algorithm (JOFS-DCA). A non-cooperative game is formulated between the BSs and then, a distributed algorithm is proposed to decide about the ON/OFF status of the BS or the level of its transmission power. In the next step, UEs decide which BS to connect to, i.e., the UE association problem. Each UE chooses the target BS considering both the RSS and averaged load of all BSs. Finally, each BS employs a distributed channel segregation method similar to [7] to choose a channel based on its look-up table. This look-up table is

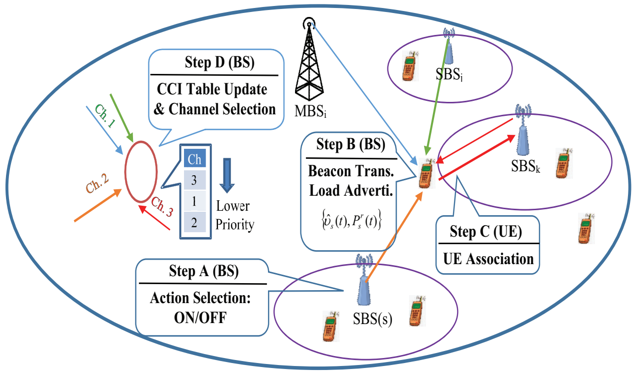

Fig. 1. System model for the energy efficiency improvement in HetNets through distributed RRM technique.

formed based on the level of co-channel interference (CCI) that each BS senses on different channels. After each BS' channel is decided, then an orthogonal division multiple access (OFDMA) scheme is used to transmit to the UEs in downlink. Simulation results are provided to evaluate the performance of the proposed algorithm in terms of average BS energy consumption and throughput.

The remainder of this paper is organized as follows. In Section II, system model is presented along with the power, signal-to-interference-noise ratio (SINR), load, and cost expressions. Section III discusses different steps of our proposed algorithm, Section IV provides the simulation results and the evaluation of our algorithm, and finally, Section V concludes the paper.

II. System Model

We Consider the downlink transmission in a heterogeneous network having the same topology as in [6] is considered. Fig. I shows the system model, which consists of a set of BSs, $\mathcal{S} = \{1, ..., S\}$. We assume only one macro base station (MBS), $s = 1$, which encompasses a variable number of small base stations, $\mathcal{S} = \{2, ..., S\}$. A total number of X users, $\mathcal{X} = \{1, ..., X\}$ are available in the system.

Power consumption of sth BS, BS(s), at time t is given by:

$$P_s^{\text{All}}(t) = \frac{P_s(t)}{\eta\alpha(1-\alpha_{\text{feed}})} + P_s^{\text{Back}} + P_s^{\text{Idle}}, \tag{1}$$

with

$$\alpha = (1-\alpha_{DC})(1-\alpha_{\text{main}})(1-\alpha_{\text{cool}}), \tag{2}$$

and

$$P_s^{\text{Idle}} = \frac{P_{\text{radio}} + P_{\text{base}}}{\alpha}, \tag{3}$$

where $P_s(t)$ is the transmission power, η is efficiency of power amplifier, P_s^{Back} is the power consumption in backhaul, P_s^{Idle} is the power consumption in OFF mode. α_{feed}, α_{DC}, α_{main} and α_{cool} represent respectively the loss fractions of feeder, AC-DC conversion, main supply and cooler system. P_{radio} and P_{base} are the power consumption of radio frequency and baseband units, respectively.

We assume a total of C available channels, $\mathfrak{C} = \{1, ..., C\}$. Each channel uses OFDMA with N_c subcarriers. A frequency-selective Rayleigh fading channel is considered which is composed of Q distinct paths. The impulse response of the propagation channel at time t is modeled according to:

$$h(\tau;t) = \sum_{q=0}^{Q-1} h_q(t)\delta(\tau-\tau_q) \ , \tag{4}$$

where $h_q(t)$ and τ_q denote the time-varying complex-valued path gain with $E[\sum_{q=0}^{Q-1} |h_q(t)|^2] = 1$ ($E[.]$ denotes the ensemble average operation) and the time delay of the qth path, respectively.

