Energy-Aware Hierarchical Cell Configuration: from Deployment to Operation

Kyuho Son, Eunsung Oh and Bhaskar Krishnamachari
Department of Electrical Engineering, Viterbi School of Engineering
University of Southern California, Los Angeles, CA, 90089
Email: {kyuho.son, eunsung.oh and bkrishna}@usc.edu

***Abstract*—This paper develops an energy-aware hierarchical cell configuration framework that encompasses both deployment and operation in downlink cellular networks. Specifically, we first formulate a general problem pertaining to total energy consumption minimization while satisfying the requirement of area spectral efficiency (ASE), and then decompose it into deployment problem at peak time and operation problem at off-peak time. For the deployment problem, we start from an observation about various topologies including the real deployment of BSs that there is a strong correlation between the area covered by an additional micro BS and the increment of ASE. Under such an assumption, we prove the submodularity of ASE function with respect to micro BS deployment and propose a greedy algorithm that is shown to be a constant-factor approximation of optimal deployment. Although the greedy algorithm can be also applied as an offline centralized solution for the operation problem, we further propose online distributed algorithms with low complexity and signaling overhead to have more practical solutions. Extensive simulations based on the acquired real BS topologies and traffic profiles show that the proposed algorithms can significantly reduce the energy consumption.**

I. Introduction

In order to meet the explosive traffic demand from bandwidth-hungry multimedia and Internet-related services in broadband cellular networks, communication engineers seek to maximally exploit the spectral resources in all available dimensions. Hierarchical cell structure (HCS) [1] where small cells such as micro, pico and femto are used as a way of incrementally increasing capacity and coverage beyond the initial deployment of macro cells, has recently emerged as a promising solution. Incrementally deploying micro base stations (BSs) is simpler than building out complex cell towers and macro BSs, and it can also reduce both capital (e.g., hardware) and operating (e.g., electricity, backhaul and site lease) expenditures, which is especially attracted to wireless network operators.

Meanwhile, with the depletion of non-renewable resources and constraints on CO_2 emissions, there is a growing consensus on the need to develop more energy-efficient networks (referred to as *green networks*). From the perspective of wireless network operators, reducing electrical energy consumption is not only a matter of being green and responsible, but also economically important. It is estimated that the operators are spending more than 10 billion dollars as of now globally with 60-80% of the total energy consumption being contributed by BS infrastructure [2]. Since BSs are being deployed by the operator targeting peak traffic usage, they are under-utilized most of the time. However, even when a site is experiencing little or no activity, the BS consumes most of its peak energy. Beyond turning off only radio transceivers, dynamic approaches [3], [4] that allow the system to entirely switch off some under-utilized BSs and transfer the corresponding load to neighboring cells during low traffic period can substantially reduce the amount of wasted energy.

Our objective and contributions: In order to unburden wireless network operators from huge capital and operating expenditures (CAPEX & OPEX) while meeting the quality of service requirement, this paper focuses on providing theoretical implications and practical solutions for the following two key questions. (i) *HCS deployment problem*: where and how many micro BSs need to be deployed? (ii) *HCS operation problem*: how to operate (i.e., switch on/off) macro and micro BSs in an energy-efficient manner during off-peak times?

A. Related Work

Most of the research on HCS has focused on resource allocation [1], e.g., spectrum allocation, power control; however, there has been relatively little work dealing with BS deployment in HCS. The studies in [5], [6] showed the benefit of HCS deployment in hexagonal networks only by simulations. In the non-HCS setting (i.e., only one type of BS), Stamatelos *et al.* [7] theoretically showed that an algorithm minimizing the overlapped coverage can maximize spectral efficiency in omni-antenna case. Srinivas *et al.* [8] proposed an algorithm which jointly considers both BS deployment and user assignment in mobile backbone networks for throughput optimization. Our work differs from the previous works in that: (i) we present an analytical framework for optimal BS deployment in HCS and (ii) run extensive simulations based on the real traffic traces and BS topologies.

Green networking has recently received significant attention. In [2]–[4], [9], the authors investigated dynamic BS operation to save energy consumptions. In addition, the concept of BS sharing, where different operators pool their BSs together to further conserve energy, was introduced in [2], [10]. However, most of the previous works [2], [3], [9], [10] attempted to see how much energy saving can be achieved rather than developing algorithms that can be implemented in practice. Although several preliminary BS switching algorithms can be found in [4], [9], they cannot capture the signal degradation due to

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being served by further BSs when a previously associated BS is switched off. To reflect this effect, in this paper, (i) we consider a more sophisticated channel model based on SINR, and (ii) propose practical and distributed algorithms for the dynamic BS operation.

