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Energy efficiency of ultra-dense small-cell downlink networks with adaptive cell breathing

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Abstract: The authors propose an *adaptive cell-breathing (ACB)* technique to improve the energy efficiency (EE) of a downlink cellular network consisting of small-cell base stations (BSs), wherein each BS adaptively adjusts its transmission power such that the received signal strength of the worst-case user is larger than a pre-defined threshold. They also propose an aggressive BS on–off (ABO) technique in which the small-cell BSs having a number of users smaller than a certain value, N_{th}, are turned off, whereas conventional techniques only turn off the empty BSs. They adopt a stochastic geometry for modelling the locations of both BSs and users. Simulation results show that the ACB technique yields a much better EE than the power on–off technique with a fixed power, including the ABO technique. In particular, the EE of the ACB technique is proportional to $(\lambda_b)^c$ $(c > 0)$, where λ_b denotes the BS density and the exponent *c* denotes the increasing ratio of the EE to λ_b in the $\log - \log$ domain. The EE of the ABO technique tends to increase as N_{th} increases.

1 Introduction

1.1 Motivations

Recently, mobile data traffic has been increased significantly. Next-generation wireless communication systems, referred to as 5G, have been investigated in order to support huge traffic demands [1]. Many wireless technologies such as (heterogeneous) small cells, massive antennas, coordinated multi-point transmission, interference management, in-band full-duplex radios, and cognitive radios, are being considered as candidates for the 5G systems [2]. Among them, the small cells are considered to be one of the most promising techniques to increase the throughput of the 5G systems since it has been known that the capacity of cellular networks linearly increases according to the base station (BS) density if inter-cell interferences can be properly dealt with [3–5]. The basic idea of small cells involves deploying BSs close to the users.

Meanwhile, improved energy efficiencies (EEs) have become desirable with regard to wireless networks due to growing concerns associated with global warming. In particular, it has been shown that nearly 60% of the total consumed energy was due to BSs in cellular networks [6]. Hence, the EE of BSs must be improved to effectively reduce the power consumption in cellular networks. In addition, it has been known that there exists a trade-off between spectral and EE in cellular networks and the trade-off can be improved via a proper resource allocation [7]. The power consumption of small cells is in general much lower than that of the conventional macro cells. However, it is not clear if small cells result in a higher EE than the conventional macro cells in a *network-wide* perspective due to the higher BS density in small-cell networks.

1.2 Related work

Recently, several studies with regard to the EE of small cells have been investigated [8–18]. The coverage and EE of small-cell networks were analysed under a *stochastic geometry* model in [8], where the optimal BS density was obtained by taking into account the network costs, including energy consumption, hardware, and backhaul cables. Lee and Huang [8] considered the scenario where each fixed-power BS is turned on unless its cell is empty, i.e. no active users served by the BS. The EE scaling laws of the downlink hexagonal cellular networks were analysed according to the radius of the cell in [9]. It was shown that the EE is proportional to $R^{-\alpha}$ with proper power control techniques, where R and α denote the cell radius and the path-loss exponent, respectively. However, in [9], only the transmission power was considered although additional power consumption existed at the BSs which may be even larger than the transmit power in practise.

Furthermore, small cells tend to be deployed in random locations and, therefore, the stochastic geometry model may be more appropriate than the hexagonal model. In [10], the network-wide EE of small-cell networks was analysed according to the BS density and the number of BS antennas under the stochastic geometry model, where it was shown that the throughput increases as the BS density increases, but the EE increases according to the BS density only when the non-transmission power ratio is low enough. Three types of BSs (macro, micro, and pico) were considered for measuring the power consumption, but both transmission and non-transmission power consumptions for each type of BS were assumed to be fixed [10].