A. SINR Expression

The downlink CCI experienced at xth UE connected to sth BS, UE_s^x, comes from the co-channel BSs using the same $c(s)$th channel and is expressed by:

$$\begin{aligned} I_{\text{UE}_s^x}(t) =& \frac{1}{N_c} \sum_{\substack{s' \in \text{BSG}(c(s)) \\ s' \neq s}} p_{\text{BS}(s')} \cdot r_{\text{UE}_s^x,\text{BS}(s')}^{-\alpha} \\ &\times \sum_{k' \in N_s^x} \left| H_{\text{UE}_s^x,\text{BS}(s')}(t;k',c(s)) \right|^2 \end{aligned} \tag{5}$$

where $\text{BSG}(c(s))$ denotes the BS group which uses the same cth channel, $p_{\text{BS}(s')} = P_{s'}(t) \cdot R^{-\alpha}$ is the normalized transmit power of beacon signal of BS(s') with R being the reference distance and α being the path-loss exponent. $r_{\text{UE}_s^x,\text{BS}(s')}$ is the normalized distance between UE_s^x and BS(s'). $H_{\text{UE}_s^x,\text{BS}(s')}(t;k,c(s))$ is obtained by the Fourier transform of the channel impulse response between UE_s^x and BS(s') at time t. N_s^x is the set of subcarriers assign by $\text{BS}(s')$ to UE_s^x. Here, we do not consider any optimal subcarrier allocation for the OFDMA system. Subcarriers are divided equally and sequentially between UEs connected to each BS and we assume $N_c \gg \mathbf{X}_s$, where $\mathbf{X}_s$ is the total number of UEs connected to BS(s). The downlink instantaneous SINR $\lambda_{\text{UE}_s^x}$ experienced at UE_s^x's antenna is given by

$$\lambda_{\text{UE}_s^x}(t) = \frac{p_{\text{BS}(s)} \cdot r_{\text{UE}_s^x,BS(s)}^{-\alpha} \sum_{k' \in N_s^x} \left| H_{\text{UE}_s^x,\text{BS}(s)}(t;k',c(s)) \right|^2}{N_c(I_{\text{UE}_s^x}(t) + N_0)} \tag{6}$$

where N_0 is the noise variance.

B. Load and Cost Function Expressions

We assume that UEs have different QoS requirements, i.e., they have different packet arrival rates and mean packet sizes. We define the instantaneous load density of each BS as the summation of the loads of all individual UEs connected to it according to:

$$\nu_s(t) = \sum_{x=1}^{X_s} \frac{\gamma_s^x}{\mu_s^x \omega' \log_2(1+\lambda_{\text{UE}_s^x}(t))} \tag{7}$$

where γ_s^x and μ_s^x are the packet arrival rate and mean packet size of xth UE connected to sth BS, $\omega' = \omega/C$ is the bandwidth of each BS and ω is the total system bandwidth. The load of each BS is inversely related to the throughput it provides for the UEs in its service. The averaged value of load, $\hat{\upsilon}_s(t)$, is calculated as:

$$\hat{\upsilon}_s(t) = \hat{\upsilon}_s(t-1) + l(t)\left(\upsilon_s(t-1) - \hat{\upsilon}_s(t-1)\right) \ , \tag{8}$$

where $l(t)$ is the learning rate. In order to ensure system stability, $l(t)$ is chosen such that the load averaging is sufficiently slower than UE association process.

A cost function similar to [6] is considered for each BS which tries to capture both load and energy consumption. The cost function for sth BS is defined by:

$$\Psi_s(t) = \varphi_s P_s^{\mathrm{All}}(t) + \psi_s \nu_s(t), \quad \varphi_s, \psi_s > 0 \tag{9}$$

where φ_s and ψ_s are weighting parameters which define the impact of energy and load, respectively.

III. Proposed Distributed RRM Algorithm

Our goal is to design a fully distributed solution which can minimize the cost function in (9) for all BSs. The proposed JOFS-DCA algorithm is summarized in Algorithm 1.