The reminder of this paper is organized as follows. In Section II, we formally describe our system model and general problem. In Section III, we deal with the deployment problem finding a minimal deployment of micro BSs for the required area spectral efficiency (ASE). Under the observation of monotone relationship between coverage and ASE increment, we prove the submodularity of the ASE function with respect to micro BS deployment and propose a greedy algorithm, which has a nice feature of constant-factor approximation. In Section IV, we focus on minimizing energy consumption through dynamic BS operation. Although the above greedy deployment algorithm can be also applied as a centralized offline solution, we further propose distributed online algorithms based on Lagrangian relaxation technique. In Section V, we evaluate the performance of the proposed algorithms and finally conclude the paper in Section VI.

II. System Description and Problem Definition

A. System Description

1) Network Model: We consider a HCS broadband wireless network where the sets of macro and micro BSs, denoted by $\mathcal{B}_M$ and $\mathcal{B}_m$, respectively, lie in the two-dimensional area $\mathcal{A} \subset \mathbb{R}^2$. Throughout the paper, subscript M is used for macro BSs, and m is for micro BSs. Let us denote by $b \in \mathcal{B} = \mathcal{B}_M \cup \mathcal{B}_m$ the index of BSs. Even though our main focus is on downlink communication, i.e., from BSs to user equipments (UEs), some aspects of our work can be applied to the uplink as well.

2) Link Model: The received signal strength from BS b to UE at location x can be expressed as $E_b(x) = p_b \cdot g_b(x)$, where p_b denotes the transmission power of BS b, $g_b(x)$ denotes the channel gain from BS b to location x, including path loss attenuation, shadowing and other factors if any. Note, however, that fast fading is not considered here because the time scale for measuring $g_b(x)$ is assumed to be much larger. Accordingly, the signal to interference plus noise ratio (SINR) at location x can be written as:

$$\Gamma(x, \mathcal{B}) = \frac{E_{b(x,\mathcal{B})}(x)}{\sum\limits_{b \in \mathcal{B},\, b \neq b(x,\mathcal{B})} E_b(x) + \sigma^2}, \qquad (1)$$

where σ^2 is noise power and $b(x, \mathcal{B})$ denotes the index of the BS at location x that provides the highest signal strength, i.e., $b(x, \mathcal{B}) = \arg\max_{b \in \mathcal{B}} E_b(x)$. Following Shannon's formula, spectral efficiency at location x is given by:

$$C(x, \mathcal{B}) = \log_2 \left(1 + \Gamma(x, \mathcal{B})\right), \quad \text{[bit/sec/Hz]} \qquad (2)$$

3) Area Spectral Efficiency: We adopt the area spectral efficiency (ASE) firstly introduced in [11] as our performance metric, which is is defined as the summation of the spectral efficiency over the reference area $\mathcal{A}$:

$$S(\mathcal{A}, \mathcal{B}) \doteq \frac{\sum_{x \in \mathcal{X}} C(x, \mathcal{B}) \cdot Pr(x)}{|\mathcal{A}|}, \quad \text{[bit/sec/Hz/m}^2\text{]} \qquad (3)$$

where $Pr(x)$ is the probability of the UE being at a specific location x; $\mathcal{X}$ is the set of locations included in the area $\mathcal{A}$ satisfying $Pr(x) > 0$ for all $x \in \mathcal{X} \subset \mathcal{A}$. We assume the homogeneous user distribution[1] such that the discrete set $\mathcal{X}$ is a rectangular lattice with a small grid size and the probability of each location is the same.

