A Greedy Algorithm for Energy-Efficient Base Station Deployment in Heterogeneous Networks

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***Abstract*—In this paper, we develop an energy-efficient base station deployment framework for heterogeneous networks. Micro base station deployment increases the total capacity of the network. However, increasing the number of micro base stations excessively may reduce the energy efficiency of the network. Therefore, in this paper, we examine the energy efficiency aspect of the micro base station deployment problem. This problem can be divided into two subproblems: choosing feasible candidate micro base station locations and selecting the optimum set of micro base stations among the candidate locations. The proposed algorithm first chooses the subset of the feasible locations as candidate locations, and then selects the micro base stations which maximize the energy efficiency of the network iteratively. It is shown that the proposed algorithm is a constant-factor approximation of the optimal solution. Our simulations demonstrate that proposed algorithm improves the energy efficiency of the network up to 12% for low-loaded scenarios and 98% for the high-loaded scenarios.**

***Index Terms*—Energy efficiency, heterogeneous cellular network, cellular network deployment.**

I. Introduction

In the last two decades, the need for a fast and ubiquitous wireless network has increased to unexpected levels. The popularity of the smartphones and mobile applications, as well as the flat rate price policy of mobile operators show that this trend will continue. In order to meet this increasing demand, network operators seek coherent solutions such as expanding the spectrum, increasing node density per area, and deploying more, and smaller, cells [1]. Due to the dense deployment of macro base stations (BSs) today, adding more macro BSs to the cellular network significantly reduces the gain because of elevated intercell interference. Heterogeneous networks (HetNets) are one of the enabling technologies that can provide significantly improved data rates while creating less intercell interference to the existing architecture. HetNets have attracted attention in the literature, see, e.g., [2]–[4]. These works demonstrate that the deployment of HetNets is very promising to improve overall capacity and it decreases the outages in the next generation wireless networks.

However, the deployment of more BSs increases the energy consumption of the network, which is one of the nontrivial causes of the growth in the emission of greenhouse gases to very high levels. As a result, green cellular communication has attracted attention, see, e.g., [5]–[8]. The main objective of the green cellular communication is to reduce energy consumption as much as possible while satisfying the demand of users. Reducing the energy consumption in wireless networks is also preferred due to the economical reasons such as decreasing maintenance costs and longer battery life time for the mobile users.

In HetNets, each additional micro BS increases both the capital expenditures (CAPEX) and operational expenditures (OPEX) of the system. CAPEX mostly consists of the infrastructure costs, e.g., BS equipment, site installation, etc. [9]. On the other hand, OPEX includes other expenses such as electric bills, site lease, backhaul transmission lease, and operation and maintenance costs [10]. Therefore, if the number of BSs which meet the network requirements is lowered, both CAPEX and OPEX of the network automatically decrease. In addition, over 80% of the power is consumed by BSs in mobile cellular networks [11]. Micro BSs consume significantly lower power than macro BSs. Therefore, they are more desirable over macro BSs to decrease the OPEX of the network. In accordance with this observation, the proposed algorithm limits the number of additional micro BSs while satisfying the increasing traffic demand of the network.

Former works on HetNets have mostly concentrated on power control and resource allocation problems, see, e.g., [12]–[15]. However, the deployment of micro BSs and the energy efficiency aspects of the problem have not been investigated to their full potential. A similar study in [16] investigates the area spectral efficiency (ASE) aspect of the micro BS deployment problem. The authors of [16] deploy micro BSs to an area which is covered by macro BSs to increase the ASE of the network. The cell boundaries are selected as candidate locations because the authors observe that the ASE improvement increases with the coverage of the BS. Then, a greedy algorithm is proposed to select micro BSs. The algorithm continues to run until the ASE requirement is reached. Reference [16] considers cell edges as good locations for the placement of new cells in order to increase ASE. However, cell edges may not always be good candidates if energy efficiency of the network is considered. In addition, the user

