Dynamic Sleep Mode Strategies in Energy Efficient Cellular Networks

Yong Sheng Soh*, Tony Q. S. Quek#†, and Marios Kountouris‡

*California Institute of Technology, 1200 East California Boulevard, Pasadena CA 91125, USA
#Singapore University of Technology and Design, 20 Dover Drive, Singapore 138682
†Institute for Infocomm Research, A*STAR, 1 Fusionopolis Way, #21-01 Connexis, Singapore 138632
‡SUPELEC, Department of Telecommunications, 91192 Gif-sur-Yvette, France

***Abstract*—Switching off base stations when the activity in the cell is low, often called cell sleeping, is one possible method of reducing energy consumption in macrocellular networks. However, this method may reduce coverage for users and hence it is not immediately clear if the energy savings can compensate for the network throughput reduction. In this paper, we propose and analyze two sleep mode strategies for energy efficient cellular networks. Using stochastic geometry, we model the switching off of base station and obtain analytical results for the coverage probabilities and the area spectral efficiency under different cell sleeping strategies. Specifically, the effect of random and strategic sleeping on the power consumption and on the energy efficiency is investigated. We first show that the performance gains depend on the level of background noise. Furthermore, numerical results show the effectiveness of an activity-based sleeping strategy in maximizing the energy efficiency of macrocellular networks.**

I. INTRODUCTION

Existing cellular architectures are designed to cater to large coverage areas, and they often fail to achieve the expected throughput to ensure seamless mobile broadband in the uplink as users move far from the base station. This is mainly due to the increase in the inter-cell interference, as well as to constraints on the transmit power of the mobile devices. Another limitation of the conventional macrocell approach is the poor indoor penetration and the presence of dead spots, which result in drastically reduced indoor coverage. Beside the issue of meeting overwhelming traffic demands, network operators have started realizing the importance of managing their cellular networks in an energy efficient manner and reducing the amount of CO_2 emission levels simultaneously [1], [2]. Although current studies show that the amount of CO_2 emission levels due to information and communication technologies is merely 2%, this figure is projected to increase significantly with the exponential increase in data traffic and mobile devices in the future. By improving energy efficiency, network operators also reduce operational costs because energy constitutes a significant part of their expenditures. Therefore, the terminology of "green cellular network" has become popular in recent years, showing the current sentiment of the telecom industries to emphasize more on energy efficiency as one of the key performance indicator for their cellular network design.

One effective technique to energy efficient networks is to introduce sleep mode in macrocell base stations (MBSs) [3]–[7]. The main motivation behind MBS sleeping is as follows: although traffic demand in cellular networks is usually assumed to be high, hence MBSs are powered on at all times, various studies have shown that there are high fluctuations in traffic demand over space and time [1]. For instance, the traffic demands in urban and rural areas or traffic demands in day and night time are entirely different. From this perspective, there is potential in energy savings by adapting the activity and optimizing the sleep mode of MBSs according to the cell traffic load and the user activity factor. However, there are several performance tradeoffs and challenges in optimizing cell sleeping. Switching off some base stations results in aggregate interference reduction as well as in larger distances between users and serving MBSs, which is not always desirable.

In this paper, we studied the problem of energy efficient cellular networks through the employment of base station sleep mode strategies [2], [8]–[10]. Two sleep mode strategies are investigated here, namely *random sleeping* and *strategic sleeping*. In random sleeping, we model a network where a fraction of MBSs is shut down uniformly with a certain probability. Lower MBS density means that the average distance to the nearest MBS is increased and hence the overall coverage is decreased. Adopting a fixed power control policy in order to eliminate coverage holes, we study the impact of random sleeping on coverage probability, area spectral efficiency, and energy efficiency. In strategic sleeping, instead of randomly switching MBSs off, MBSs are shut down when their activity levels are low, i.e. when traffic demands are low, where the activity level is modeled according to a certain distribution. Using a stochastic geometry based model, we derived the coverage probability and the network throughput under the above sleeping strategies, as a means to understand tradeoffs in green cellular networks. The use of stochastic geometry as a tool to model and analyze large, dense wireless networks has gained increasing popularity in recent years [11]–[14]. The popularity is largely due to the ability to incorporate realistic assumptions in the model while still obtaining very tractable expressions of performance measures. The standard approach, which is also adopted here, is to model base station locations as points drawn from a homogeneous Poisson point process (PPP). In this work, two optimization problems are formulated in the form of power consumption minimization under coverage constraint and energy efficiency maximization.

