Energy-Efficient Base Station Deployment in Heterogeneous Networks

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Abstract—In this letter, we address the base station (BS) deployment problem in heterogeneous networks (HetNets) and propose an energy-efficient solution. Supporting the network with additional BSs increases the total capacity of the network. However, this process may reduce the energy efficiency of the network. The proposed algorithm studies the energy efficiency aspect of the micro BS deployment problem. The deployment problem can be divided into two subproblems: choosing candidate locations for micro BSs and selecting the optimum set among these candidates. Inhomogeneous distribution of the candidate locations is misleading for different user sets. Selecting the optimum micro BSs among the candidate locations is a combinatorial problem. To provide an approximate solution to this problem, we propose a greedy algorithm. Our simulation results demonstrate that by optimizing the BS location and the number of BSs to be deployed, the energy efficiency of the system with only macro BSs can be improved up to 1.4–1.65 times for a range of realistic micro BS transmit power levels.

Index Terms—Energy efficiency, heterogeneous cellular networks, deployment.

I. INTRODUCTION

DEPLOYMENT of HetNets is one of the enabling technologies that can provide significant data rates and increase the network coverage. In HetNets, macro BSs are overlaid by a layer of low power BSs. Decreasing the link distances and increasing the accessibility rate of users are the significant advantages of HetNets. Recently, the deployment of HetNets has attracted attention in the literature, see, e.g., [1]–[3].

To meet the increasing mobile traffic demand, mobile operators typically employ more resources, which results in the use of more energy, and consequently, the growth of greenhouse gases. To remedy this effect, green cellular communication has attracted attention, see, e.g., [4]–[6]. In addition to environmental advantages, reducing the energy consumption at BSs has an economical benefit. The focus on this letter is to meet the increasing traffic demand while limiting the infrastructure costs and generation of greenhouse gases.

Most of the research on HetNets has concentrated on power control and resource allocation problems, see, e.g., [7]–[10]. On the other hand, the BS deployment problem for energy efficiency of HetNets has not been investigated to its full potential. An example for such a study is the one in [11]. The authors of [11] aim to deploy micro BSs to an area which is covered by only macro BSs. They observe that the most appropriate

candidate points for micro BSs are the cell boundaries of the macro BSs. Among the candidate locations, they iteratively select the micro BS which provides the largest Area Spectral Efficiency (ASE) increment. The process continues until the target value is reached. We observe that the cell boundaries may not always be good candidates if the cumulative interference is considered. The algorithm we will present is designed to overcome this limitation. Reference [12] proposes a heuristic BS deployment algorithm. The algorithm in [12] first places a selected number of BSs to initial appropriate locations and then, it shifts the location of BSs iteratively to minimize outage. Pre-selected initial locations affect the convergence time of the algorithm. However, system characteristics (e.g., path loss and shadowing) are strictly dependent on the locations of the BSs. When the BSs are shifted, these parameters become different from the initial case. Although the algorithm works sufficiently well for the test cases, we observe that obtaining these parameters at each iteration is impractical for real BS topologies. The study in [13] investigates the impact of deployment strategies in a hexagonal grid structure. The authors investigate the deployment of different number of micro BSs as an underlay to the macrocell layer and study its effect on the capacity and energy consumption. They find out that the power savings from the deployment of micro BSs are moderate in fully loaded networks, while large gains can be achieved at low to medium loads. In [13], micro BSs are only located on the cell edges. These locations are chosen because the signal level of macro BSs is very low. However, energy efficiency of these locations is not considered in the network.

The work we will present in this letter does not have the restriction of considering only cell boundaries as potential new locations and it does not require obtaining updated data for BSs at every iteration. In addition, this work can be employed in both hexagonal and real BS topologies. Moreover, this work takes into account the feasibility of the candidate locations which is not considered in other works. Furthermore, the proposed algorithm finds the set of micro BS locations that maximizes the energy efficiency while satisfying the increasing capacity demand of the network.

The remainder of this letter is organized as follows. Section II introduces the system model. Section III describes our problem, presents the proposed algorithm, and compares the performance of the proposed algorithm with the optimal solution. Numerical results demonstrating the performance improvements are presented in Section IV and concluding remarks are made in Section V.

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II. SYSTEM MODEL

In this section, we first present our network model, and then describe our formulation and definition of energy efficiency.