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distribution affects the energy efficiency of the network and the proposed algorithm in [16] works poorly for the clustered user distribution scenarios. The algorithm we will present is designed to overcome this limitation. In [17], the authors aim to minimize the outage of the network by deploying additional low power BSs. The authors of [17] first deploy certain number of micro BSs to the network area, and then they iteratively shift the location of these BSs. However, system characteristics, the path loss and shadowing, are strictly dependent on the location of the BSs. Although the proposed algorithm works well for the test cases, obtaining these parameters in every iteration may be impractical in real BS topologies. In [18], the authors investigate the energy efficiency of the micro BSs on hexagonal grids. They demonstrate that the power savings depend on the network load. Moderate gains are observed in fully loaded networks. In this work, micro BSs are located to the cell edges to minimize the intercell interference. However, depending on the user distribution in the network, larger gains can be obtained in terms of energy efficiency with different sets of micro BSs.

In this paper, the work we present is not affected by the user distributions and can be implemented in both clustered and dispersed networks. In addition, the proposed algorithm considers the feasibility of the candidate locations and minimizes the effect of environmental conditions. Moreover, this algorithm can be implemented in both hexagonal grid and real BS topologies. Furthermore, the proposed algorithm finds the set of micro BS locations that maximizes the energy efficiency of the network while satisfying the increasing capacity demand of the network.

The remainder of this paper is organized as follows. Section II introduces the system model. Section III presents the problem and discusses the possible approaches to solve it. Section IV describes the proposed algorithm and compares the performance of the algorithm with the optimal solution. Numerical results and the performance improvements are presented in Section V and concluding remarks are made in Section VI.

II. System Model

In this section, the system model, power consumption of the BSs, and the energy efficiency problem formulation are presented.

Consider a wireless network in which all mobile users are served by sets of macro and micro BSs, denoted by $\mathcal{B}_M$ and $\mathcal{B}_m$, respectively. The subscript M is used to indicate macro BSs and m is for micro BSs throughout the rest of the paper. All BSs in the network area are denoted by $\mathcal{B}$, i.e., $\mathcal{B} = \mathcal{B}_M \cup \mathcal{B}_m$. The mobile users are associated with the BS which provides the highest signal strength at the location of the user. If more than one BS provides equal power at the user location, the user selects one of the BSs randomly. We assume that the mobile users always have data to transmit, and thereby they require a bandwidth allocation. 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 $P_M^{(n)}$ and $P_m^{(n)}$ are the transmit power of a macrocell M and a microcell m on subcarrier n, respectively. We note that although in this paper we focus on the downlink communication, the same ideas can be applied for the uplink as well. 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. Similarly, the SINR for microcell user k on subcarrier n can be written as

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

For simplicity, we use the same symbol $\gamma_k^{(n)}$ for SINR of both macro and microcell users. In the sequel, the capacity of user k can be written as

$$C(k, \mathcal{B}) = \sum_{n=1}^{N_k} W_k^{(n)} \log_2(1 + \gamma_k^{(n)}) \qquad \text{[bits/sec]} \quad (3)$$

where $W_k^{(n)}$ denotes the bandwidth of subcarrier n of user k and N_k is the number of subcarriers assigned to user k. In this work, equal bandwidth scheduling is employed [19]. In this scheduling, each BS shares its resources equally among its users. In LTE systems, the smallest granularity which can be assigned to a user is a resource block with 12 subcarriers. Therefore, if K users are associated with the BS b with N_{RB} RBs, $K_h = \mod(N_{RB}, K)$ of the users get $12(\lfloor N_{RB}/K \rfloor + 1)$ subcarriers, whereas the rest of the users receive $12\lfloor N_{RB}/K \rfloor$ subcarriers. In this work, we assume that a BS allocates equal power on its subcarriers.