4) Coverage: Let us denote by $\mathcal{A}_{i<j}$ the set of locations that have better SINR from BS i than j. We further denote by $\mathcal{A}_{i=j}$ the set of boundaries having the same SINR from both BSs i and j. Then, the set of locations covered by BS k (or simply, coverage) can be written as:

$$\mathcal{A}_k(\mathcal{B}) \doteq \{x | x \in \mathcal{A} \text{ s.t. } b(x, \mathcal{B}) = k\} = \bigcap_{b \in \mathcal{B},\, b \neq k} \mathcal{A}_{k>b}. \qquad (4)$$

B. General Problem Statement

Consider an area of interest $\mathcal{A}$ served by a wireless network operator whose access network consists of only macro BSs $\mathcal{B}_M$. We assume that the daily traffic profile repeats periodically [2]–[4], and that the required ASE S_{th}^t over time t corresponding to the traffic profile is already known. Suppose that the maximum required ASE $S_{th}^{t^*}$ at the peak time $t^* = \arg\max_t S_{th}^t$ during a day $t \in [t_0, t_0 + D)$ almost approaches to the one that can be provided by turning on all the macro BSs $\mathcal{B}_M$, i.e., $S(\mathcal{A}, \mathcal{B}_M) \simeq S_{th}^{t^*}$. Thus, the operator wants to upgrade its access network by micro BSs which are considered as the cost-effective way of incrementally increasing capacity inside the initial macro cell deployment.

General problem: We want to minimize the total BS energy consumption during a day while providing $\zeta \geq 1$ times higher ASE than before the upgrade. We can mathematically formulate this problem as the following optimization problem:

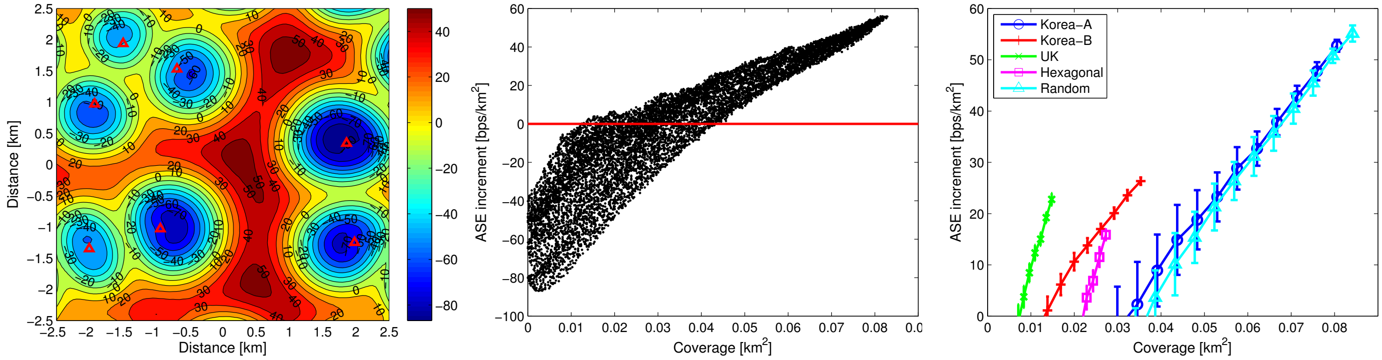
$$\begin{aligned} \textbf{(P)} \quad & \min_{\{\mathcal{B}^t\}} \int_{t_0}^{t_0+D} \left(P_M \cdot \left|\mathcal{B}_M^t\right| + P_m \cdot \left|\mathcal{B}_m^t\right|\right) dt \\ & \text{s.t.} \quad S(\mathcal{A}, \mathcal{B}^t) \geq \zeta \cdot S_{th}^t, \quad \forall t \in [t_0, t_0 + D), \end{aligned} \qquad (5)$$

where $\mathcal{B}^t$ denotes the set of BSs that are turned on at time t; P_M and P_m are operational power consumptions of macro and micro BSs, respectively.

Problem separation: The above general problem **(P)** can be separated into two subproblems: **(P1)** micro BSs *deployment problem* considering the peak time t^* and **(P2)** BSs *operation problem* during the off-peak period $t \neq t^*$.

It is desirable for the operator to minimize the cost for expanding its infrastructures while guaranteeing the required ASE. Therefore, the first problem is *to find a minimal deployment of micro BSs which can support the peak time ASE.* Note that this deployment issue is an offline problem that can be handled in a network coordinator. Once the micro BS deployment targeted at the peak time is done, the next problem

[1] Please refer to our technical paper [12] for the further results of the heterogeneous user distribution.