Consider a wireless network with multiple macro and micro BSs. These BSs are to be deployed over a fixed geographical area $\mathcal{A}$. The users are randomly positioned in $\mathcal{A}$. The users always have data to transmit. The signal-to-interference-plus-noise ratio (SINR) of a macrocell associated user k on subcarrier n can be written as

$$\gamma_k^{(n)} = \frac{P_M^{(n)} g_{k,b}}{\sum\limits_{b' \in \mathcal{B}_M, b' \neq b} P_M^{(n)} g_{k,b'} + \sum\limits_{b' \in \mathcal{B}_m} P_m^{(n)} g_{k,b'} + \sigma^2} \quad (1)$$

where $\mathcal{B}_M$ and $\mathcal{B}_m$ denote the set of macro and micro BSs respectively. The subscript M is used to indicate macro BSs, while m is for micro BSs. All BSs in $\mathcal{A}$ are denoted by $\mathcal{B}$ i.e., $\mathcal{B} = \mathcal{B}_M \cup \mathcal{B}_m$. The transmit power of a macrocell M and a microcell m on subcarrier n are given by $P_M^{(n)}$ and $P_m^{(n)}$, respectively. The channel gain from BS b to user k is denoted by $g_{k,b}$. The channel gain includes the path loss attenuation, shadow fading, and multi-path fading components. The thermal noise effective over a subcarrier is denoted by σ^2. The SINR for microcell user k on subcarrier n can be written in a similar fashion. For simplicity, we use the same symbol $\gamma_k^{(n)}$ for SINR of both macro and microcell users. In this letter, users are associated with the BS which provides the highest signal strength at the user location. If the received power levels from more than one BSs are equal, the user can choose any of these BSs. The capacity of user k within the BS configuration $\mathcal{B}$ is denoted by $C(k, \mathcal{B})$, and is given, in terms of the received SINR $\gamma_k^{(n)}$ and the bandwidth of subcarrier n, $W_k^{(n)}$, by

$$C(k, \mathcal{B}) = \sum_{n=1}^{N_k} W_k^{(n)} \log_2 \left(1 + \gamma_k^{(n)} \right) \quad \text{[bits/sec]} \quad (2)$$

where N_k denotes the number of subcarriers assigned to user k. In this work, we used equal bandwidth scheduling [14]. Each BS shares their resource blocks (RBs) equally among its users. In LTE systems, each RB contains 12 subcarriers. All subcarriers of an RB are assigned to the same user for each BS. When there are K users who are associated with a BS and share N_{RB} RBs, $K_h = \mod(N_{RB}, K)$ users obtain $\lfloor N_{RB}/K \rfloor + 1$ RBs, whereas the rest of the users obtain $\lfloor N_{RB}/K \rfloor$ RBs. In this letter, we assume that each BS allocates equal power on its subcarriers.

In this letter, our purpose is to maximize the energy efficiency of the network. The energy efficiency depends on the throughput and the consumed power in the network. Traditionally, macro BSs are designed to provide coverage over large areas without any energy efficiency concerns and the consumed power in the network increases as the coverage area becomes larger. Micro BSs are designed to cover relatively smaller areas and thereby consume less power compared to the macro BSs. The power consumption at the BSs can be broken down into various components, e.g., power amplifier, signal processing, battery supply, and cooling devices, see, e.g., [15]. There are several power consumption models proposed in the literature for different BS types, see, e.g., [16], [17]. In this work, we used the power consumption model proposed in [16]. It is given by

$$\begin{aligned} P_M &= P_{0,M} + \Delta_M P_{tx} \\ P_m &= P_{0,m} + \Delta_m P_{tx} \end{aligned} \quad (3)$$

where P_M, P_m, and P_{tx} denote the average consumed power per macro BSs, micro BSs, and transmission power, respectively. The coefficients Δ_M and Δ_m are the transmission power consumption scales. $P_{0,M}$ and $P_{0,m}$ denote power offsets which are independent of the transmission power.

In this work, we are not using any power control methods, so the power consumption at the BSs is always constant for each BS and all BSs transmit at the full power. Then, the energy efficiency of the system can be described as

$$\eta_{EE}(\mathcal{B}) = \frac{\sum\limits_{k \in \mathcal{K}} C(k, \mathcal{B})}{N_B \cdot P_M + N_b \cdot P_m} \quad \text{[bits/Joule]} \quad (4)$$

where N_B and N_b are the number of macro BSs and micro BSs in the network, respectively, and P_M and P_m are the power consumption of macro and micro BSs, respectively.