The energy efficiency of the network can be improved by either increasing the total capacity of the network while consuming the same power or decreasing the consumed power of the network and providing the same capacity. Traditional macro BSs provide better coverage and data rate, however they consume significantly higher power than the micro BSs. In addition, in densely deployed networks, this gain is substantially reduced due to intercell interference. On the other hand, the transmission power of micro BSs is significantly less than the macro BSs, thereby they cover less area. However, they consume less power and do not interfere with the other transmissions as severe as macro BS transmissions. Therefore, they are more energy efficient than the macro BSs especially in densely deployed networks. For this reason, in this work, micro BSs are deployed to the network as an underlay for macro BSs to maximize the energy efficiency of the network and to satisfy the traffic demand.

The power consumption of a BS consists of two parts. The first part is the static power consumed by the BS with no transmission. The second part depends on the load and the transmission power of the BS. There are several power consumption models proposed in the literature, see, e.g., [20]–[22]. In this work, we use the power consumption model proposed in [20]. It is given by

$$\begin{aligned} P_M &= P_{0,M} + \Delta_M P_{tx} \\ P_m &= P_{0,m} + \Delta_m P_{tx} \end{aligned} \tag{4}$$

where P_M, P_m, and P_{tx} are the average consumed power per macro BSs, micro BSs, and transmission power, respectively. Δ_M and Δ_m scale the transmission power depending on the load. $P_{0,M}$ and $P_{0,m}$ denote the static part of the power consumption of the macro and micro BSs, respectively.

As stated earlier, we assume that users always have data to transmit with full buffer. In addition, no power control algorithm is used. Therefore, BSs are fully utilized and Δ_M and Δ_m are constant for all BSs. Then, the energy efficiency of the network can be written as

$$\eta_{EE}(\mathcal{B}) = \frac{\sum_{k \in \mathcal{K}} C(k, \mathcal{B})}{N_B \cdot P_M + N_b \cdot P_m} \qquad \text{[bits/Joule]} \tag{5}$$

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

III. Problem Definition

In this section, we will first present the BS deployment problem. Then, we will discuss possible approaches to solve the problem.

A network operator would like to improve the capacity of the network with additional micro BSs to meet increasing traffic demand. In order to maximize the energy efficiency of the network and to limit CAPEX and OPEX, the network operator would like to deploy the micro BSs to optimum locations. In real-life scenarios, users are mobile and several user distributions can occur with different probabilities. During the peak hours, more users are active and total traffic of the network reaches to its maximum. However, most of the time BSs are underutilized. In [23], the authors present that 49.2% of the time, the total traffic of the network is below the 20% of the peak hour traffic. However, even if most of the time the traffic demand is low, additional micro BSs are to be deployed for the peak hour traffic. Existing BSs are sufficient during the off-peak hours and the additional BSs are needed during heavy traffic. Therefore, operators must consider only the user distributions with high load periods for the deployment. Therefore, we formulate the deployment problem as

$$\begin{aligned} \max \quad & \pi_r \eta_{EE}(\mathcal{B}) \\ \text{s.t.} \quad & \sum_{k \in \mathcal{K}_r} C(k, \mathcal{B}) \geq \lambda \cdot C_r \qquad \text{for all } r \in \mathcal{R} \end{aligned} \tag{6}$$

where C_r denotes the network capacity when only macro BSs are deployed for scenario r. The multiplier $\lambda \geq 1$ is the desired capacity increase over the C_r. π_r is the probability that scenario r occurs, and $\mathcal{R}$ and $\mathcal{K}_r$ represent the set of scenarios and users in scenario r, respectively.