(a) Contour plot of ASE increment (Korea-A)

(b) Scatter plot between coverage and ASE increment (Korea-A)

(c) Quantile plot between coverage and ASE increment (all topologies)

Fig. 1: Several interesting observations from various topologies including the real layout of macro BSs.

is *how to efficiently operate these micro BSs along with the existing macro BSs for energy conservation during the off-peak period*. The solutions for the operation problem should be online distributed algorithms in order to be implemented in practical systems.

III. HCS Deployment Strategy

First, we aim at finding a minimal deployment of micro BSs (i.e., minimizing the total power consumption) while satisfying the raised ASE requirement at the peak time, $t = t^*$:

$$\textbf{(P1)} \quad \min_{\mathcal{B}_m} \quad |\mathcal{B}_m| \tag{6}$$

$$\text{s.t.} \quad S(\mathcal{A}, \mathcal{B}_M \cup \mathcal{B}_m) \geq \zeta \cdot S_{th}^{t^*} = \zeta \cdot S(\mathcal{A}, \mathcal{B}_M). \tag{7}$$

Note that the deployment problem **(P1)** can be also interpreted as a CAPEX minimization. **(P1)** is basically a combinatorial problem, and that makes it difficult to find an optimal solution, especially, if the number of candidate locations is large.

A. Key Observations

We shall start by presenting several observations from various real topologies which help us to gain insight and develop an efficient algorithm. We acquired real macro BS topologies in the part of Korea [13] and Manchester, UK [2], [14] as well as typical hexagonal and random topologies. Listed here is brief information about the number of macro BSs and the size of observation area in the topologies that we used: (i) Korea-A: 7 BSs in 5x5 km^2, (ii) Korea-B: 15 BSs in 4.5x4.5 km^2, (iii) UK: 6 BSs in 2.5x2.5 km^2, (iv) hexagonal: 7 BSs in 4x4 km^2, and (v) random: 6 BSs in 5x5 km^2.

We focus on the deployment of *one new micro BS* in the area that is covered by the existing set of macro BSs. The contour plot in Fig. 1(a) shows how much ASE a micro BS can improve according to the location of deployment. Although this is a snapshot from the topology of Korea-A, similar trends could be observed in the other topologies as well.

Observation 1: As long as a new micro BS is placed not to close to the one of existing macro BSs, ASE can be expected to increase before the upgrade. Especially, the ASE increment becomes large as the distances from macro BSs increase.

The wireless network operators are supposed to deploy a micro BS at the location where ASE can be improved. Therefore, throughout the paper, we only consider the set of candidate locations for the micro BS deployment as follows:

$$\forall k \in \mathcal{K}, \quad S(\mathcal{B} \cup \{k\}) > S(\mathcal{B}), \tag{8}$$

Now we examine how much area the micro BS can cover according to the location of deployment and investigate the correlation with ASE increment. In Fig. 1(b), ASE increment has a distinct tendency to increase with coverage. Interestingly, it becomes sharper as the coverage increases and this trend can be verified over the other topologies as well in the quantile plots in Fig. 1(c). This is desirable because we are interested in the locations that give high performance improvement. In such locations with small variance, we can almost surely assert that coverage and ASE increment have a near-monotonic relationship. Results from monotone test[2] (90.4∼97.0% depending on the topologies) also support the following observation.

Observation 2: The larger area can be covered by a new micro BS, the higher ASE increment is likely to be expected.

Motivated by this observation, we assume that the following monotone relationship holds throughput the paper.

$$\begin{aligned} &|\mathcal{A}_k(\mathcal{B} \cup \{k\})| \geq |\mathcal{A}_{k'}(\mathcal{B}' \cup \{k'\})| \\ &\quad \Rightarrow S(\mathcal{B} \cup \{k\}) - S(\mathcal{B}) \geq S(\mathcal{B}' \cup \{k'\}) - S(\mathcal{B}'), \end{aligned} \tag{9}$$

where k (or k') is the index of the micro BS.

These two observations are intuitively understandable. Consider the area covered by the micro BS far from existing macro BSs. Since the signals from the macro BSs are weak, the micro BS will provide the highest SINR to a large extent area. In addition to this large coverage, the area originally had low spectral efficiency, resulting in the high increment of ASE.

[2]We randomly pick two points having positive ASE increments in Fig. 1(b) and check whether the slope between these points are positive or not.