III. PROBLEM DEFINITION AND PROPOSED SOLUTION

In this section, we first present the BS deployment problem, discuss the proposed solution, and then compare the performance of the algorithm with the optimal solution.

A. Problem Definition

Consider that only macro BSs are initially deployed over an area $\mathcal{A}$ and the network operator seeks an energy-efficient solution to meet the increasing traffic demand. The goal is to maximize the system energy efficiency while satisfying the increased capacity demand for the network with the minimum number of additional micro BSs to limit capital expenses. Let us assume C_r denotes the network capacity when only macro BSs are deployed for scenario r, and it is asked to be increased to $\lambda \geq 1$ times C_r by deploying micro BSs for all network scenarios. Then, the deployment problem can be formulated as

$$\max_{|\mathcal{B}_c|} \quad \pi_r \eta_{EE}(\mathcal{B})$$

$$\text{s.t.} \quad \sum_{k \in \mathcal{K}_r} C(k, \mathcal{B}) \geq \lambda \cdot C_r \qquad \text{for all } r \in \mathcal{R} \quad (5)$$

where $\mathcal{B}_C$ denotes the set of candidate micro BSs, π_r denotes the probability that scenario r occurs, and $\mathcal{R}$ and $\mathcal{K}_r$ represent the set of scenarios and users in scenario r respectively.

This deployment problem consists of two subproblems. The first one is to choose the candidate locations. Different algorithms can be used to determine these locations. As stated earlier, authors in [11] suggest that the cell boundaries of the macro BSs are the most appropriate candidate locations for the micro BSs. The success of the algorithm in [11] is highly dependent on the macro BS locations and the user distributions. If the users are clustered close to the locations of macro BSs, this approach may not work properly. To come up with an algorithm independent from these parameters, we divide the network area to rectangles and a convenient point in each grid is chosen as a candidate location for the micro BS. In some grids,

there may be a couple of convenient locations depending on the landform and structures. In these grids, the closest candidate location to the grid's center is selected. On the other hand, there may not be any feasible location in some grids because of the same reasons. No candidate micro BS is chosen in these grids. This approach eliminates the effects of the locations of both macro BSs and users on the results as they are independent from these parameters. The second problem is to find the optimum number of micro BSs to be deployed among the candidate locations. Let us assume there are two candidate micro BSs. Then, four different scenarios exist: *i*) no micro BS is deployed, *ii*) only micro BS A is deployed, *iii*) only micro BS B is deployed, and *iv*) both micro BSs A and B are deployed. There is not any direct correlation between all these cases because the interference is unpredictable and all the cases have to be investigated individually. Therefore, this optimization problem is a combinatorial problem. It quickly becomes untractable, especially when the number of candidate locations is large [11]. In its place, we propose a greedy algorithm which is described next.

B. Proposed Algorithm

We propose a simple algorithm to find an energy-efficient set of micro BSs among the candidate locations. At the first iteration, the proposed algorithm selects the micro BS which provides the highest improvement based on the weighted summation of energy efficiency gain over all scenarios. Let b, $b \in \mathcal{B}_C$ denote this micro BS. At the second iteration, the algorithm recalculates the capacity of every user, including the selected microcell BS and the existing macrocell BSs $\mathcal{B}_M \cup b$. Again, the micro BS which provides the highest improvement based on the weighted summation of energy efficiency gain over all scenarios is selected, but now over the set $\mathcal{B}_c \setminus b$. The proposed algorithm continues until the desired network capacity is achieved for all scenarios. Each micro BS consumes equal amount of power because no power control algorithm is used. Therefore, the total consumed power of the system will be independent of which candidate micro BS is selected. The complexity of the optimal solution increases polynomially with $|\mathcal{B}_C|$. However, the suggested solution for this problem only requires about $|\mathcal{B}_C| \times |\mathcal{B}_m^*|$ iterations if we assume $|\mathcal{B}_C| \gg |\mathcal{B}_m^*|$ where $\mathcal{B}_m^*$ is the number of micro BSs when the solution is acquired. The proposed algorithm is given next, under the heading Algorithm 1.