Algorithm 1 : Proposed algorithm.

Input: $\mathcal{C}(s,t)$, $\hat{u}_{s,i}(t)$, $\hat{r}_{s,i}(t)$, $p_{s,i}(t)$
Output: $a_s(t+1)$, $\mathcal{A}(x, t+1)$
Initialization: $\mathcal{S} = \{1, ..., S\}$;
$\mathcal{X} = \{1, ..., X\}$; $\mathfrak{C} = \{1, ..., C\}$; $t = 0$
while do
  $t \leftarrow t - 1$,
  for $\forall s \in \mathcal{S}$ **do**
    Find $a_s(t) = f\left(p_{s,i}(t-1)\right)$,
  end for
  Beacon signal transmission
  and load advertising, $\hat{\upsilon}_s(t)$, (8)
  for $\forall x \in \mathcal{X}$ **do**
    if $(x \in \mathcal{W}) \vee (x \in \mathcal{O})$ **then**
      Find $\mathcal{A}(x,t)$, (12)
    end if
  end for
  for $\forall s \in \mathcal{S}$ **do**
    for $\forall c \in \mathfrak{C}$ **do**
      CCI power measurement, $I_{\mathrm{BS}(s)}(t;c)$, (11)
      Average power computation, $\bar{I}_{\mathrm{BS}(s)}(t;c)$, (13)
    end for
    CCI Table update, (Table II)
    Channel selection, $\mathcal{C}(s,t)$, (14)
  end for
  Updating instantaneous values, $\upsilon_s(t)$, $\Psi_s(t)$, (7), (9)
  Updating $\hat{u}_{s,i}(t)$, $\hat{r}_{s,i}(t)$, $p_{s,i}(t)$, (15), (16), (17)
end while

A. Strategy selection

In the first step of the algorithm, BSs decide their action, i.e. OFF/ON mode. A non-cooperative game is used to design the decision process. In this game, the players are the BSs, strategies are different power levels chosen by BSs and the utility function of each BS is defined according to, $u_s(t) = -\Psi_s(t)$. In this paper, we use variable i to refer to each strategy and $a_s(t)$ captures the strategy selected by sth BS at time t. Each BS selects its action, $a_s(t)$, at time t based on a probability distribution, $p_{s,i}(t-1)$, associated with each action, i.e., $p_{s,i}(t-1)$ is a mixed strategy. Assuming f as a probabilistic mapping function, $a_s(t)$ is given by $a_s(t) = f\left(p_{s,i}(t-1)\right)$, where $a_s(t) \in i = \{1, ..., 4\}$. Each strategy i introduces the cell range expansion bias (CREB) for BSs, which is defined in terms of the transmission power level, $\zeta_s(t)$, and for time t is given by:

$$P_s(t) = \zeta_s(t) P_s^{\mathrm{Max}} \tag{10}$$

where P_s^{Max} is the maximum allowed transmission power for BSs in the system. Table I shows the selected transmission power level for different strategies. Please note that MBS can only select two strategies, $i = 1$ and $i = 4$, whereas small base stations (SBSs) can select all four available strategies.

TABLE I
TRANSMISSION POWER LEVELS

Strategy Identification Number (i)	Transmission Power Level ($\zeta_s(t)$)
1	0
2	1/3
3	2/3
4	1

B. Beacon transmission

Each BS periodically broadcasts the beacon signal on the selected channel. The instantaneous CCI power $I_{\mathrm{BS}(s)}(t;c)$ measured at BS(s) on the cth channel ($c = 0 \sim C-1$) at time t is represented by:

$$\begin{aligned} I_{\mathrm{BS}(s)}(t;c) = &\frac{1}{N_c} \sum_{\substack{s' \in \mathrm{BSG}(c(s)) \\ s' \neq s}} p_{\mathrm{BS}(s')} \cdot r_{\mathrm{BS}(s),\mathrm{BS}(s')}^{-\alpha} \\ &\times \sum_{k=0}^{N_c-1} \left| H_{\mathrm{BS}(s),\mathrm{BS}(s')}(t;k,c) \right|^2, \end{aligned} \tag{11}$$

