Energy-Efficient Base-Station Topologies for Green Cellular Networks

Won-Yong Shin†, Hyoseok Yi‡, and Vahid Tarokh†

†Division of Mobile Systems Engineering, College of International Studies, Dankook University, Yongin 448-701, Republic of Korea
‡School of Engineering and Applied Sciences, Harvard University, Cambridge, MA 02138, USA

Email: wyshin@dankook.ac.kr; {hyoseok, vahid}@seas.harvard.edu

Abstract—We consider the problem of energy-efficient base-station (BS) planning for green cellular network design. There exist a number of criteria for greenness in the literature, but we focus only on the energy-normalized throughput. We first model energy consumption for a heterogeneous network, consisting of macro and micro base-stations, and a network topology. Then, we propose an iterative algorithm for the green BS planning problem in the one-dimensional case: 1) We find the positions of base-stations that maximize the energy-normalized throughput for a fixed number of base-stations, and 2) find the optimal number of base-stations which maximizes the energy-normalized throughput. In this work, we evaluate the energy-normalized throughput accounting for adaptive modulation rates with power control, which is a common feature of modern communications systems. The convergence to a local maximum for the proposed algorithm is shown using computer simulations, and the corresponding energy-normalized throughputs are evaluated for a number of system model parameters.

I. INTRODUCTION

The exponential growth of communications systems has caused concerns about their carbon footprint and energy consumption. Studies have shown that the operating cost of base-stations, driven in part by inefficient diesel power generators, largely drives up the energy bills and accounts for more than half of the expenses incurred by a telecommunications service provider. In addition, concerns about greenhouse gas emissions and global temperature changes have been growing. Given that telecommunications is responsible for over 1% of the entire world’s carbon footprint [1], the communications industry must find ways to reduce its carbon footprint.

For these reasons, green communications and the issues of energy efficiency [2]–[5] are coming to the center stage of cellular communications research. From a telecommunications operator’s points of view, the following two benefits can arise from green communications: reduced energy and network deployment costs, and improved environmental effects. As pointed out in [6], [7], power consumption of networks is a critical issue for service providers since it not only directly relates to the operation cost [8], [9] but also can have significant environmental impacts [10]–[12].

These have given some importance to the mathematical formulation of green communications network design. Obviously, there exists a large body of work on network topology design and base-station (BS) planning [13], [14], but these do not take greenness into account. For example, the notion of spectral efficiency per unit area was introduced in [13] to measure the performance of cellular systems, in which end-users continuously adapt their rate relative to their fading and interference conditions. In [14], the authors considered the problem of computing the optimal positions of a fixed number of base-stations that maximizes the average signal-to-interference-and-noise ratio (SINR) of end-users. This approach approximately achieves the maximum average downlink throughput.

Recently, there has been a lot of interest in green architecture design [8], [9], [15]–[17]. In [8], [9], the trade-offs between the deployment cost, throughput, and energy consumption in cellular networks were considered, under simplified models that may not fully account for hardware constraints and multiuser/multi-cell scenarios. In [15], [16], the BS density (or equivalently the cell size) was optimized in terms of improving the overall energy consumption for a required target spectral efficiency per unit area. Small-cell networks [17], such as femtocells and picocells, were also introduced to further reduce overall power usage. However, in spite of the above contributions, much work must be done on both identification and modeling of the underlying measures for greenness, and also on energy-efficient communications in general heterogeneous cellular networks.

In this paper, we formulate the BS planning problem mathematically while accounting for energy efficiency. We focus mainly on the energy-normalized throughput as our greenness measure, defined as the ratio of the sum-rate to the total energy consumption. We first study a practical green network topology for a heterogeneous network consisting of two tiers, in which macro and micro base-stations are deployed. Then, we propose a solution for the simplified scenario of a one-dimensional network such as the network covering a highway. For this scenario, we develop an iterative algorithm. More specifically, we find the assignments of users to base-stations...
and the positions of base-stations in terms of maximizing the energy-normalized throughput of the network end-users for a given number of base-stations. We then find the optimal numbers of macro and micro base-stations associated with the maximum energy-normalized throughput. In this work, we evaluate the downlink sum-rate normalized to the total energy by taking into account its quantized level along with power control, leading to an energy saving effect. Power control is also beneficial in terms of maximizing the sum-rate by decreasing the amount of out-of-cell interference. This is a common feature of recent communications systems such as next generation mobile Worldwide Interoperability for Microwave Access (WiMAX) and Third-Generation Partnership Project Long Term Evolution (3GPP LTE), in which adaptive modulation and coding (AMC) techniques are performed. The convergence to a local maximum for the proposed algorithm is verified by computer simulations, and the corresponding energy-normalized throughputs are evaluated for a number of system model parameters. Note that numerous random initial positions of base-stations are used so as to approach the global maximum. Our results indicate that when base-stations are optimally located, our power control algorithm leads to a significant performance improvement with respect to the energy-normalized throughput over no power control case.