In particular, we investigate the impact of random sleeping and strategic sleeping on the power consumption and energy efficiency. A first result is that sleep mode strategies perform best in the interference limited regime, but there are less effective and possibly detrimental in the noise-limited regime. Our numerical results suggest that strategic sleeping is able to mitigate some of the effects of background noise.

II. System Model

A. Network Model

We consider a single-tier cellular network consisting of macro base stations (MBSs) located according to a homogeneous PPP Θ_{M} of intensity λ_{M} in the Euclidean plane. Users are distributed according to a different independent stationary point process of intensity μ. Each user is associated with its geographically closest MBS. Since Θ_{M} is a stationary process, the distribution of distance R_{M} from a generic macrocell user to the nearest MBS remains the same regardless of the locations, and its probability density function (PDF) is given by $f_{R_{\mathrm{M}}}(r) = 2\pi\lambda_{\mathrm{M}} r \exp(-\lambda_{\mathrm{M}}\pi r^2)$. We assume universal frequency reuse among base stations and that each MBS serves only one user. If there are multiple users in a Poisson-Voronoi cell, some form of orthogonal resource sharing (e.g. frequency or time division) is performed.

For notational convenience, we denote a BS by its location while the user is at the origin 0. For downlink transmission of a MBS x to the typical user, the signal-to-interference-plus-noise ratio (SINR) experienced by a macrocell user is given by

$$\mathsf{SINR}_{\mathrm{M}}(x) = \frac{P_{\mathrm{t}} h_x g(x)}{\sum_{y\in\Theta(x)} P_{\mathrm{t}} h_y g(y) + \sigma^2} \tag{1}$$

where $\Theta(x)$ denotes the set of nodes interfering with x, P_{t} denotes the transmit power, and h_x, h_y are the power coefficients due to small-scale fading from x, y respectively. We assume that $h_x \sim \exp(1)$ and $h_y \sim \exp(1)$ (Rayleigh fading). The background noise is additive white Gaussian with variance σ^2. The path loss function is denoted by $g(x) = \|x\|^{-\alpha}$, where α is the path loss exponent.

B. Power Consumption model

The power consumption at each MBS is given by $P_{\text{tot}} = P_{\mathrm{M0}} + \beta\Delta_{\mathrm{m}} P_{\mathrm{M}}$ where P_{M0} is the static power expenditure of the MBS, β is a ratio that represents the fixed power control, P_{M} is the RF output power of the MBS, and Δ_{m} is the slope of the load-dependent power consumption in MBS [1]. A fixed power control policy is adopted here in order to avoid creating *coverage holes* or areas where the target SINR is below an acceptable level due to switching off MBS. To ensure a similar level of coverage as before sleeping, we assume that all awake MBS transmit with power $P_{\mathrm{t}} = \beta P_{\mathrm{M}}$.

C. Performance Metrics

Using (1) we can define the *success probability* from x to u as $\mathbb{P}(\mathsf{SINR}_{\mathrm{M}}(x \to u) > \gamma)$, where γ is a prescribed quality of service (QoS) threshold. By averaging the success probability over the distance to the nearest node, we obtain the *coverage probability* of a typical macrocell user given by $\mathbb{P}_{\mathrm{M}}(\gamma)$.

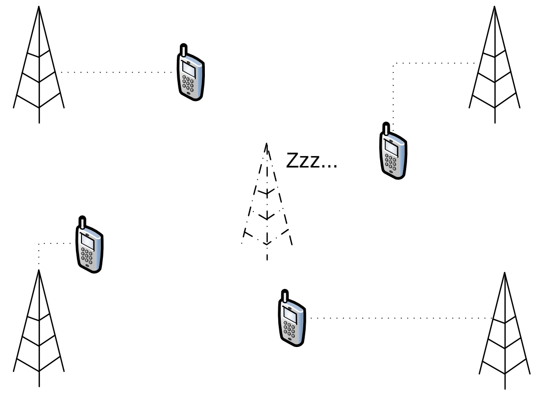

Fig. 1. Random Sleeping.

The throughput attained at a given BS-user link is given by $\mathbb{P}(\mathsf{SINR} > \gamma)\log_2(1+\gamma)$ and the area spectral efficiency (network throughput is defined as $\mathcal{T} = \lambda_{\mathrm{M}}\mathbb{P}(\mathsf{SINR} > \gamma)\log_2(1+\gamma)$.