Algorithm 1 Greedy Base Station Deployment Algorithm

1: Initialize $\mathcal{B}_m = \emptyset$ and $\eta_{EE}(\mathcal{B}) = \eta_{EE}(\mathcal{B}_M)$
2: **while** $\sum_{k \in \mathcal{K}_r} C(k, \mathcal{B}) < \lambda \cdot C_r$ for all $r \in \mathcal{R}$ **do**
3:     $\mathcal{B} = \mathcal{B}_M \cup \mathcal{B}_m$
4:     $b = \arg\max_{b \in \mathcal{B}_C} \sum_{r \in \mathcal{R}} \pi_r (\eta_{EE}(\mathcal{B} \cup b) - \eta_{EE}(\mathcal{B}))$
5:     $\mathcal{B}_m \longleftarrow \mathcal{B}_m \cup b$
6:     $\mathcal{B}_\mathcal{C} \longleftarrow \mathcal{B}_\mathcal{C} \setminus b$
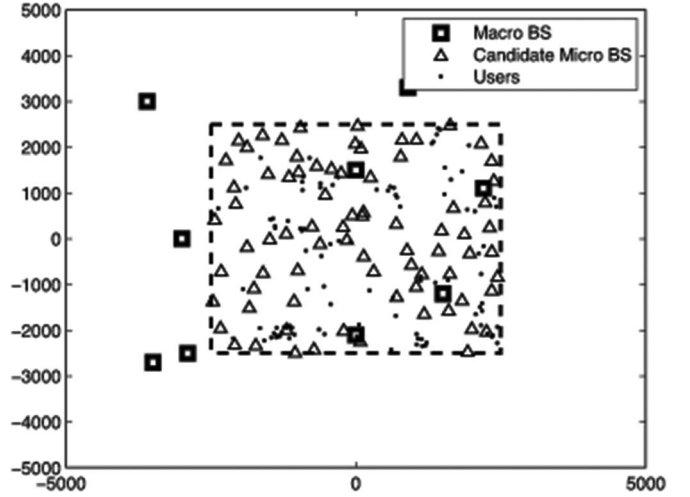7: **end while**

Fig. 1. Macro BSs, candidate micro BSs, and user distribution for a sample scenario.

C. Optimality Analysis

In [18], it is shown that the performance of the optimal solution cannot be better than a factor of $e/(e-1)$ from the performance of the greedy heuristic algorithm, if following three conditions are satisfied: *i*) $\eta_{EE}(\emptyset) = 0$, *ii*) nondecreasing, and *iii*) submodular. The energy efficiency function is not a nondecreasing function; however, if we assume the number of deployed micro BSs which satisfies the constraint is equal for the optimal solution and the proposed algorithm, we can check the total capacity of the network to determine the gap between proposed algorithm and the optimal solution. Authors in [11] show that the ASE satisfies these three properties. When the ASE of a network is calculated over the constant area and constant bandwidth, it behaves as the capacity. Consequently, the capacity of the network also satisfies these three properties. Therefore, if the number of deployed BSs is equal for the optimal solution and the proposed algorithm, the proposed algorithm performs better than $(e-1)/e$ times the optimal solution.