In other words, transmission power control, sleep mode operations of the BS, or power on-off techniques were not adopted to improve the EE. In [11], EE of massive multiple-input multiple-output (MIMO) systems and smal cell systems are mathematically analysed and compared under the stochastic geometry model. It was shown that small cell systems always outperform massive MIMO systems in the view point of EE. In [12], EE of heterogeneous networks which consist of femto- and pico-cells was mathematically analysed under the stochastic geometry model and the a disjoint channel allocation between femto- and pic-cells was proposed to maximise EE. Although the performance of macro-cell was not considered, the interference from macro-cell to those femto- and pico-cells was taken into account in the analysis. However, in both [11, 12], the power control of the BSs was not considered.

In [13], an energy-efficient transmission power control technique was proposed for small cell networks and the optimal BS density that maximises the EE was obtained for a given user density under the stochastic geometry model. The transmission power of each BS was determined such that the probability that the

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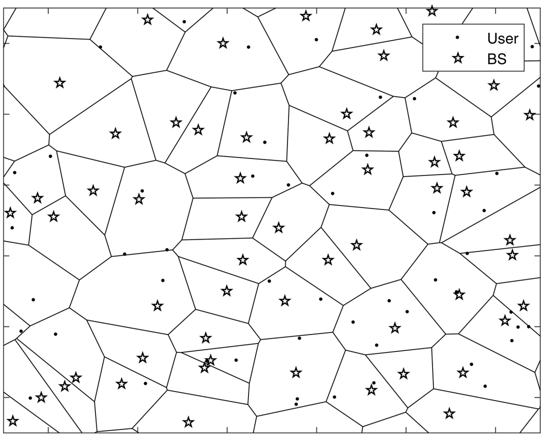

Fig. 1 *Example of the Voronoi cell structure when $\lambda_b = \lambda_u$*

(long-term) received signal power for a particular user, served to the BS, is smaller than the predesignated minimum power, is less than a constant. The transmission power of the BS tends to decrease as the BS density increases, but it is also fixed for a given BS density. However, in the stochastic geometry model, the cell shape is very irregular and the resultant outage probability of the BSs may be very different from each other. Furthermore, in [13], only in the empty cell, referred to as the void cell, the BS was turned off, as in [8]. In [14], several sleep modes were proposed for improving EE of heterogeneous small-cell networks and the authors validated that their proposed schemes outperform the conventional random sleeping policy. However, the proposed sleeping policies in [14] may not feasible in practical networks because they involve many network parameters and require iterations. In [15], an optimisation-based resource management framework was proposed for improving EE of heterogeneous networks, where cell activation, user association, and spectrum allocation are simultaneously considered. However, as noted by the authors of [15], the optimisation-based framework requires that the central controller knows the traffic intensity of all user groups and the spectral efficiency of all communication links, which seem to be impossible in practical cellular networks.

In [16], the authors proposed a joint power control and user scheduling scheme for ultra-dense small-cell networks where the locations of small BSs and users are fixed. The proposed approach is applicable when the number of BSs tends to infinity so that the interference from other cells can be approximated by mean field. Different from the above mentioned references, Samarakoon *et al.* [16] considered a certain traffic arrival pattern for the users and, hence, the target of user scheduling is to achieve stable queues but not the fair resource (or time) sharing among the active users as in [8–15]. Consequently, their proposed scheme is not applicable for the systems where the active users are modelled by stochastic geometry model.

In [17], deploying dense networks was proposed to maximise EE in *uplink* networks where the power control of each user is further considered. The EE performance was analysed under the stochastic geometry model. Although the power control was considered in [17], the interference behaviour in uplink is much different from downlink which is the focus of this paper. In [18], under the stochastic geometry model of BSs, how to place additional BSs to improve the system capacity and outage was investigated when the BSs have fixed transmission power.