Lastly, we define the energy efficiency E_{eff} as the following

$$EE = \frac{\text{Average Network Throughput}}{\text{Average Network Power Consumption}} = \frac{\mathcal{T}}{\lambda_{\mathrm{M}} P_{\text{tot}}}. \tag{2}$$

III. Base Station Sleep Mode Strategies

In this section, we present the two main policies that we propose and analyze as a means to optimize the power consumption at each MBS. We investigate policies of dynamically switching off MBS, where the power consumed by a switched off MBS in sleep mode is P_{SL}.[1]

A. Random Sleeping

In random sleeping, we model the sleeping strategy as a Bernoulli trial such that each station continues to operate with probability q and sleeps (is turned off) with probability $1-q$, independently (see Fig. 1). Therefore, after applying random sleeping at the macro tier, the average power consumption of the macrocell network is given by

$$P_{\mathrm{RS}} = \lambda_{\mathrm{M}} q (P_{\mathrm{M0}} + \beta\Delta_{\mathrm{m}} P_{\mathrm{M}}) + \lambda_{\mathrm{M}}(1-q)P_{\mathrm{SL}}. \tag{3}$$

B. Strategic Sleeping

Instead of randomly switching MBSs off, we can also switch off MBSs when their activity levels are low, e.g when load or traffic demands are low. Specifically, we model this strategic sleeping as a function $s : [0,1] \mapsto [0,1]$ which says that if the activity level of the coverage area associated with the MBS has activity level x, then it operates with probability $s(x)$ and sleeps with probability $1-s(x)$, independently (see Fig. 2). This sleep mode strategy can be seen as a load-aware policy and it can incorporate traffic profile in the optimization

[1]Note that we consider that $P_{\mathrm{SL}} < P_{\mathrm{M0}}$ which is a valid assumption for future base stations with sleeping mode capabilities.

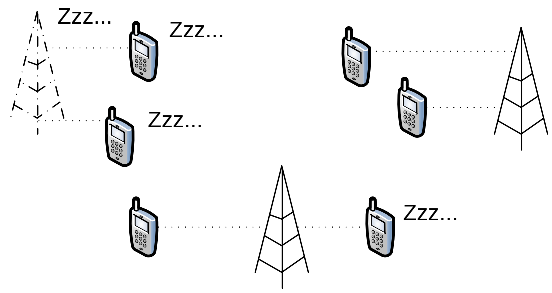

Fig. 2. Strategic Sleeping.

problem. The average power consumption of the macrocell networks after employing strategic sleeping is given by

$$P_{\mathrm{SS}} = \lambda_{\mathrm{M}}\mathbb{E}\{s\}(P_{\mathrm{M}0} + \beta\Delta_{\mathrm{m}}P_{\mathrm{M}}) + \lambda_{\mathrm{M}}(1 - \mathbb{E}\{s\})P_{\mathrm{SL}} \quad (4)$$

where $\mathbb{E}\{s\} = \int_0^1 s(x)f_{\mathcal{A}}(x)\mathrm{d}x$ and $f_{\mathcal{A}}(x)$ is the PDF of $\mathcal{A}$ and $\mathcal{A}$ denotes the random activity within a cell and takes values in $[0, 1]$.

The rationale behind the proposed strategic sleeping is the following: while random sleeping models a network that is adapted according to fluctuating activity levels during the day, strategic sleeping goes a step further and models a network that is adaptive to the fluctuating activity levels within the location. Furthermore, the strategic sleeping model may be used as method of measuring the impact of cooperation among MBSs. Let us illustrate this with an example. Suppose that we have a pair of cooperating MBSs. If the activity level in the combined coverage area is expected to be below half of the full capacity, then the pair may choose to keep only one of them awake. Then, the awake MBS may serve both coverage areas or the coverage areas can be be reassigned among all remaining awake MBSs. The above cooperation model can be modeled by strategic sleeping by having, say, both MBS to stay awake with probability $s = 0.5$. An explicit association between neighboring MBSs is technically absent but we hope that this model may nevertheless be seen as a way to measure the energy savings by introducing cooperation within the network.

IV. Power Consumption Minimization Subject to Coverage Constraint

A. Power Consumption Minimization with Random Sleeping

The random sleeping strategy is equivalent to modeling the active MBSs as a marked PPP with intensity $q\lambda_{\mathrm{M}}$, where the transmission power of the active MBSs is increased to βP_{M}.

Theorem 1. *In a macrocellular network with random sleeping, the coverage probability of a randomly located macrocell user is given by*

$$\mathbb{P}_{\mathrm{RS}}(\gamma) = 2\pi q\lambda_{\mathrm{M}} \int_{r=0}^{\infty} r\exp(-\pi r^2 q\lambda_{\mathrm{M}}) \exp(-\pi r^2 q\lambda_{\mathrm{M}}\rho(\gamma,\alpha))\exp(-r^{\alpha}\gamma\sigma^2/\beta P_{\mathrm{M}})\mathrm{d}r \quad (5)$$

where $\rho(\gamma, \alpha) = \gamma^{2/\alpha}\int_{\gamma^{-2/\alpha}}^{\infty} \frac{1}{1+u^{\alpha/2}}\mathrm{d}u$.