Finding the optimal number of BSs and the position of the BSs are extremely complex problems. Similar problems have been studied in the literature under the facility location research formulation [24]. Facility location problems focus on the optimal placement of facilities to minimize the costs while providing service constraints. The relation between the energy efficient BS deployment and facility location problems is straightforward. One approach to simplify this problem is to select the set of candidate locations in the network area. These locations must be selected wisely to improve the performance of the algorithm. After selecting these locations, the second part of the problem is the determination of the optimal set of BSs among these candidates. Due to intercell interference, the individual and cumulative performance of the BSs are not directly correlated. Especially, if the BSs are located close to each other, cumulative performance of the BSs can be worse than the individual performance of each BS. Therefore, this optimization problem is a combinatorial problem. It quickly becomes untractable when the number of scenarios and the candidate locations are large. Thus, we propose a greedy algorithm which is described in the next section.

IV. Proposed Algorithm and Optimality Analysis

In this section, we first present the candidate selection and greedy deployment algorithm, and then discuss its performance.

A. Candidate Selection

The authors in [16] suggest that the boundaries of the existing cells can be good candidate locations. However, [16] does not consider the distribution of the users in the network and works poorly especially when the users are clustered close to macro BSs. In addition, these locations may not be available to deploy BSs depending on the the landform and structures. Second approach can be selecting all feasible locations as candidates. However, depending on the network size, these locations can be innumerably many and even heuristic approaches will be impractical to implement. Therefore, some of the feasible locations should be eliminated to improve the performance of the algorithm in a smart way. In order to overcome these problems, in this paper, we divide the network area into equal grids and select a candidate location in each grid. This approach performs well for both clustered and dispersed networks. However, it does not guarantee that a feasible location exists in every grid. In addition, if more than one feasible location exists in a grid, selection of the candidate location is another problem to solve. Therefore, the following approach is proposed. If all the neighboring grids of the center grid have at least one feasible location, the candidate location which is closest to the center of the grid is selected as a candidate. In cases where some of the neighboring grids do not have any feasible location, the closest feasible location to the centroid of the center grid and neighboring grids with no feasible location is selected as a candidate. An example scenario is shown in Fig. 1. In this figure, feasible locations, candidate locations, and the center of the centroid are denoted

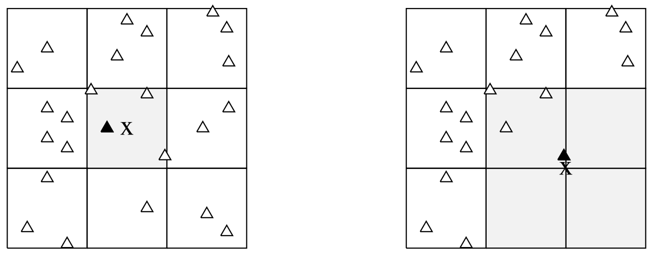


Figure 1. A candidate location selection example.

by empty triangles, filled triangles, and X, respectively. In the first case, all neighboring grids have at least one candidate. Therefore, a feasible location which is closest to the center of the grid is selected as the candidate. On the other hand, in the second case, three of the neighboring grids do not have any feasible location. Therefore, the feasible location which is closest to the centroid of these four grids is selected as the candidate location. This approach limits the effects of the user distribution to the performance of the proposed algorithm.

B. Deployment Algorithm

We propose a greedy algorithm that selects one micro BS to deploy in each iteration. The algorithm selects the candidate micro BS which maximizes the weighted sum of the energy efficiency of all scenarios as next micro BS. This process continues until the required capacity of all scenarios are satisfied. In each iteration, the proposed algorithm assumes the previously selected micro BSs are deployed, and then calculates the energy efficiency over the updated set of BSs. This approach significantly reduces the complexity of the algorithm. The complexity of the optimal solution increases polynomially with $|\mathcal{R}|$ and $|\mathcal{B}_C|$ where $\mathcal{B}_C$ denotes the set of candidate micro BSs. The proposed algorithm solves the problem in linear time. In this work, we assume that one type of micro BSs is deployed, however this work can be extended to cases where different types of BSs are to be deployed such as the deployment of picocells and femtocells. The proposed algorithm is given next, under the heading Algorithm 1.