1.3 Contributions

In this paper, under the stochastic geometry model of the cell topology, we propose an adaptive cell-breathing (ACB) technique in downlink cellular networks in which each BS adaptively adjusts its transmission power such that the received signal power of the worst-case user, located in the farthest cell boundary from the BS, is higher than the pre-defined power. Hence, the minimum signal-to-noise ratio of all users in the network could always be guaranteed. It is notable that with ACB, different BSs may set different transmission power. We further propose an aggressive power on–off technique with a fixed transmit power, in which the BS supporting smaller users over a pre-defined threshold could be turned off in order to improve the EE. Notice that the conventional power on–off techniques only turn off the BSs in the empty cells. Previously, there has been several studies on cell breathing for different purposes [19, 20]. In [19], the authors observed the effect of cell breathing in cellular networks, where the transmission power of BSs is adapted to the BS density. However, in the network scenarios considered in [19], the BSs are deployed in a regular manner, i.e. hexagonal cell deployment, and all the BSs share the same transmission power. In [20], load balancing in wireless local area networks was achieved through cell breathing where the transmission power of beacon is adapted to the user density in each cell while the transmission power of data packets is still fixed to achieve the high data rate.

1.4 Organisation

The remaining of this paper is organised as follows. The system model is described in Section 2. Section 3 presents the two proposed techniques: ACB technique and aggressive BS on–off (ABO) technique. Section 4 shows the numerical results. Finally, Section 5 concludes the paper.

2 System model

We consider a downlink cellular network in which BSs and users are spatially distributed according to two independent homogeneous Poisson point processes (PPPs). All the BSs and users are assumed to be equipped with a single antenna. Each user is assumed to be associated with the nearest BS, which is also called *user-centric* cell association [21]. The resulting network structure is known as a Voronoi tessellation. Since the user association is based on the user locations, it only depends on the large-scale fading of the users. If multiple users are located within a cell, they are served fairly with a round-robin scheduler. Fig. 1 illustrates an example of the Voronoi cell structure. It is observed that the size and shape change dynamically over different cells.

Let λ_b and λ_u represent the density values of the BSs and users, respectively. Then, the probability that m users exist in a certain area S is given by

$$\mathbb{P}_{\mathrm{u}}(m) = \frac{(\lambda_u S)^m}{m!} \mathrm{e}^{-\lambda_u S}, \tag{1}$$

which is a well-known Poisson distribution. Thus, the number of users within a cell tends to change when the size of the (Voronoi) cell changes. Moreover, according to PPP, the locations of the users are uniformly distributed in the area S. In practise, there may exist users' movement as well as different traffic patterns of the users. Those phenomenon can be abstractly reflected by varying the number of active users in a certain area over time. As one candidate mathematical model, PPP for the number of active users is considered in this paper. Note that the proposed algorithm is assumed to be updated periodically in order to sufficiently capture the dynamics of networks such as users' movement and traffic patterns. Similarly, the number of BSs also follows a Poisson distribution and the probability that there are m BSs within a certain area S is given by

$$\mathbb{P}_{\mathrm{b}}(m) = \frac{(\lambda_b S)^m}{m!} \mathrm{e}^{-\lambda_b S}. \tag{2}$$

With user-centric cell-association, the area distribution of each Voronoi cell S is approximated as a Gamma distribution with a shape parameter 3.5 and a mean of $1/\lambda_b$ [22], which is expressed as

$$f_S(s) \simeq \frac{3.5^{3.5}}{\Gamma(3.5)} \lambda_b^{3.5} s^{2.5} \mathrm{e}^{-3.5\lambda_b s}, \tag{3}$$

where $\Gamma(\cdot)$ denotes the Gamma function,

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$$\Gamma(x)=\int_0^{\infty} t^{x-1}\mathrm{e}^{-t}\,\mathrm{d}t\,. \tag{4}$$

The probability that no users exist in a particular cell, also referred to as void-cell probability or empty-cell probability, is given by

$$\mathbb{P}_{\mathsf{empty}}=\int_0^{\infty}\mathrm{e}^{-\lambda_u x} f_S(s)\,\mathrm{d}s \simeq \left(1+\frac{\lambda_u}{3.5\lambda_b}\right)^{-3.5}. \tag{5}$$

The BS of an empty cell is often assumed to operate in *sleep mode* to reduce the power consumption and interference toward other cells [23].