Proof: The proof follows by using results from [13]. □

We formulate now a power consumption minimization problem subject to a coverage probability constraint, which can be interpreted as a QoS constraint. In the case of random sleeping, the optimization problem is given by

$$\mathcal{P}_{\mathrm{RS}} : \begin{cases} \min\limits_{q} & \lambda_{\mathrm{M}}q(P_{\mathrm{M}0} + \beta\Delta_{\mathrm{m}}P_{\mathrm{M}}) + \lambda_{\mathrm{M}}(1-q)P_{\mathrm{SL}} \\ \text{s.t.} & \mathbb{P}_{\mathrm{RS}}(\beta,\gamma) \geq \epsilon \end{cases} \quad (6)$$

where q is the fraction of MBSs that are still operating.

Note that the objective function is an increasing function in q. It can be shown that the constraint (5) is an increasing function q too. Hence the minimum power consumption occurs when q satisfies the constraint tightly. Thus, $q^{\star}_{\mathrm{PC,RS}}$ is determined by the following fixed point equation:

$$\epsilon = 2\pi q^{\star}_{\mathrm{PC,RS}}\lambda_{\mathrm{M}} \int_{r=0}^{\infty} r\exp(-\pi r^2 q^{\star}_{\mathrm{PC,RS}}\lambda_{\mathrm{M}}) \exp(-\pi r^2 q^{\star}_{\mathrm{PC,RS}}\lambda_{\mathrm{M}}\rho(\gamma,\alpha))\exp(-r^{\alpha}\gamma\sigma^2/\beta P_{\mathrm{M}})\mathrm{d}r \quad (7)$$

B. Power Consumption Minimization with Strategic Sleeping

We study here the effect of turning off MBS based on the strategic sleeping strategy described above. Instead of using the coverage probability as our performance measure, we shall instead look at the coverage probability *per active user*. That is to say, we shall find the average coverage probability among all the users who are currently active at a certain time[2]. For that, we assign independent and identically distributed random variables $\mathcal{A}$ to each MBS in Θ_{M}, such that $\mathcal{A} \in [0, 1]$. We represent $\mathcal{A}$ as the random user activity within the Poisson-Voronoi cell that the MBS covers. That is to say, for any user located in a Poisson-Voronoi cell of a MBS with activity level a, the user is *active* with probability a, i.e. it is actually connected to the MBS with probability a. Therefore, we can model the sleeping strategy as a function $s : [0, 1] \mapsto [0, 1]$, which says that if the activity level of the MBS has activity level x, then it operates with probability $s(x)$ and sleeps with probability $1 - s(x)$. Since the process in which the MBS are determined to be active is independent between MBSs, the active MBSs form a marked PPP. Hence the active MBSs distribute as a homogeneous PPP with intensity $\lambda_{\mathrm{M}}\mathbb{E}\{s\} = \lambda_{\mathrm{M}}\int_0^1 s(x)f_{\mathcal{A}}(x)\mathrm{d}x$. where $f_{\mathcal{A}}(x)$ is the PDF of $\mathcal{A}$. The coverage probability that captures the activity of the macrocell user is computed as follows:

Theorem 2. *The coverage probability of the active macrocell user under strategic sleeping is given by*

$$\begin{aligned} &\mathbb{P}_{\mathrm{SS}}(\beta,\gamma) \\ &= \left\{ \int_0^1 xs(x)f_{\mathcal{A}}(x)\mathrm{d}x \int_{r=0}^{\infty} \exp(-\pi r^2\lambda_{\mathrm{M}}\mathbb{E}\{s\}\rho(\gamma,\alpha)) \right. \\ &\quad \exp(-r^{\alpha}\sigma^2\gamma/\beta P_{\mathrm{M}})g_1 r\mathrm{d}r \\ &+ \int_0^1 x(1-s(x))f_{\mathcal{A}}(x)\mathrm{d}x \sum_{i=2}^{\infty}\left\{ \int_{r=0}^{\infty}\exp(-r^{\alpha}\sigma^2\gamma/\beta P_{\mathrm{M}}) \right. \\ &\quad \left.\left. \exp(-\pi r^2\lambda_{\mathrm{M}}\mathbb{E}\{s\}\rho(\gamma,\alpha))g_i r\mathrm{d}r \right\}\right\} \frac{1}{\mathbb{E}\{a\}}, \end{aligned} \quad (8)$$