The outline of this paper is given next. In Section II, we describe our system and channel models. The optimization problem is formulated in Section III, and the main algorithm is presented in Section IV. Simulation results are provided in Section V verifying the performance of our algorithm. Finally, we make our conclusion and discuss directions for future research in Section VI.

II. SYSTEM AND CHANNEL MODELS

We consider a wireless cellular network that serves \( N \) end-users uniformly and independently distributed in a given area (the extension to non-uniform distribution is straightforward). It is assumed that the users do not change their positions during data transmission. It is also assumed that each end-user is served only by one BS. Although only, two BS types, named macro and micro base-stations will be considered, the extension to more types is trivial. This corresponds to a heterogeneous network consisting of two tiers.

We assume that there are \( L \) macro base-stations and \( M \) micro base-stations in the network, where \( L \) and \( M \) are to be optimized according to the given system parameters. We assume that macro and micro base-stations, respectively, referred to as \( h_{i,l} \) and \( h_{m,j} \), are located at positions \( i \) and \( m \), for \( i = 1, \cdots, L \) and \( j = 1, \cdots, M \). Suppose that there are no spatial constraints on the positions of base-stations in our current model, whereas in practice, there are spatial constraints on the positions due to regulatory and physical issues.

Additionally, the followings are preliminarily assumed:

- A downlink scenario is taken into account, where end-users are assumed to receive data only from the BS in their corresponding cell (i.e., home cell BS). This assumption can be generalized if we were to extend our work to future next generation cellular systems.
- The transmission model captures only the long term fading, i.e., path-loss attenuation with path-loss exponent \( \alpha \). Thus, no shadowing and short-term fading are assumed. This assumption can later be expanded to capture all aspects of channel statistics.
- All the base-stations are transmitting in the same time/frequency resource block. Again, we can later expand on this assumption to capture more general networks.
- We assume that all the base-stations of the same type (e.g., macro and micro) operate with equal transmit power.
- Each BS divides its resource (e.g., time/frequency) equally among the users that it is serving.
- We are not assuming any use of any sophisticated multiuser detection schemes, i.e., interference rejection schemes, at each receiver. This makes modeling simpler, but will later be expanded up on for future next generation cellular systems.
- The signals sent from the BS in the corresponding cell are not treated as interference.
- The total network energy includes both transmit-dependent energy (e.g., power consumed by radio amplifier) and transmit independent one (e.g., site cooling power consumption).
- Assuming conventional macro sites, the site power consumed by each macro BS, denoted by \( P_{BS,l} \), is expressed as

\[
P_{BS,l} = a_l P_{t,l} + b_l,
\]

where \( P_{BS,l} \) and \( P_{t,l} \) denote the average consumed and radiated power\(^1\) per macro site, respectively. The coefficient \( a_l \) indicates the power conversion efficiency, accounting for the power amplifier efficiency, feeder loss, and so forth, of a macro site. Here, \( b_l \) is the power consumption independent of \( P_{t,l} \) of the site, which includes circuit power as well as site cooling consumption.
- The power model \( P_{BS,m} \) of a micro BS is similarly assumed to be given by

\[
P_{BS,m} = a_m P_{t,m} + b_m,
\]

where \( P_{t,m} \) denotes the average radiation power\(^1\) at the micro site. The factors \( a_m \) and \( b_m \) are the power conversion efficiency and the power consumption independent of \( P_{t,m} \), respectively.

\(^1\)Since \( P_{t,l} \) and \( P_{t,m} \) are maximum available power of macro and micro BS, we can reduce them by applying power control, which will be described in detail in section III.
Note that the total power consumption over the whole network is thus given by
\[ L P_{BS,i} + M P_{BS,m}. \]

We group end-users into a number of disjoint sets as follows. Let \( I_{l,i} = \{ i_{l,1}, i_{l,2}, \cdots, i_{l,N_l} \} \) denote a set of users associated with macro BS \( b_{l,i} \). In other words, \( I_{l,i} \) contains the indices of the \( N_l \) users that are served by \( b_{l,i} \), for \( i = 1, \cdots, L \). Similarly, let \( I_{m,j} = \{ j_{m,1}, j_{m,2}, \cdots, j_{m,N_m} \} \) denote the set of end-users associated with micro BS \( b_{m,j} \), where \( N_m \) is the number of users served by \( b_{m,j} \), for \( j = 1, \cdots, M \).