B. Constant-Factor Approximation Greedy Algorithm

Prior to introducing a natural greedy algorithm for **(P1)**, we define a real-valued set function $F : \mathcal{B}_m \to \mathbb{R}$ as follows:

$$F(\mathcal{B}_m) \doteq S(\mathcal{B}_M \cup \mathcal{B}_m) - S(\mathcal{B}_M), \tag{10}$$

which returns the ASE increment by additionally deploying the set of micro BSs $\mathcal{B}_m$.

Greedy deployment algorithm

1: Initialize $\mathcal{B}_m^{\text{greedy}} = \emptyset$
2: **do while** $S(\mathcal{A}, \mathcal{B}_M \cup \mathcal{B}_m^{\text{greedy}}) < \zeta \cdot S_{th}^{t^*}$
3: $\quad k^* = \arg\max_{k \in \mathcal{K}} F(\mathcal{B}_m^{\text{greedy}} \cup \{k\}) - F(\mathcal{B}_m^{\text{greedy}})$,
4: $\quad \mathcal{B}_m \leftarrow \mathcal{B}_m \cup \{k\}$
5: **end do**

The greedy algorithm starts with the empty set $\mathcal{B}_m^{\text{greedy}} = \emptyset$, and iteratively adds the micro BS location having the highest increment among the set of candidate locations $\mathcal{K}$ until ASE reaches a target value, i.e., satisfying the constraint (7).

Theorem 3.1: The ASE increment achieved by an optimal placement with the same number of micro BSs as the greedy algorithm cannot be more than a factor of $e/(e-1)$ from the ASE increment achieved by the greedy algorithm.

$$\max_{|\mathcal{B}_m| = |\mathcal{B}_m^{\text{greedy}}|} F(\mathcal{B}_m) \le \frac{e}{e-1} F(\mathcal{B}_m^{\text{greedy}}), \tag{11}$$

where the constant e is base of the natural logarithm.

Proof: In order to prove the theorem, we first need to show that the ASE increment function satisfies the following three properties: (i) $F(\emptyset) = 0$, (ii) increasing, and (iii) submodular. $F(\emptyset) = 0$ is trivial and F is an increasing function by the assumption (8). To prove the submodularity, it is enough to check that for all $\mathcal{B}_m \subseteq \mathcal{B}_{m'} \subseteq \mathcal{K}$ and for an arbitrary chosen $k \in \mathcal{K} \setminus \mathcal{B}_{m'}$, the following condition holds.

$$F(\mathcal{B}_m \cup \{k\}) - F(\mathcal{B}_m) \ge F(\mathcal{B}_{m'} \cup \{k\}) - F(\mathcal{B}_{m'}) \tag{12}$$

Since $\mathcal{B}_m$ is the subset of $\mathcal{B}_{m'}$ and F is increasing, we have the following two inequalities:

$$F(\mathcal{B}_m) \le F(\mathcal{B}_{m'}) \quad \text{and} \tag{13}$$

$$\begin{aligned} \left|\mathcal{A}_k(\mathcal{B}_M \cup \mathcal{B}_m \cup \{k\})\right| &= \left|\bigcap\nolimits_{b \in \mathcal{B}_M \cup \mathcal{B}_m} \mathcal{A}_{k>b}\right| \\ \ge \left|\bigcap\nolimits_{b \in \mathcal{B}_M \cup \mathcal{B}_{m'}} \mathcal{A}_{k>b}\right| &= \left|\mathcal{A}_k(\mathcal{B}_M \cup \mathcal{B}_{m'} \cup \{k\})\right| \end{aligned} \tag{14}$$

By the assumption (9) and the definition of F, the coverage inequality (14) can be converted into the ASE inequality:

$$\begin{aligned} F(\mathcal{B}_m \cup \{k\}) &= S(\mathcal{B}_M \cup \mathcal{B}_m \cup \{k\}) - S(\mathcal{B}_M \cup \mathcal{B}_m) \\ &\ge S(\mathcal{B}_M \cup \mathcal{B}_{m'} \cup \{k\}) - S(\mathcal{B}_M \cup \mathcal{B}_{m'}) \\ &= F(\mathcal{B}_{m'} \cup \{k\}). \end{aligned} \tag{15}$$

Combining (13) and (15) completes the submodularity in (12).