[2]We assume that μ is also the density of *active* users in random sleeping.

where $g_i(r)$ is the PDF of the i-th nearest point from a PPP, such that $g_i(r) = \frac{2\pi^i r^{2-1}\lambda_{\mathrm{M}}^i}{(i-1)!}\exp(-\pi r^2\lambda_{\mathrm{M}})$. For special cases of $\sigma^2 = 0$, $\mathbb{P}_{\mathrm{SS}}(\beta,\gamma)$ can be simplified as

$$\mathbb{P}_{\mathrm{SS}}(\beta,\gamma) = \frac{1+\rho(\gamma,\alpha)\mathbb{E}\{as(a)\}/\mathbb{E}\{a\}}{(1+\mathbb{E}\{s\}\rho(\gamma,\alpha))(1+\rho(\gamma,\alpha))}. \tag{9}$$

Proof: See Appendix. □

C. Minimization Problem

The minimization problem in the case of strategic sleeping is formulated in a similar way as for random sleeping, i.e.

$$\mathcal{P}_{\mathrm{SS}}: \begin{cases} \min\limits_{s} & \lambda_{\mathrm{M}}(\mathbb{E}\{s\}(P_{\mathrm{M0}}+\beta\Delta_{\mathrm{m}}P_{\mathrm{M}}) \\ & \quad + (1-\mathbb{E}\{s\})P_{\mathrm{SL}}) \\ \text{s.t.} & \mathbb{P}_{\mathrm{SS}}(\beta,\gamma) \geq \epsilon. \end{cases} \tag{10}$$

Solving the above optimization problem is more challenging in the case of strategic sleeping since before stating that the constraint is satisfied by equality, we first need to compute the optimal strategy as shown in the following lemma.

Lemma 1. *For a fixed $\mathbb{E}\{s\}$, the strategy that optimizes the success probability per active user is to have $s(a) = 1_{\{a\geq a_0\}}(a)$ for some a_0. In other words, it takes the form of a threshold function where we switch on the MBS if the activity is greater than a certain a_0.*

Proof: The proof is omitted due to space constraints and can be found in [15]. □

Following the lemma, the optimal solution $s^\star(a)$ can be characterized by a single variable a_0, which we denote as $a^\star$. The optimization problem is solved using equality for the QoS constraint, in which case, we characterize the solution based on $a^\star$.

Theorem 3. *The optimal $s^\star(a)$, denoted as $a^\star$, satisfies*

$$\epsilon = \frac{1}{\mathbb{E}\{a\}}\Big\{\mathbb{P}(\mathsf{SINR} > \gamma|N_{\mathrm{ord}} = 1)\int_{a^\star}^{1} x f_{\mathcal{A}}(x)\mathrm{d}x + \mathbb{P}(\mathsf{SINR} > \gamma|N_{\mathrm{ord}} > 1)\int_{0}^{a^\star} x f_{\mathcal{A}}(x)\mathrm{d}x\Big\} \tag{11}$$

where $\mathbb{P}(\mathsf{SINR} > \gamma|N_{\mathrm{ord}} = 1) = \int_{r=0}^{\infty}\exp(-\pi r^2\lambda_{\mathrm{M}}\mathbb{E}\{s\}\rho(\gamma,\alpha))\exp(-r^\alpha\sigma^2\gamma/\beta P_{\mathrm{M}})g_1 r\mathrm{d}r$ *and* $\mathbb{P}(\mathsf{SINR} > \gamma|N_{\mathrm{ord}} > 1) = \sum_{i=2}^{\infty}\int_{r=0}^{\infty}\exp(-\pi r^2\lambda_{\mathrm{M}}\mathbb{E}\{s\}\rho(\gamma,\alpha))\exp(-r^\alpha\sigma^2\gamma/\beta P_{\mathrm{M}})$ $g_i r\mathrm{d}r$.

1) Interference-Limited Regime: Unlike the case of random sleeping, the strategic sleeping has an effect on the coverage probability even in the interference-limited regime ($\sigma^2 = 0$). Using (9) which is the coverage probability in the interference limited case, we can characterize the property of the strategic sleeping such that the coverage probability of the active macrocell user is at least as good as the case without any sleeping mode.