In this paper, we consider a well-known power consumption model of the BS, which is widely adopted in the literature and by standard organisations [10]:

$$P_{\mathsf{BS}}=\frac{1}{\eta}P_{\mathrm{t}}+P_{\mathrm{c}}+P_0, \tag{6}$$

where η, P_{t}, P_{c}, and P_0 denote the power amplifier efficiency, transmission power, circuit power required for RF chain operations (including base-band processing), and non-transmission power consumption, respectively. Reports on the practical power consumption suggested that the P_{c} is approximated as being linearly proportional to P_{t}, and thus we assume that the $P_{\mathrm{c}}=\beta P_{\mathrm{t}}$ ($\beta>1$). P_0 may include the power consumption from cooling and power supply losses which is required regardless of data transmission. P_0 tends to become reduced as the cell-size decreases [24]. Furthermore, if BS on–off techniques are applied and a cell is turned off (or operating during sleep mode), then only P_0 may be needed in (6).

$P_{\mathrm{t},i}$ denotes the transmission power of the ith BS in the network. The received signal-to-interference and noise ratio at an arbitrary user 0, which is served by BS 0, is given by

$$\gamma_0=\frac{g_{00}d_{00}^{-\alpha}LP_{\mathrm{t},0}}{\sum_{i\neq 0}g_{i0}d_{i0}^{-\alpha}LP_{\mathrm{t},i}+N_0B}, \tag{7}$$

where L denotes the path-loss at a reference distance (1 m) [9], d_{i0} denotes the distance between user 0 and BS i, α denotes the path-loss exponent, and g_{ij} denotes the (Rayleigh fading) channel gain between BS i and user j. g_{ij} is assumed to be identically and independently distributed over i and j and to have a unit mean. N_0 and B denote the noise spectral density at the receiver and the channel bandwidth, respectively. The achievable rate of user 0 is given by

$$R_0=B\log_2(1+\gamma_0)\,. \tag{8}$$

Then, the area throughput is defined as

$$T_{\mathsf{area}}=\lambda_b(1-\mathbb{P}_{\mathsf{empty}})\mathbb{E}[R], \tag{9}$$

where $\mathbb{E}[R]$ is the average throughput of an arbitrary cell

$$\mathbb{E}[R]=\int_0^{\infty}B\log_2(1+\gamma)f_{\gamma_0}(\gamma)\,\mathrm{d}\gamma, \tag{10}$$

where $f_{\gamma_0}(\gamma)$ is the probability density function (PDF) of γ_0 and is obtained by considering the spatial distribution of the BSs and channel gain. Unfortunately, the PDF does not have a mathematically tractable form in general. The area power consumption is defined as

$$P_{\mathsf{area}}=\lambda_b\left[(1-\mathbb{P}_{\mathsf{empty}})\left(\frac{1}{\eta}P_{\mathrm{t}}+P_{\mathrm{c}}\right)+P_0\right]. \tag{11}$$

Finally, the network EE is defined as

$$\eta_{\mathrm{EE}}=\frac{T_{\mathsf{area}}}{P_{\mathsf{area}}}\,. \tag{12}$$

3 Proposed power management techniques

3.1 ACB technique

In this subsection, the overall process of the proposed ACB technique is presented. First, each BS exchanges its location information such as GPS information with neighbouring BSs. Then, each BS computes the distance from itself to the farthest cell boundary. d_i^{max} denotes the distance from the farthest cell boundary to the ith BS. Each cell may have a significantly different d_i^{max} due to the random shapes of the (Voronoi) cell. Users are associated with the nearest BS and if no users exist within a cell, the corresponding BS is turned off. The transmission power of the ith BS is adjusted to satisfy the minimum required signal power of the worst-case user who is assumed to be located d_i^{max} away from the BS. P_{min} denotes the minimum required average signal power at the users. P_{min} depends on the target service provided over the network and is assumed to be identical over the cells. Then, the transmission power of the ith BS for the ACB technique should be adapted as