where $r_{\mathrm{BS}(s),\mathrm{BS}(s')}$ is the normalized distance between BS(s) and BS(s'). $H_{\mathrm{BS}(s),\mathrm{BS}(s')}(t;k,c)$ is obtained by the Fourier transform of the channel impulse response between BS(s) and BS(s') at time t and $E[|H_{\mathrm{BS}(s),\mathrm{BS}(s')}(t;k,c)|^2] = 1$. We assume that the beacon signal contains the load information of the BS as well. Please note that a more precise method is to measure the interference at the UE, as we are studying the downlink transmission. However, intuitively we deduct that interference measurement at the BS can still serve as a good approximation, given the fact that SBSs' coverage is much smaller than MBS.

C. UE association

If the UE belongs to the set of recently slept BSs, $\mathcal{W}$, or if it belongs to the set of UEs which have dropped due to overload, $\mathcal{O}$, or if the UE has newly joined the network, then it should be assigned to a new BS. In order to connect to a new BS, UEs receive the load estimate of all BSs through the beacon signal and choose the BS they want to connect to by evaluating an association function. This association function is based on two metrics, i.e., the RSS and the load condition of each BS. The reason to choose two metrics is to ensure a minimum required QoS for UEs and at the same time to prevent overloading of BSs. The UE's association criteria is formulated according to:

$$\begin{aligned} \mathcal{A}(x,t) = &\arg\max_{s \in S} \Big\{ \hat{\upsilon}_s(t)^{-\tau} p_{\mathrm{BS}(s)} \cdot r_{\mathrm{UE}^x, BS(s)}^{-\alpha} \\ &\times \sum_{k=1}^{N_c} \left| H_{\mathrm{UE}^x,\mathrm{BS}(s)}(t;k,c(s)) \right|^2 \Big\} \end{aligned} \tag{12}$$

where τ is a coefficient, which indicates the impact of each BS's traffic load.

TABLE II
CCI TABLE AT THE BS(S)

Channel #	Average CCI Power	Priority
#1	$\overline{I}_{\mathrm{BS}(s)}(t;1)$	2
#2	$\overline{I}_{\mathrm{BS}(s)}(t;2)$	1
...	$\overline{I}_{\mathrm{BS}(s)}(t;3)$	...
#C	$\overline{I}_{\mathrm{BS}(s)}(t;4)$	n

D. Channel Selection

We use the first order filtering to compute the average CCI power. The average CCI power $\overline{I}_{\mathrm{BS}(s)}(t;c)$ computed at sth BS on the cth channel at time t is given by

$$\overline{I}_{\mathrm{BS}(s)}(t;c) = (1-\beta)\cdot I_{\mathrm{BS}(s)}(t;c) + \beta\cdot \overline{I}_{\mathrm{BS}(s)}(t-1;c), \quad (13)$$

where β denotes the forgetting factor. Using the average CCI powers on all available channels, the CCI table is updated for all available channels ($c = 0 \sim C-1$). The channel having the lowest average CCI power is selected as

$$\mathcal{C}(s,t) = \arg\min_{c\in\mathfrak{C}} \overline{I}_{\mathrm{BS}(s)}(t;c)\ , \quad (14)$$

which is used until the next CCI table updating time t+1. The averaging interval of the first order filtering is given as 1/(1-β). If a too small β is used, averaging is not enough and the measured average CCI power varies like the instantaneous CCI power. Therefore, the channel reuse pattern varies at every CCI table updating time. Hence, $\beta \approx 1$ is recommended [8]. In this paper, β=0.95 is used for the computer simulation.