Lemma 2. *The sleeping strategy x improves the coverage probability of the active macrocell user if it satisfies the following inequality*

$$\mathbb{E}\{as(a)\} > \mathbb{E}\{s\}\mathbb{E}\{a\} \tag{12}$$

Proof: Omitted as it follows after standard algebraic manipulations. □

The consequence of Lemma 2 is that, for a fixed $\mathbb{E}\{s\}$, if we want to maximize $\mathbb{E}\{as(a)\}$, we need to match large values of s with high activity. In fact, it suffices to choose $s(x)$ increasing as stated in the following lemma.

Lemma 3. *If $s(x)$ is increasing in x, then the coverage probability of the active macrocell user in the strategic sleeping case is at least as good as the non sleeping case.*

Proof: The proof follows from a stronger result which states that, for two increasing measurable functions f, g, the covariance is positive (this can be shown using results from [16]). □

V. Energy Efficiency Optimization

In this section we analyze and optimize the energy efficiency metric defined above for both random and strategic sleeping. Although the energy efficiency optimization problem can be formulated analytically, no closed-form expressions can be derived for the general case. For that, we resort to numerical evaluation as a means to understand the behavior of energy efficiency under dynamic sleeping strategies.

In the simulation results, for comparison purposes, we fix the density of MBSs and active users when comparing between random sleeping and strategic sleeping. As a result, for strategic sleeping, when we perform the simulation for the PPP representing the users, we will start with an original density of μ/q, where q is the fraction of MBSs that are awake. Next, we draw random variables representing the activity of each coverage cell. Upon thinning, the density of the active users becomes μ. The parameters used are as follows: $\alpha = 4$, P_{t} = 43 dBm, $\sigma^2 = 0.1$, $\gamma = -10$ dB, P_{SL} = 75W, P_{M0} = 130W, $\Delta_{\mathrm{m}} = 4.7$, $P_M = 20.0$W.

A. Random Sleeping

Fig. 3 shows the energy efficiency in the random sleeping model as a function of the awake MBS. Note that the plots are also duplicated in Figs. 4 - 6. First, we observe that expectedly the energy efficiency decreases with increasing noise σ^2. Second, consider the case when $\mu = 10^{-3}\mathrm{m}^{-2}$. The optimal $q^\star$ that maximizes the energy efficiency is 1, due to the fact that increasing the number of active base stations allows the network to support more users, so the MBS does not need to share resources among users, thus increasing the area spectral efficiency. This observation remains valid when $\mu = 10^{-3}\mathrm{m}^{-2} = \lambda_M$. However, since the density of both MBSs and users are equal, the effect of having less MBSs that need to divide resources among multiple users is marginal. This is reflected in the plots which suggest little change in the energy efficiency when $q \to 1$.

The case where $\mu = 10^{-3}\mathrm{m}^{-2}$ demonstrates the other extreme when there might be more than necessary MBSs to

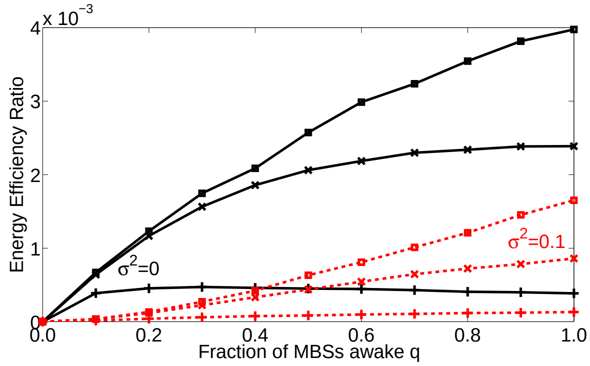

Fig. 3. Energy Efficiency in Random Sleeping $\lambda_M = 10^{-4}\mathrm{m}^{-2}$. Solid lines show the case where $\sigma^2 = 0$, dotted lines $\sigma^2 = 0.1$. The square, the "$\times$" and the "$+$" plots show the case where $\mu = 10^{-5}\mathrm{m}^{-2}$, $10^{-4}\mathrm{m}^{-2}$ and $10^{-3}\mathrm{m}^{-2}$, respectively.

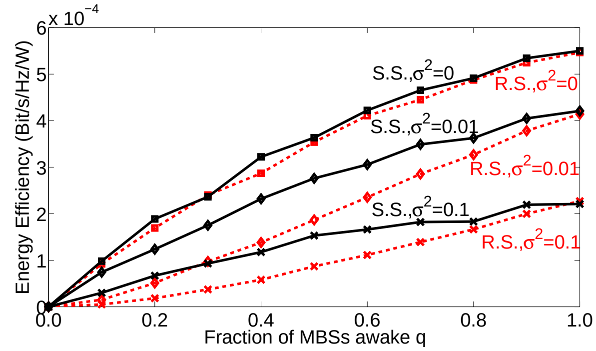

Fig. 4. Comparison of Energy Efficiency Ratio in Random Sleeping (R.S.) and Strategic Sleeping (S.S.), $\lambda_M = 10^{-4}\mathrm{m}^{-2}$ and density of active users is $10^{-3}\mathrm{m}^{-2}$.