Algorithm 1 Greedy Base Station Deployment Algorithm

Initialize $\mathcal{B}_m = \emptyset$ and $\eta_{EE}(\mathcal{B}) = \eta_{EE}(\mathcal{B}_M)$
while $\sum_{k \in \mathcal{K}_r} C(k, \mathcal{B}) < \lambda \cdot C_r$ for all $r \in \mathcal{R}$ **do**
  $\mathcal{B} = \mathcal{B}_M \cup \mathcal{B}_m$
  $b = \arg\max_{b \in \mathcal{B}_\mathcal{C}} \sum_{r \in \mathcal{R}} \pi_r \left(\eta_{EE}(\mathcal{B} \cup b) - \eta_{EE}(\mathcal{B})\right)$
  $\mathcal{B}_m \longleftarrow \mathcal{B}_m \cup b$
  $\mathcal{B}_\mathcal{C} \longleftarrow \mathcal{B}_\mathcal{C} \backslash b$
end while

C. Optimality Analysis

The proposed algorithm is a greedy heuristic algorithm. Therefore, it does not guarantee that the obtained solution is optimal. However, it is shown that in [25] if the greedy algorithm satisfies *i)* $\eta_{EE}(\emptyset) = 0$, *ii)* η_{EE} is nondecreasing, and *iii)* η_{EE} is submodular, then it can be claimed that the algorithm performs better than $(e-1)/e$ times the performance of the optimal solution. The energy efficiency function violates the condition (*ii*). However, in [16], it is shown that ASE satisfies all these three properties. ASE is defined as summation of total capacity over an area times bandwidth. Therefore, over constant area and bandwidth, we can claim that capacity also satisfies these three properties. If we assume that the number of deployed micro BSs which satisfies the constraint is equal for the optimal solution and the proposed algorithm, then we can state that η_{EE} performs better than $(e-1)/e$ times the performance of the optimal solution.

Table I
SIMULATION PARAMETERS

Parameter	Setting
Channel bandwidth	10 MHz
Total number of data RBs	50 RBs
User to Macro PL model	$128.1 + 37.6 \log_{10}(d)$
User to micro PL model	$140.7 + 36.7 \log_{10}(d)$
Effective thermal noise power	-174 dBm/Hz
User noise figures	9 dB
Macro antenna gain	14 dBi
Micro antenna gain	5 dBi
User antenna gain	0 dBi
Macro- and microcell shadowing	8 dB and 10 dB
Traffic model	Full buffer

V. NUMERICAL RESULTS

In this section, we first investigate the effects of the number of grids and number of active users on the performance of the algorithm, and then compare the performance of the proposed algorithm with the algorithm in [16]. A sample scenario for the deployment of macro BSs, a set of candidate micro BSs, and user distribution are provided in Fig. 2. Ten macro BSs are deployed in the 10x10km^2 simulation area. In order to avoid the edge effects, we collect the data over the 5x5km^2 area in the center as suggested in [16]. For simplicity, we assume that 15 different scenarios exist with equal probability. In order to observe the effect of the number of active users on the performance of the algorithm, we create three different types of scenarios: low-, moderate-, and high-loaded. Five of the scenarios are created as low-loaded with 30 active users. Another five of the scenarios are created as moderate-loaded with 100 active users, and the rest five of the scenarios are created as high-loaded with 200 active users. In all these scenarios, users are distributed uniformly over the observation area. All users are associated with the BSs in the observation area. The simulation models and parameters are provided in Table I [19]. We assume that 3-sector antennas are used for macro BSs and omnidirectional antennas are used in the micro BSs. Multiple antenna transmission is not investigated in this work. The transmission and total operational powers for macro and micro BSs are summarized in Table II.