$$P_{\mathrm{t},i}^{\mathsf{ACB}}=\ \min\left(\frac{P_{\mathsf{min}}(d_i^{\mathsf{max}})^{\alpha}}{L},P_{\mathrm{t}}^{\mathsf{max}}\right), \tag{13}$$

where $P_{\mathrm{t}}^{\mathsf{max}}$ denotes the practical transmission power limit at the BS. The small-scale (Rayleigh) channel gain is ignored since it has a unit gain on the average sense in general. As each BS adapts its transmission power to maintain the *average* minimum required power at the farthest cell boundary, the transmission power is independent of the types of the small-scale fading (e.g. Rayleigh, Nakagami-m etc). Note that (13) is obtained in a distributed manner at each BS and thus additional information exchange is not required for the BSs. Additionally, if $P_{\mathrm{t}}^{\mathsf{max}}$ is large enough, the proposed ACB technique can always satisfy the minimum required signal power at the users by adjusting the transmission power according to d_i^{max} for each cell. However, [13] satisfies the minimum signal-power condition with a probabilistic manner because it sets the transmission power of the BSs to a fixed value for all cells.

3.2 ABO technique

In this subsection, instead of adjusting the transmission power according to each cell size as ACB, we propose another power management technique which aggressively turns off the BS power to save energy when the number of users is small and, hence, improves the EE. In the proposed ABOtechnique, cells having the number of users smaller than a predefined threshold N_{th} are turned-off. The number of users belonging to the ith cell is denoted as N_i. Then, the ith BS is turned-off if $N_i\leq N_{\mathsf{th}}$. Therefore, ABO can be considered as the generalisation of the existing BS on–off techniques in which only empty BSs are turned-off. With the proposed ABO, if a BS is turned-off, the corresponding users are assumed to wait until the BS is turned-on again and to be served later. Although the transmission power of the BSs is constant as $P_{\mathrm{t}}^{\max}$ with ABO, turning off the BS power more aggressively can firstly saves energy consumption and, then, reduces the inter-cell interference which may improve the spectral efficiency of the other cells. With the proposed ABO technique under the threshold N_{th}, the probability that a cell BS is turned-off is approximated by

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Table 1 System parameters

channel bandwidth	10 MHz
path loss at 1 m	1.425×10^{-4}
path-loss exponent α	3.5
N_0	3.98×10^{-21} W/Hz
$P_t^{\max}$	3 W
$P_{\min}$	10^{-12} W
non-transmission power P_0	0 or 4.3 W
circuit power constant β	4
power amplifier efficiency η	0.32
small-scale channel	Rayleigh