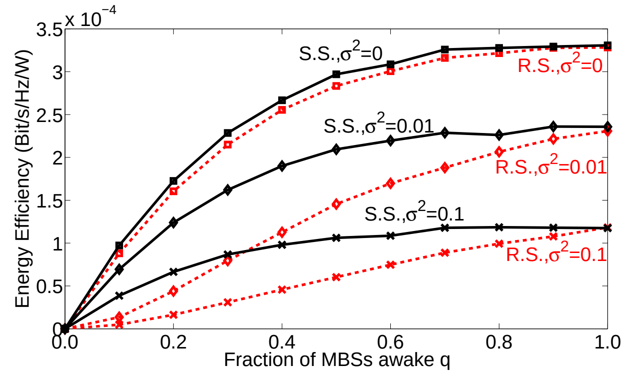

Fig. 5. Comparison of Energy Efficiency Ratio in Random Sleeping (R.S.) and Strategic Sleeping (S.S.), $\lambda_M = 10^{-4}\mathrm{m}^{-2}$ and density of active users is $10^{-4}\mathrm{m}^{-2}$.

serves all users in the network. In the interference-limited regime, the energy efficiency can be increased by shutting down a large fraction of the MBSs. In the noise-limited regime, however, there appears to be little change in reducing q, initially. This can be explained by the fact that the effect of increasing the MBS density to improve coverage is approximately equally off set by the increase in power consumption (for this particular choice of system parameters).

We summarize the observations with the following claims: in the case where $\sigma^2 = 0$, the most energy efficient configuration is to have MBSs running as close to full capacity as possible. In the noise-limited regime, however, it would be more efficient to deploy more MBSs and hence improve coverage. However, the gains in coverage will eventually be overwhelmed by the increase in power consumption when the density of MBSs is sufficiently high.

B. Random Sleeping vs. Strategic Sleeping

In this set of simulations, we choose the activity model such that the activity is modeled by a Bernoulli trial so that each cell has activity level 1 with probability q, 0 otherwise. Likewise, the strategy is to stay awake with probability 1 if the activity level is 1.

Fig. 4, Fig. 5, and Fig. 6 shows the case where strategic sleeping is employed. We see that in all cases, strategic sleeping offers an improvement over random sleeping. This is somehow expected since strategic sleeping, in a way, switches on MBSs only where users are active. However, we see that strategic sleeping offers little improvement when $\sigma^2 = 0$, but significantly more improvement when $\sigma^2 > 0$. This could be explained by the fact that when noise is present, placing the MBS nearer to the user will have a huge impact on the coverage. In a way, strategic sleeping maintains the average distance to the nearest MBS, just like in the case when all MBSs are awake.

VI. Conclusion

In this paper, we investigated the design of energy efficient cellular networks through the employment of base station sleep mode strategies. Using a stochastic geometry based model, we derived the coverage probability and energy efficiency under sleeping strategies and formulated optimization problems in the form of power consumption minimization and energy efficiency maximization. In particular, we investigated the impact of random sleeping and strategic sleeping on the power consumption and energy efficiency. A first result is that that sleep mode strategies perform best in the interference-limited regime, but there are less effective and possibly detrimental in the noise-limited regime. Our numerical results suggest that strategic sleeping is able to mitigate some of the effects of background noise.

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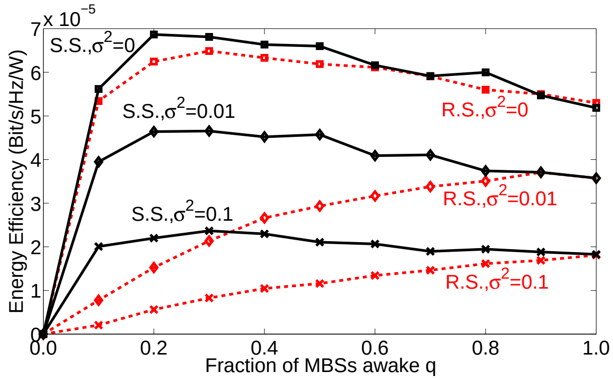

Fig. 6. Comparison of Energy Efficiency Ratio in Random Sleeping (R.S.) and Strategic Sleeping (S.S.), $\lambda_M = 10^{-4}\text{m}^{-2}$ and density of active users is 10^{-5}m^{-2}.