Nemhauser *et al.* [15] studied a maximization problem for a nondecreasing submodular set function with $F(\emptyset) = 0$,

$$\max_{\mathcal{Z}} F(\mathcal{Z}) \quad \text{s.t.} \quad |\mathcal{Z}| \le K, \tag{16}$$

and they obtained that

$$\frac{\text{(value of greedy approximation)}}{\text{(value of optimal solution)}} \ge 1 - \left(\frac{K-1}{K}\right)^K. \tag{17}$$

Since our $F(\cdot)$ is an increasing submodular function with $F(\emptyset) = 0$, the greedy algorithm is guaranteed to find a constant-factor approximation solution $\mathcal{B}_m^{\text{greedy}}$, such that

$$\frac{F(\mathcal{B}_m^{\text{greedy}})}{\max_{|\mathcal{B}_m| = |\mathcal{B}_m^{\text{greedy}}|} F(\mathcal{B}_m)} \ge 1 - \left(\frac{|\mathcal{B}_m^{\text{greedy}}| - 1}{|\mathcal{B}_m^{\text{greedy}}|}\right)^{|\mathcal{B}_m^{\text{greedy}}|} \ge 1 - \frac{1}{e}. \quad \blacksquare$$

Corollary 3.1: So far we have assumed that micro BSs have the same operational power P_m. However, the above constant-factor approximation result can be extended to general cases [16], where BSs have different operational powers. We only need to change the greedy algorithm as follows, i.e., finding the location with highest ASE increment per unit power:

$$k^* = \arg\max_{k \in \mathcal{K}} \frac{F(\mathcal{B}_m^{\text{greedy}} \cup \{k\}) - F(\mathcal{B}_m^{\text{greedy}})}{P_k}. \tag{18}$$

IV. HCS Operation Strategy

Since BSs are deployed to support the peak time traffic, they will be under-utilized most of off-peak times, i.e., $t \neq t^*$. If an appropriate dynamic BS operation algorithm is not employed, then a considerable amount of energy will be wasted. Thus, our objective at the off-peak period is to find a dynamic operation of BSs that minimizes the total operational power consumption while satisfying the raised ASE requirement:

$$\begin{aligned} \textbf{(P2)} \quad & \min_{\mathcal{B}^t} \; P_M \cdot \left|\mathcal{B}_M^t\right| + P_m \cdot \left|\mathcal{B}_m^t\right| \\ & \text{s.t.} \;\; S(\mathcal{A}, \mathcal{B}^t) \ge \zeta \cdot S_{th}^t. \end{aligned} \tag{19}$$

The operation problem **(P2)** is a combinatorial optimization problem as well. Thus, in the following consecutive subsection, we propose a suboptimal offline centralized algorithm and two online distributed BS switching algorithms.

Since there is a similarity between deployment and operation problems in nature, we may use the generalized deployment algorithm in (18) as a centralized algorithm for the operation problem. This centralized algorithm not only requires many feedbacks from all BSs to the network coordinator but also should be started from the empty set (i.e., turning off all BSs), which makes it difficult to be implemented in practice. In order to overcome such difficulties, we consider the design of simple and distributed online algorithms.

A. Distributed BS Switching Algorithm

Using the Lagrangian relaxation with a multiplier λ, the BS operation problem **(P2)** can be separated by the summation of the switching problem at each BS as follows.

$$\begin{aligned} L(\mathcal{B}^t, \lambda) &= \sum_{b \in \mathcal{B}^t} P_b + \lambda \left[\zeta \cdot S_{th}^t - S(\mathcal{A}, \mathcal{B}^t)\right] \\ &= \sum_{b \in \mathcal{B}} \underbrace{\left[P_b a^t(b) + \frac{\lambda}{|\mathcal{A}|} \left\{ \frac{\zeta |\mathcal{A}|}{|\mathcal{B}^t|} S_{th}^t - \sum_{x \in \mathcal{X}_b} C(x, \mathcal{B}^t) \right\} \right]}_{L_b(a^t(b), \lambda)}, \end{aligned}$$

where $a^t(b)$ denotes the indicator of BS status, i.e., $a^t(b) = 1$ when the BS b is on at time t, and 0 otherwise; $\mathcal{X}_b$ denotes the set of locations in the serving area of BS b. The network coordinator updates the Lagrangian multiplier using gradient descent method with a small step size $\epsilon > 0$, i.e.,

$$\lambda \leftarrow \lambda + \epsilon \left[\zeta \cdot S_{th}^t - S(\mathcal{A}, \mathcal{B}^t) \right], \tag{20}$$

where $S(\mathcal{A}, \mathcal{B}^t)$ can be calculated by collecting a local ASE in each BS as follows:

$$S(\mathcal{A}, \mathcal{B}^t) = \frac{1}{|\mathcal{A}|} \sum_{b \in \mathcal{B}^t} |\mathcal{A}_b| \cdot S(\mathcal{A}_b, \mathcal{B}^t). \tag{21}$$