$$\begin{aligned}
\mathbb{P}_{\text{off}}(N_{\text{th}}) &= \int_0^\infty \left(\sum_{i=0}^{N_{\text{th}}} \frac{(\lambda_u s)^i}{i!} \mathrm{e}^{-\lambda_u s} \right) f_S(s)\,\mathrm{d}s \\
&= \sum_{i=0}^{N_{\text{th}}} \frac{\lambda_u^i}{i!} \int_0^\infty \left(s^i \mathrm{e}^{-\lambda_u s} \right) f_S(s)\,\mathrm{d}s \\
&\simeq \sum_{i=0}^{N_{\text{th}}} \frac{\lambda_u^i}{i!} \int_0^\infty \left(s^i \mathrm{e}^{-\lambda_u s} \right) \left[\frac{(3.5\lambda_b)^{3.5}}{\Gamma(3.5)} s^{2.5} \mathrm{e}^{-3.5\lambda_b s} \right] \mathrm{d}s \\
&= \sum_{i=0}^{N_{\text{th}}} \frac{\lambda_u^i}{i!} \frac{(3.5\lambda_b)^{3.5}}{\Gamma(3.5)} \int_0^\infty \left[s^{i+2.5} \mathrm{e}^{-(\lambda_u + 3.5\lambda_b)s} \right] \mathrm{d}s \\
&= \sum_{i=0}^{N_{\text{th}}} \frac{\Gamma(i+3.5)}{i!\Gamma(3.5)} \frac{\lambda_u^i (3.5\lambda_b)^{3.5}}{(\lambda_u + 3.5\lambda_b)^{i+3.5}} \\
&= \left(1 + \frac{\lambda_u}{3.5\lambda_b}\right)^{-3.5} \sum_{i=0}^{N_{\text{th}}} \frac{\Gamma(i+3.5)}{i!\Gamma(3.5)} \left(1 + \frac{3.5\lambda_b}{\lambda_u}\right)^{-i},
\end{aligned} \tag{14}$$

where the approximation in the third line is obtained from (3) and the fifth line is obtained by replacing $t = (\lambda_u + 3.5\lambda_b)s$ and applying the definition of Gamma function shown in (4). As (6) depends only on the density parameters λ_b and λ_u, (14) does not depend on the type of small-scale fading as well.

4 Numerical results

In this section, extensive simulations are performed to validate the performance of the proposed power management techniques. The system parameters considered in the simulations are summarised in Table 1. For the channel model, according to [9] we set the channel bandwidth as 10 MHz, the path-loss at 1 m as 1.425×10^{-4}, the path-loss exponent α as 3.5 and the noise spectral density N_0 as 3.98×10^{-21} Watt/Hz (i.e. -174 dBm/Hz). According to [24], the maximum transmission power of macro BS, micro BS, and pico BS are equal to 20, 6.3, and 0.13 W, respectively. In this paper, we show the performance *tendency* of the proposed algorithms for varying densities of BS. From Figs. 2–5, the horizontal axis ranges from 4 to 4×10^4 BS/km^2, which implies the cell radius of the BS ranges from 10 to 300 m. Considering the cell radius, the simulation environment covers from pico-cell to micro-cell environments. Thus, we set the maximum transmission power to be 3 W, which is larger than 0.13 W and is smaller than 6.3 W. Under the channel model shown in Table 1, if $P_t^{\max}$ is set to 3 W, the received power at 300 m away from the BS is 10^{-12} W, which is set to the reference for $P_{\min}$ in this paper. The non-transmission power P_0 of 4.3 W, the circuit power constant β of 4, and the power amplifier efficiency η of 0.32 are set based on [10, 24]. In this paper, we only consider Rayleigh fading as a small-scale fading since Rayleigh distribution has been considered as a representative small-scale fading distribution. As noted before, the proposed techniques can be extended to other small-scale fading models with Nakagami-*m* and Rician distributions, because they are designed only with large-scale fading effects.

Fig. 2 reveals the area throughput normalised to the bandwidth of the proposed ACB and ABO techniques over a varied the BS density λ_b when the user density $\lambda_u = 100\,3800$ users/km^2. In this figure, it is assumed that $P_0 = 0$, implying that the *ideal* operation of the turned-off BS and conventional BS on–off techniques are a special case of the proposed ABO technique with $N_{\text{th}} = 0$. For ACB and ABO with $N_{\text{th}} = 0$, the normalised area throughput increases as λ_b increases since the distance between users and their serving BSs become smaller as λ_b increases. On the other hand, for ABO with $N_{\text{th}} = 2$, the normalised area throughput increases within the low BS density regime but it decreases in the high BS density regime. In the case of a high BS density, many small BSs are turned-off and the corresponding users are assumed to be served some other time; thus, the spatial reuse effect from dense BSs becomes weakened. The throughput decreases as N_{th} increases with the ABO technique. Note that the ACB technique outperforms the ABO regardless of BS density for the same user density.