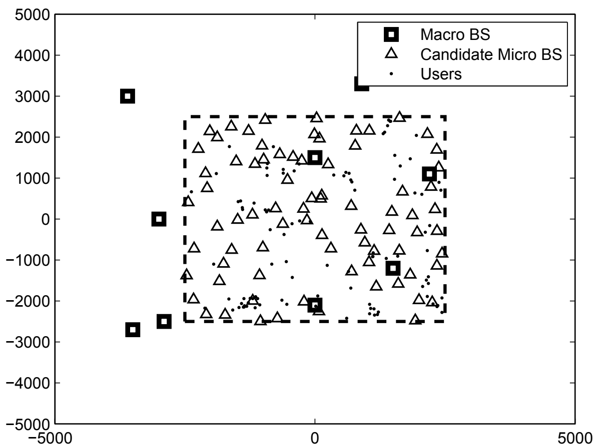


Figure 2. Macro BSs, candidate micro BSs, and user distribution for a sample scenario.

Table II
POWER CONSUMPTION MODELS OF DIFFERENT BS TYPES [20]

BS Type	P_M (W)	P_m (W)
Macro 20W	865	–
Micro 1W	–	38

In Fig. 3, we investigate the effects of the number of the grids on the performance of the proposed algorithm. The edge length of the grids are decreased to the half in each case. We start with 4 grids and increase the number of grids until it reaches 65536. The performance of the algorithm significantly improves until the number of grids reaches 1024. However, the increase is slowed down after 1024. Increasing the number of grids from 1024 to 65536 improves the energy efficiency of the algorithm by 1%. However, due to the increase of the number of candidate locations, the complexity of the algorithm increases polynomially. After a certain number of grids, increasing the number of grids does not improve the performance of the algorithm notably and it requires a longer convergence time.

In Fig. 4, we compare the performance of three different types of user scenarios when the number of grids is selected as 1024. When the number of active users in the network increases, more micro BSs should be deployed to maximize the energy efficiency of the network. The energy efficiencies of the network reach the maximum when 8, 20, and 28 micro BSs are deployed for low-, moderate-, and high-loaded scenarios, respectively. In future networks, it is expected that the number of active users in the network will be higher during the peak hours. Therefore, more additional micro BSs can be deployed to improve the energy efficiency of the network. In addition, the networks with more active users are more energy-efficient than the others. This improvement is the combination of multi-user diversity and increasing micro BS users.

Figs. 5(a)-(b) show the performance of the proposed algorithm and the algorithm in [16]. In this work, we particularly compare the energy efficiency gain and the total capacity improvement of the network. Both algorithms start with no micro BS and in each iteration one micro BS is deployed. In this simulation, moderate-loaded scenarios are considered. The number of grids is chosen as 1024 for the proposed algorithm. As the number of micro BSs is increased, the total throughput of the network increases monotonically. On the other hand, the energy efficiency is shaped such that it monotonically increases up to a certain point and then starts to decrease. In Fig. 5(a), 10 micro BS is required for the proposed algorithm, when λ is equal to 1.5. On the other hand, the algorithm in [16] cannot reach the required capacity improvement, the maximum capacity improvement is slightly over 30%. The total capacity improvements of the proposed algorithm is 36% better than the algorithm in [16] when both algorithms reach their maximum. Similar energy efficiency improvement is observed.

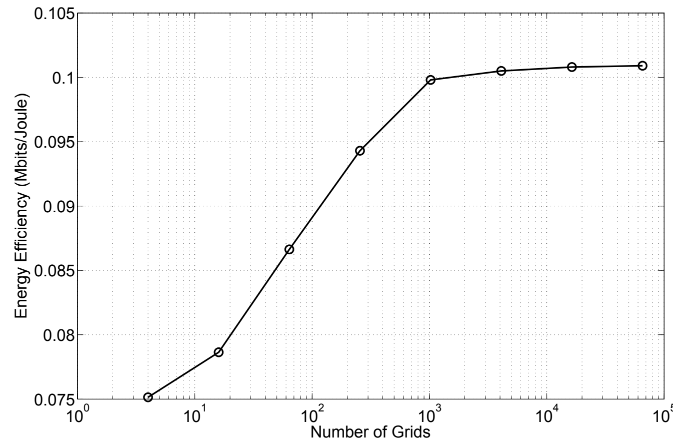


Figure 3. Grid size vs. the average energy efficiency.