E. Mixed strategy update

Utility estimation, $\hat{u}_{s,i}(t+1)$, regret, $\hat{r}_{s,i}(t+1)$ and probability distribution, $p_{s,i}(t+1)$ of ith strategy for sth BS at time $t+1$ are given by

$$\begin{aligned}
&\hat{u}_{s,i}(t+1) = \hat{u}_{s,i}(t) + c_b(t)\ \cdot \mathbf{1}(t)\ \cdot (u_s(t) - \hat{u}_{s,i}(t))\\
&\hat{r}_{s,i}(t+1) = \hat{r}_{s,i}(t) + d_s(t+1)\left(\hat{u}_{s,i}(t) - u_s(t) - \hat{r}_{s,i}(t)\right)\\
&p_{s,i}(t+1) = p_{s,i}(t) + e_s(t+1)\left(G_{s,i}(\hat{r}_{s,i}(t)) - p_{s,i}(t)\right)
\end{aligned} \quad (15)$$

with

$$\mathbf{1}(t) = \begin{cases} 1 & (if\ a_s(t+1) = a_s(t)) \\ 0 & (if\ a_s(t+1) \neq a_s(t)) \end{cases} \quad (16)$$

and

$$G_{s,i}(\hat{r}_{s,i}(t)) = \frac{\exp\left(\sigma_s \hat{r}_{s,i}(t)\right)}{\sum_{i'\in \mathrm{A}_s} \exp\left(\sigma_s \hat{r}_{s,i'}(t)\right)}\ , \quad (17)$$

where $G_{s,i}(\hat{r}_{s,i}(t))$ is the Boltzmann-Gibbs (BG) distribution, which is used to encourage those played actions with lower regrets and discourage actions with higher regrets. In (15), σ_s is the temperature parameter. For further information on BG distribution and its role in this game to reach the equilibrium please refer to [9]. $c_b(t)$, $d_b(t)$ and $e_b(t)$ are learning rates which decay inversely proportional to time and should meet the following conditions:

$$\begin{aligned}
&\lim_{t\to\infty}\sum_{m=1}^{t} c_s(m) = +\infty, && \lim_{t\to\infty}\sum_{m=1}^{t} d_s(m) = +\infty,\\
&\lim_{t\to\infty}\sum_{m=1}^{t} e_s(m) = +\infty, && \lim_{t\to\infty}\sum_{m=1}^{t} c_s^2(m) < +\infty,\\
&\lim_{t\to\infty}\sum_{m=1}^{t} d_s^2(m) < +\infty, && \lim_{t\to\infty}\sum_{m=1}^{t} e_s^2(m) < +\infty,\\
&\lim_{t\to\infty}\frac{d_s(t)}{c_s(t)} = 0, && \lim_{t\to\infty}\frac{e_s(t)}{d_s(t)} = 0.
\end{aligned} \quad (18)$$

TABLE III
SIMULATION PARAMETERS

Parameter	**Value**
Network	
Noise Variance, N_0	-174dBm/Hz
Arrival Rate, γ_s^x/μ_s^x	180kbps
MBS	
Max. Trans. Power, P_s^{Max}	46dBm
Ave. MBS-SBS Distance (m)	75
Ave. MBS-UE Distance (m)	35
SBS	
Max. Trans. Power, P_s^{Max}	30dBm
Ave. SBS-SBS Distance (m)	40
Ave. SBS-UE Distance (m)	10
Path loss (d:distance of BS and user (m)) (unit: dB)	
MBS - UE	15.3+37.6$\log_{10}$(d)
SBS - UE	27.9+37.6$\log_{10}$(d)
Learning Parameters	
Boltzmann temperature, σ_s	10
Weighting Parameters, φ_s, ψ_s	10, 5

IV. COMPUTER SIMULATION

We simulate s scenario similar to Fig. I, where a MBS is collocated with several SBSs. Simulation parameters are summarized in Table III. Two benchmarks are considered for comparison purposes. First is a baseline approach, in which all BSs are always on. Second is the energy-efficient ON/OFF switching algorithm proposed in [6]. Fig. 2 and Fig. 3 show the average energy consumption per BS for different numbers of UEs for $S = 2$ BSs and $S = 25$ BSs, respectively. The number of channels for the proposed algorithm is $C = 4$ in all scenarios. We observe that both the proposed algorithm and the one in [6] have considerably higher EE than the baseline approach but their performance is quite identical for lower number of (density) of BSs. However in more dense scenarios ($S = 25$ BSs), the proposed algorithm slightly outperforms the one in [6] for moderate number of connected UEs in the system. Maximum improvement is about 12%. Fig. 4 shows the average cost per BS for different number of UEs, $S = 25$ BSs and $C = 4$. When both power consumption and load are taken into consideration, the proposed algorithm shows substantial improvement, compared to the two other algorithms. Finally, Fig. 5, compares the average throughput per BS for different number of BSs. Again the proposed algorithm significantly outperforms the two other algorithms.