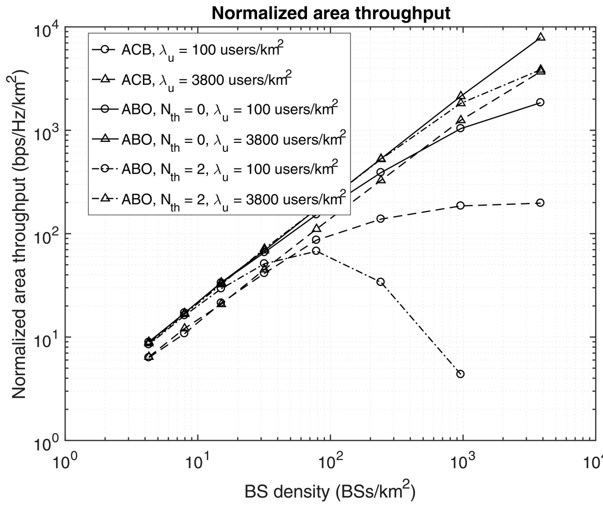

Fig. 2 *Normalised area throughput versus BS density with a fixed λ_u*

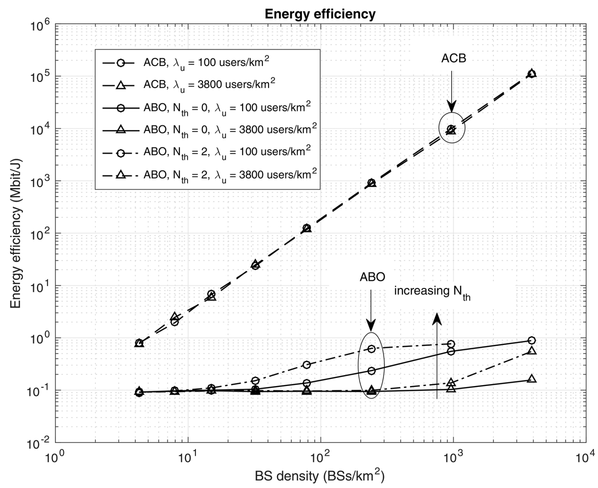

Fig. 3 *EE versus BS density with a fixed λ_u*

Fig. 3 presents the EE of the proposed ACB and ABO techniques under the same simulation parameters as shown in Fig. 2. The EE of both the ACB and ABO techniques increases as λ_b increases. However, the ACB technique significantly outperforms the ABO technique. For example, the EE of the ACB technique is nearly 1000 times higher than that of the ABO technique with $N_{\text{th}} = 0$ when $\lambda_b = 1000$ and $\lambda_u = 100$. One interesting phenomenon is that ACB yields a nearly linear increment on the EE according to the BS density in the log – log domain, implying that the EE of the ACB technique is proportional to $(\lambda_b)^c$ $(c > 0)$ where c denotes the increasing ratio of the EE to the BS density in the log – log domain, i.e. the slope of the ACB curves shown in Fig. 3. The EE of the ABO technique increases as the N_{th} increases

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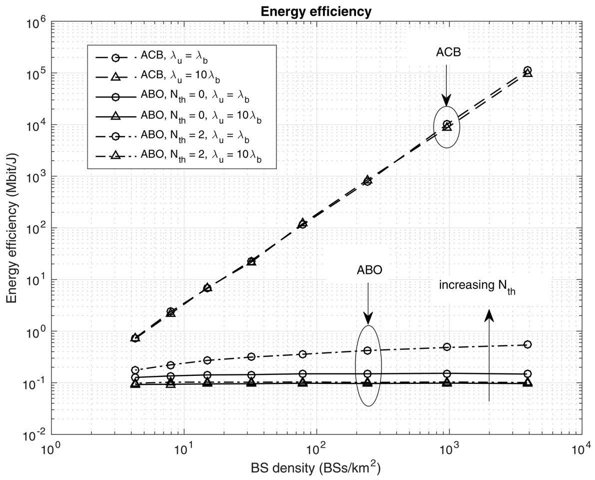