IV. NUMERICAL RESULTS

In this section, the performance of the proposed algorithm is studied. We consider that the deployment of macro BSs, candidate micro BSs, and the users are as shown in Fig. 1. There are 10 macro BSs in our simulation area, $10 \times 10 \text{ km}^2$. However, to avoid edge effects, we observe only the center $5 \times 5 \text{ km}^2$ area as in [11]. 5 scenarios with equal probability are considered in simulation. The user distributions in different scenarios are independent from each other. We assume that there are 100 randomly distributed users in the observation area for all scenarios. They are associated within the BSs in the observation area. The simulation models and parameters are taken from Table A.2.1.1.2_3 of [14]. In this letter, we compare the performance of three different type of micro BSs for the proposed algorithm and the algorithm in [11]. In particular, the total capacity increase and energy efficiency of the network are investigated. Multiple antenna transmission is not investigated in this work. We assume that 3-sector antennas are used for
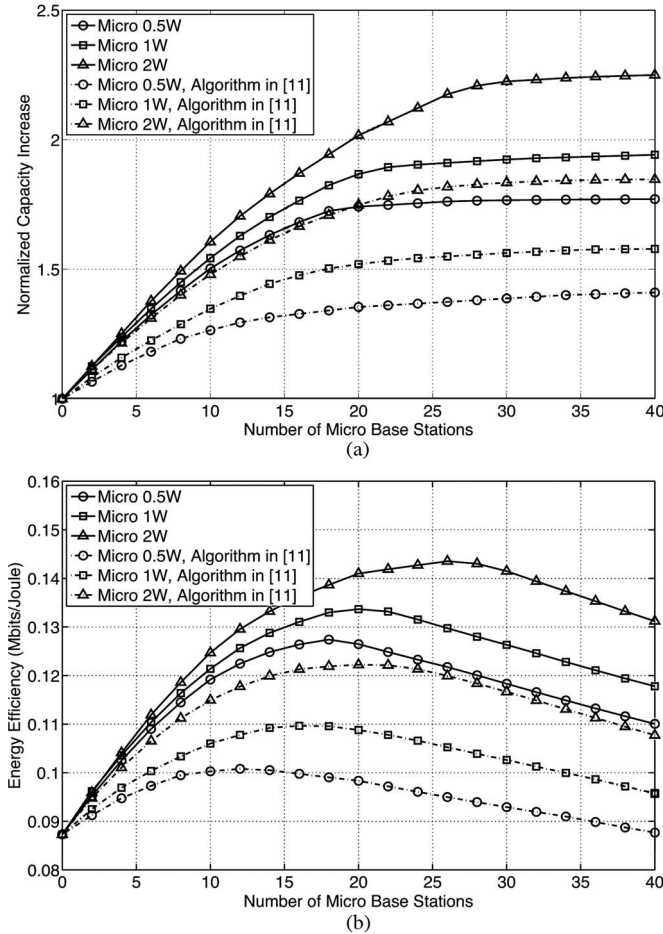
Fig. 2. Network total capacity (a) and energy efficiency of the system (b) are depicted per iteration.

macrocell BSs and omnidirectional antennas are used in the microcell BSs. Typical transmission and total operational powers for macro and micro BSs are taken from Table 1 in [11].

Fig. 2(a), (b) compare the total capacity increase and energy efficiency of the proposed algorithm and the algorithm in [11] for micro BSs with different transmission power. In all cases, BSs transmit at full power. The total capacity increase versus the number of BSs is plotted in Fig. 2(a) and the energy efficiency of the system is shown in Fig. 2(b). Both algorithms start with no micro BS deployment and iteratively increase the number of BSs in the network as described in the selection rule in Algorithm 1. As the number of micro BSs increases, it can be observed that the total capacity of the network increases monotonically. We investigate the system performance for micro BSs with different transmission power to observe its effect on total capacity and energy efficiency. For the micro BSs transmit power levels 0.5 W, 1 W, and 2 W, we look at the number of micro BSs that maximize energy efficiency and satisfy the total capacity constraint for both algorithms.

When λ is chosen as 1.75, the required number of BSs is 10, 16, and 23 for the proposed algorithm for 0.5 W, 1 W, and 2 W respectively. Whereas, the algorithm proposed in [11] can only achieve the required capacity when 23 micro BSs are deployed for the 2 W case. In addition, it is observed that the total capacity gain of the proposed algorithm is 33%, 27%, and 25% better

than the algorithm in [11] for the 0.5 W, 1 W, and 2 W transmitters. Note that, at the same time, the proposed algorithm has improved the energy efficiency 1.46 times (0.087 Mbits/Joule to 0.127 Mbits/Joule) for 0.5 W, 1.53 times (0.087 Mbits/Joule to 0.134 Mbits/Joule) for 1 W, 1.64 times (0.087 Mbits/Joule to 0.144 Mbits/Joule) for 2 W, compared to the network with macro BSs only case.

V. CONCLUSION

A greedy energy-efficient BS deployment framework is developed for HetNets. The proposed algorithm deploys micro BSs iteratively and maximizes the energy efficiency of the network. The proposed heuristic method significantly decreases the complexity of the BS deployment problem. Increasing the number of micro BSs becomes energy inefficient after a certain point. Through simulation results, it is shown that the proposed algorithm significantly improves the energy efficiency and the capacity of the network.

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