V. CONCLUSION

In this paper, we proposed a joint ON/OFF switching and dynamic channel allocation algorithm which can significantly

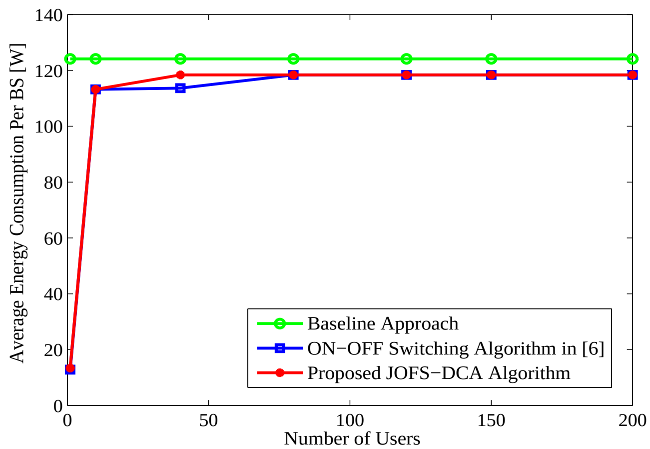

Fig. 2. Average energy consumption per base station for different number of UEs and $S = 2$ BSs and $C = 4$.

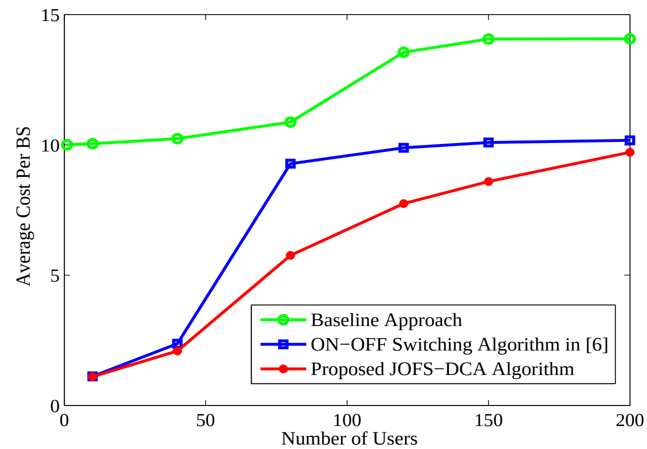

Fig. 4. Average cost per base station for different number of UEs and $S = 25$ BSs and $C = 4$.

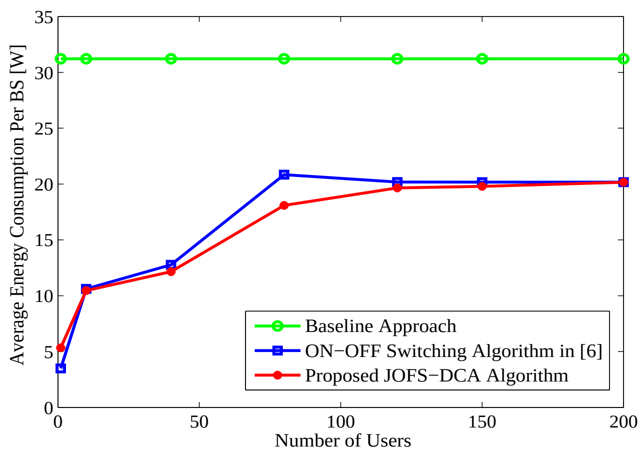

Fig. 3. Average energy consumption per base station for different number of UEs and $S = 25$ BSs and $C = 4$.