Fig. 4 *EE versus BS density*

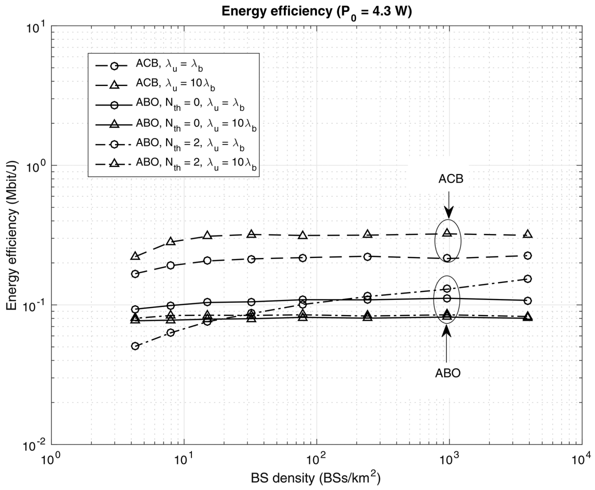

Fig. 5 *EE versus BS density with* $P_0 = 4.3\,\text{W}$

even though the improvement is marginal, compared with the ACB technique.

In Figs. 2 and 3, the user density is assumed to be fixed; however, the densities of the BSs and users may be correlated highly in practise. Fig. 4 presents the EE for a varied λ_b while λ_u is linearly proportional to λ_b. The EE of the ACB technique increases linearly as the BS density increases and the effect of user density is negligible with the ACB technique. The EE of the ABO technique also increases, although the slope is quite small. The EE is improved as N_{th} increases especially in the case of a low user density.

In the previous figures, it is assumed that $P_0 = 0$ since the power consumption in sleep mode is expected to be significantly reduced with advanced power management techniques especially for small cell BSs. However, in practise, P_0 can not be neglected. Thus, in Fig. 5, the EE of the proposed techniques with a non-zero P_0 is shown. In this simulation, it is assumed that $P_0 = 4.3\,\text{W}$ Note that P_0 of this paper is equal to P_{sleep} of [24]. The definition of P_0 in [24] is the minimum non-zero (RF) output power that indicates the minimum consumed power when the BS is transmitting data, while P_{sleep} in [24] denotes the sleep mode power consumption. Thus, P_{sleep} in [24] has a similar meaning to P_0 in the power consumption model of this paper which is a typical value for pico-cell BSs [24]. In this case, the ACB technique still yields a much better EE than that of the ABO technique. In particular, the EE of the ACB technique with a higher user density outperforms it with a lower user density, while the effect of user density on the EE of the ACB technique is negligible when $P_0 = 0$.

5 Conclusion

In this study, two power management techniques to improve the EE of ultra-dense small-cell networks were considered: ACB and ABO. In the ACB algorithm, the BS is turned-off only when there exist no users within its coverage and it always guarantees a certain signal strength at all users within its coverage by adjusting its transmission power dynamically. Thus, the ACB is more appropriate for the traffic requiring a strict quality-of-service. However, in the ABO algorithm, the BS may be turned off if the number of users within a cell is smaller than a certain value and it does not adjust its transmission power. Thus, the ABO is more appropriate for the best-effort, while the ABO algorithm can operate with significantly smaller complexity than the ACB algorithm. There exists a trade-off between two proposed algorithms. It was shown through extensive simulations that the proposed algorithms can improve the EE of the small cell networks. In particular, the ACB achieves a linear increment on the EE according to the BS density in the log – log domain. For the future work, we need to further investigate the EE of the heterogeneous networks in which the macro- and micro-cells coexist.

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