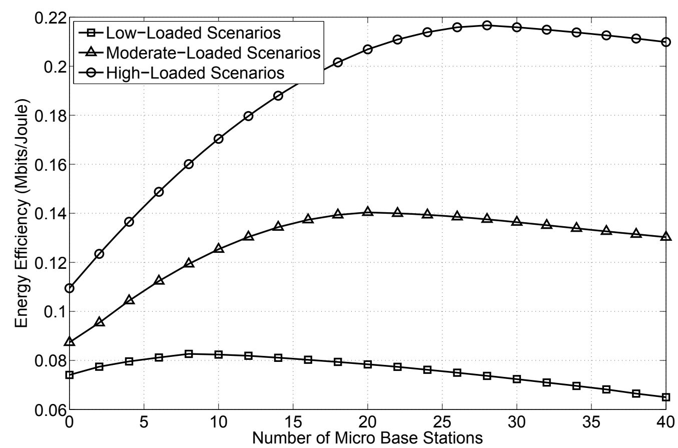
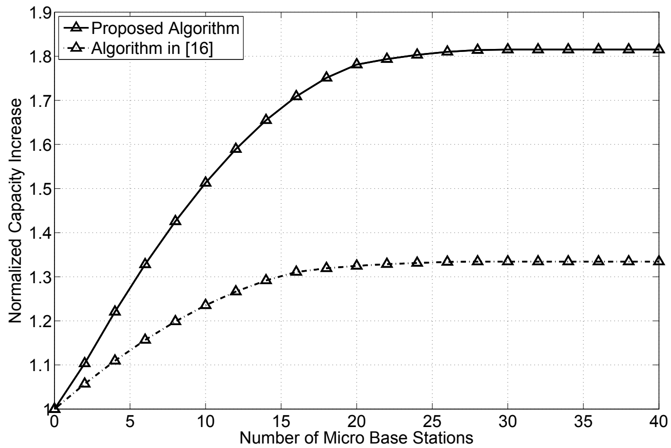


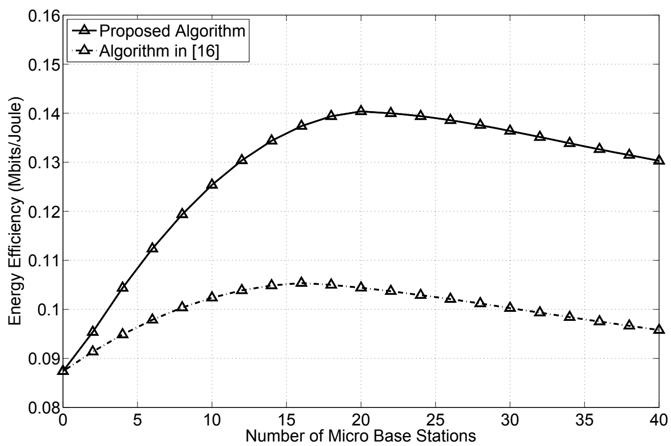
Figure 4. The number of active users vs. the energy efficiency.

VI. CONCLUSION

A greedy BS deployment algorithm is proposed to improve the energy efficiency of the network. Imprudent increase of the number of micro BSs may harm the energy efficiency of the



(a)



(b)

Figure 5. Network total capacity (a) and energy efficiency of the system (b) are depicted per iteration.

network. The proposed algorithm first selects a set of feasible micro BS locations wisely, and then greedily deploys a subset of them until the required capacity of the network is satisfied. Due to the heuristic nature of the algorithm, the complexity of the algorithm is significantly reduced. The simulations show that the proposed algorithm increases both the energy efficiency and the throughput of the network, while satisfying the capacity requirements.

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