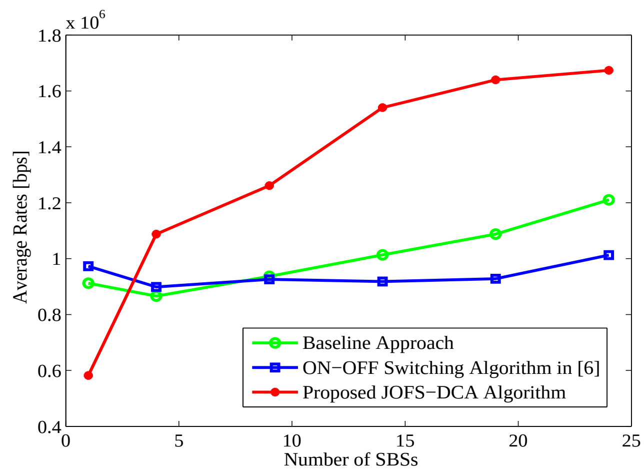

Fig. 5. Average throughput per base station for different number of base stations and $X = 100$ UEs and $C = 4$.

improve the average throughput. A non-cooperative game-theoretic approach was used to design the base station (BS) ON/OFF switching problem. Later, each BS prioritises the available channels based on their level of interference and chooses the one with the least averaged received interference. The algorithm is fully distributed and base stations do not need to exchange any information. The proposed algorithm shows a comparable performance with a benchmark from energy-efficiency point of view, with slight improvement in dense scenarios. However, it significantly outperforms the benchmark in terms of average BS throughput, in dense small cell deployment scenarios.

References

[1] E. Hossain, M. Rasti, H. Tabassum, and A. Abdelnasser, "Evolution toward 5g multi-tier cellular wireless networks: An interference management perspective," *IEEE Trans. on Wir. Com.*, vol. 21, no. 3, pp. 118–127, Jun. 2014.

[2] Y. Chen, S. Zhang, S. Xu, and G. Li, "Fundamental trade-offs on green wireless networks," *IEEE Com. Mag.*, vol. 49, no. 6, pp. 30–37, Jun. 2011.

[3] R. Wang, J. Thompson, H. Haas, and P. Grant, "Sleep mode design for green base stations," *IET Com.*, vol. 5, no. 18, pp. 2606–2616, Dec 2011.

[4] R. Thakur, A. Sengupta, and C. Siva Ram Murthy, "Improving capacity and energy efficiency of femtocell based cellular network through cell biasing," in *2013 11th Inter. Sym. on Modeling Optim. in Mobile, Ad Hoc Wire. Netw. (WiOpt)*, May 2013, pp. 436–443.

[5] Y. Zhu, Z. Zeng, T. Zhang, L. An, and L. Xiao, "An energy efficient user association scheme based on cell sleeping in lte heterogeneous networks," in *17th Inter. Sym. on Wire. Pers. Multimedia Com. (WPMC2014)*, September 2014, pp. 1–5.

[6] S. Samarakoon, M. Bennis, W. Saad, and M. Latva-aho, "Opportunistic sleep mode strategies in wireless small cell networks," in *IEEE Inter. Conf. on Com. (ICC)*, June 2014, pp. 2707–2712.

[7] R. Sugai, M. T. Sirait, Y. Matsumura, K. Temma, and F. Adachi, "Impact of shadowing correlation on interference-aware channel segregation based dca," in *IEEE Veh. Tech. Society Asia Pacific Wir. Com. Sym. (APWCS2014)*, August 2014, pp. 1–4.

[8] Y. Matsumura, S. Kumagai, T. Obara, T. Yamamoto, and F. Adachi, "Channel segregation based dynamic channel assignment for wlan," in *IEEE Inter. Conf. on Com. Sys. (ICCS)*, Nov 2012, pp. 463–467.

[9] M. Bennis, S. Perlaza, and M. Debbah, "Learning coarse correlated equilibria in two-tier wireless networks," in *IEEE Inter. Conf. on Com. (ICC)*, June 2012, pp. 1592–1596.