For any given λ, BS b needs to be turned off for energy saving if beneficial, i.e., $L_b(0, \lambda) \leq L_b(1, \lambda)$. This yields the following condition:

$$\frac{\lambda |\mathcal{A}_b| \cdot \{ S(\mathcal{A}_b, \mathcal{B}^t) - S(\mathcal{A}_b, \mathcal{B}^t - \{b\}) \}}{|\mathcal{A}|} \leq P_b. \tag{22}$$

This can be interpreted as follows: (*i*) The less decrement in spectral efficiency the BS has and/or (*ii*) the larger operational power, the more likely the BS is switched off. Hence, we propose BS switching algorithms as follows.

SINR-based (S-OFF1): At each time t, each BS receives the Lagrangian multiplier λ from the the network coordinator. If the performance decrement in spectral efficiency per unit operational power is less than a certain threshold, then the BS will be switched off.

$$\frac{|\mathcal{A}_b| \cdot \{ S(\mathcal{A}_b, \mathcal{B}^t) - S(\mathcal{A}_b, \mathcal{B}^t - \{b\}) \}}{P_b} \leq \frac{|\mathcal{A}|}{\lambda}. \tag{23}$$

The BS switching-on procedure can be accomplished by the reverse way of the switching-off procedure. Without any additional calculation in off-state, the BS b is switched on when the target ASE reaches the same value that the BS was originally switched off.

SNR-based (S-OFF2): In **(S-OFF1)**, each BS requires SINR estimations before and after turning-off from UEs in its coverage. To reduce the signal processing overhead of UEs, we further propose much simple **(S-OFF2)** based on SNR estimations.

$$\frac{|\mathcal{A}_b| \cdot \{ S_{\sigma^2}(\mathcal{A}_b, \mathcal{B}^t) - S_{\sigma^2}(\mathcal{A}_b, \mathcal{B}^t - \{b\}) \}}{P_b} \leq \frac{|\mathcal{A}|}{\lambda}. \tag{24}$$

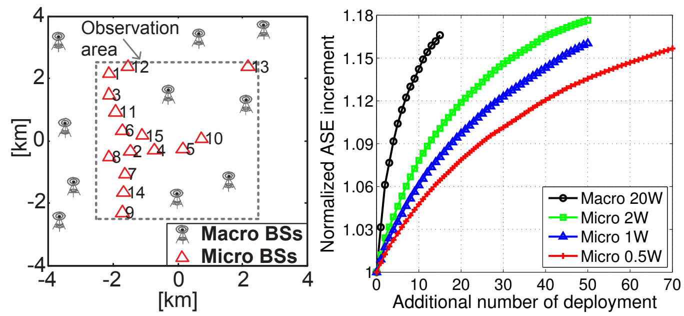
where $S_{\sigma^2}(\mathcal{A}, \mathcal{B}) = \frac{1}{|\mathcal{A}|} \sum_{x \in \mathcal{X}} \log_2(1 + E_{b(x,\mathcal{B})}(x)/\sigma^2)$. It should be noted that ASE can be approximately calculated based on the value of SNR instead of exact SINR in (24).

V. Numerical Results

We consider the deployment of macro BSs as shown in Fig. 2(a) for our simulation. There are 10 macro BSs in $8 \times 8\text{km}^2$. In order to avoid edge effects, we only observe the area of $5 \times 5\text{km}^2$. Typical transmission and total operational powers for macro and micro BSs are summarized in Table I [17]. For more detailed descriptions of simulation setups, refer to our technical report [12].

TABLE I: Additional total power consumptions required for the target ASE increment.

BS Types TX / OP Powers [in W]		Macro 20 / 865	Micro 2 / 43	Micro 1 / 38	Micro 0.5 / 35
Target ASE Increment	10%	4325W	645W	836W	1050W
	15%	9515W	1476W	1672W	2240W



(a) (b)

Fig. 2: HCS deployment: (a) snapshot after the deployment of 15 micro BSs and (b) normalized ASE increment according to the deployment of different types of BSs.