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VII. Appendix

A. Proof of Theorem 2

The first step is to condition on the activity of a typical cell $a(x)$. Next, enumerate all the MBSs in increasing order of distance from the user, starting from 1.[3] Let N_{ord} denote the order of the MBS the user connects to and $f_{\mathcal{A}}(x)$ the probability density function of $\mathcal{A}$. The success probability per link is thus given by

$$\begin{aligned}\mathbb{P}_{\text{SS}} &\overset{(a)}{=} \frac{1}{\mathbb{E}\{a\}}\int_0^1 x\mathbb{P}(\mathsf{SINR} > \gamma|x) f_{\mathcal{A}}(x)\mathrm{d}x \\ &\overset{(b)}{=} \frac{1}{\mathbb{E}\{a\}}\int_0^1 \{x\mathbb{P}(N_{\text{ord}} = 1)\mathbb{P}(\mathsf{SINR} > \gamma|N_{\text{ord}} = 1) \\ &\quad + x\mathbb{P}(N_{\text{ord}} > 1)\mathbb{P}(\mathsf{SINR} > \gamma|N_{\text{ord}} > 1)\} f_{\mathcal{A}}(x)\mathrm{d}x \\ &\overset{(c)}{=} \frac{1}{\mathbb{E}\{a\}}\int_0^1 \{xs(x)\int_{r=0}^{\infty} \exp(-\pi r^2 \lambda_{\text{M}} \mathbb{E}\{s\}\rho) \\ &\quad \exp(-\pi r^2\lambda_{\text{M}})\exp(-r^\alpha\gamma\sigma^2/P_{\text{M}})\mathrm{d}r \\ &\quad + x(1-s(x))\mathbb{P}(\rightarrow |N_{\text{ord}} > 1)\} f_{\mathcal{A}}(x)\mathrm{d}x \end{aligned} \tag{13}$$

where (a) is by definition of a coverage probability weighted over the active user links, (b) partitions into the event of the nearest MBS being awake and the event of the nearest MBS being asleep, (c) is from the Laplace transform of the remaining active interferers, distributed as a PPP with intensity $\mathbb{E}\{s\}\lambda_{\text{M}}$, and the PDF of the nearest MBS. This leaves us $\mathbb{P}(\mathsf{SINR} > \gamma|N_{\text{ord}} > 1)$.

$$\begin{aligned} \mathbb{P}_{\text{SS}}(\rightarrow |N_{\text{ord}} > 1) &\overset{(a)}{=} \sum_{i=2}^{\infty} \mathbb{P}(N_{\text{ord}} = i)\mathbb{P}(\rightarrow |N_{\text{ord}} = i) \\ \overset{(b)}{=} \sum_{i=2}^{\infty} \mathbb{E}\{s\}(1-\mathbb{E}\{s\})^{i-2} &\int_{r=0}^{\infty} \exp(-\pi r^2\lambda_{\text{M}}\mathbb{E}\{s\}\rho) \\ 2(\lambda_{\text{M}}\pi)^i r^{2i-1} &\exp(-\pi r^2 \lambda_{\text{M}})\exp(-r^\alpha\gamma\sigma^2/P_{\text{M}})\mathrm{d}r \end{aligned} \tag{14}$$

where (a) splits into the events "connect to the $i-$th MBS", (b) is the Laplace transform of the interference term and the PDF of the $i-$th MBS. Assuming $\alpha = 4$ allows us to simplify into the following:

$$\begin{aligned} \mathbb{P}(\rightarrow |N_{\text{ord}} > 1) &= \sum_{i=2}^{\infty} \mathbb{E}\{s\}(1-\mathbb{E}\{s\})^{i-2} \frac{1}{(1+\mathbb{E}\{s\}\rho)^i}\mathrm{d}r \\ &= \frac{1}{1+\rho}\frac{1}{1+\mathbb{E}\{s\}\rho}, \end{aligned} \tag{15}$$

thus arriving at the final expression

$$\begin{aligned} \mathbb{P}_{\sigma^2=0} = \frac{1}{\mathbb{E}\{a\}}&\int_0^1 \{\frac{xs(x)}{1+\mathbb{E}\{s\}\rho} \\ &+ x(1-s(x))\mathbb{P}(\rightarrow |N_{\text{ord}} > 1)\} f_{\mathcal{A}}(x)\mathrm{d}x. \end{aligned} \tag{16}$$

[3]The distance of each MBS from the user is almost surely distinct.