A. Base Station Deployment

On top of the deployment of macro BSs, we consider the deployment of micro BSs to further increase ASE in the area of interest. Fig. 2(a) show the snapshots after 15 micro BSs additionally deployed by the proposed greedy deployment algorithm. As expected, the micro BSs tend to be placed in the boundaries of the cell because this makes each micro BS cover larger area, resulting in more ASE increment.

In Fig. 2(b), we investigate the performance improvement according to the additional deployment of BSs having different transmission powers. Four types of BSs are considered: the macro BS with transmit power of 20W and the micro BSs with transmit power of 0.5W, 1W and 2W, respectively. Note that there are diminishing marginal returns on the normalized ASE increment. To meet the target ASE increment of 10%, while only five additional macro BSs are needed, 15, 22 or 30 micro BSs (three to six times more than macro BSs). Nevertheless, the transmission power consumptions (p_M and p_m) of additional micro BSs are much less than that of additional macro BSs. For example, while 100W is consumed by the macro BSs, only 30W, 22W, or 15W is consumed by the micro BSs. When we reflect the total power consumptions (P_M and P_m), the advantage of micro BSs becomes more clear. Table I shows the required the additional total power consumptions for different target ASE increment. Compared to the case of macro BSs, deploying micro BSs can reduce more than 3kW and 6kW for the target ASE increments of 10% and 15%, respectively. This corresponds to about 70% energy savings.

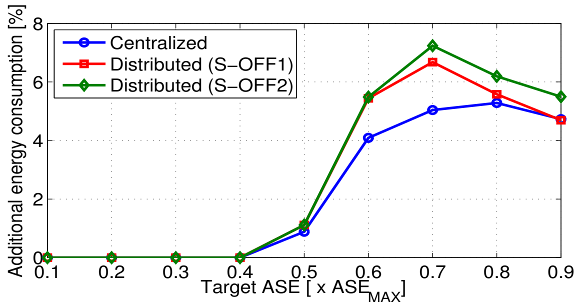


Fig. 3: Additional energy consumption compared to that of an optimal exhaustive search.

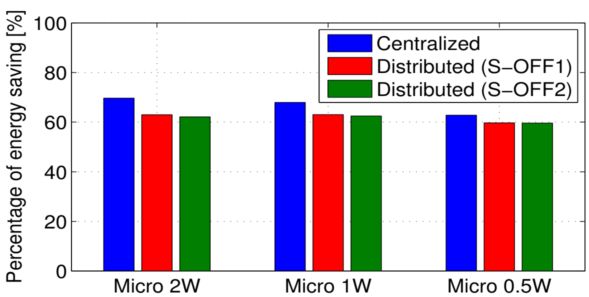


Fig. 4: Energy saving during one week.

B. Base Station Operation

We now examine the performance of the proposed BS operation algorithms in Section IV. Fig. 3 shows the percentage of additional power consumption for different algorithms by varying the normalized required ASE compared to the result of an optimal exhaustive search. Note that such simple distributed algorithms can closely approximate the complex centralized algorithm. Moreover, their maximum deviations from the optimal solution are less than 7%.

In order to obtain the realistic amount of energy saving, we further consider real traffic traces recorded in a metropolitan urban area during one week as shown in [2]. Fig. 4 shows the percentage of total energy saving during one week. As can be seen, around 60-70% of energy consumption can be reduced by dynamic BS operation. Given that OPEX of wireless network operators for electricity is more than 10 billion dollars globally [2], this could translate to huge economic benefit to the operators.

VI. Conclusion

In this paper, we proposed an energy-aware hierarchical cell configuration framework that provide both theoretical and practical guidelines on how wireless network operators manage their BSs. We specifically focused on a problem pertaining to total energy consumption minimization while satisfying the requirement of ASE, and decomposed it into deployment problem at peak time and operation problem at off-peak time. For the deployment problem, we proposed a constant-factor approximation greedy algorithm. For the operation problem, we propose two distributed online switching algorithms. Extensive simulations based on the acquired real BS topologies and the traffic profiles show that the proposed algorithms can considerably reduce the total energy consumption by up to 60-70%, depending on the configurations.

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