Given our model, assuming that an end-user is served by macro BS \( b_{l,i} \), the desired signal power received by an end-user at point \( x_n \) is modeled as
\[ P_r = \frac{P_t}{\|x_n - l_i\|^\alpha}, \tag{1} \]
where \( \alpha > 2 \) denotes the path-loss exponent. The interference power experienced by the user from all the other base-stations is given by
\[ P_I = \sum_{k=1,k \neq i}^L \frac{P_t}{\|x_n - l_k\|^\alpha} + \sum_{k' = 1}^M \frac{P_t}{\|x_n - m_{k'}\|^\alpha}. \tag{2} \]
Using (1) and (2), the received SINR at user \( n \) can be expressed as
\[ \text{SINR}_n = \frac{P_r}{N_0 B + P_I}, \]
\[ = \frac{P_t}{N_0 B + \sum_{k=1,k \neq i}^L \frac{P_t}{\|x_n - l_k\|^\alpha} + \sum_{k' = 1}^M \frac{P_t}{\|x_n - m_{k'}\|^\alpha}}, \tag{3} \]
where \( N_0 \) and \( B \) denote the noise power spectral density and the bandwidth, respectively. The case where an end-user is covered by a micro BS \( b_{m,j} \) can also be modeled in a similar fashion.

### III. Optimization Problem

Let \( R_n \) denote the achievable rate of end-user \( n \). Then, it follows that
\[ R_n = \log(1 + \text{SINR}_n), \]
for \( n \in \{ 1, 2, \cdots, N \} \). We now quantize the achievable rate \( R_n \) according to the simplified 7-step table \( A_i \in \{ 0, 1, 2, 3, 5, 10, 20 \} \). The quantized rate \( \bar{R}_n \) of user \( n \) is then given by
\[ \bar{R}_n = f_a (R_n), \quad \text{where } f_a(x) = \max A_i \text{ for } \forall A_i < x. \tag{4} \]
In this case, the transmit power at the corresponding BS \( i \) to user \( n \) can then be reduced to
\[ P_{t,i} = \left( 2^{\bar{R}_n} - 1 \right) \cdot \left( N_0 B + P_I \right) \cdot \|x_n - l_i\|^\alpha \tag{5} \]
if user \( n \) is assigned to the macro base-stations, which directly comes from (3) and (4). When user \( n \) is assigned to the micro base-stations, \( P^n_{t,m} \) can be computed in a similar fashion. Note that \( P^n_{t,i} \) is not greater than \( P_{t,i} \).

Since each BS divides its resource equally among the users that it is serving, the rate received at each user is given by
\[ R_n = \frac{R^n_{B,i}}{N_{l,i}} \quad \text{and} \quad R_n = \frac{R^n_{B,j}}{N_{m,j}}, \]
if user \( n \) is served by macro BS \( b_{l,i} \) and micro BS \( b_{m,j} \), respectively.

The main objective is then to find the numbers of macro and micro base-stations, \( L \) and \( M \), and their positions \( l_i \) and \( m_j \), respectively, for \( i = 1, \cdots, L \) and \( j = 1, \cdots, M \), in order to maximize the energy-normalized throughput, defined as the ratio of the sum-rate to the total energy consumption.

In other words, the optimization problem of interest is given by:
\[ \max_{L,M,L,M} \frac{\sum_{n=1}^N R_n}{L \sum_{i=1}^L P_{BS,i} + \sum_{j=1}^M P_{BS,j}}, \tag{6} \]
where \( P_{BS,i} = a_l \langle P^n_{t,i} \rangle_n + b_l \) and \( P_{BS,j} = a_m \langle P^n_{t,m} \rangle_n + b_m \).

Here \( \langle \rangle_n \) denotes the expectation taken over the end-users which are assigned to the base-station \( l \) or \( m \).

### IV. Main Algorithm

In this section, we provide a preliminary solution for a one-dimensional network such as the network covering a highway. Consider a linear network of length \( D > 0 \), where all the users and base-stations are co-linear (on the same line). In this case, the vectors \( l_i, m_j \), and \( x_n \), representing positions addressed in Section II, are reduced to the scalars \( l_i, m_j \), and \( x_n \), respectively, for \( i = 1, \cdots, L \), \( j = 1, \cdots, M \), and \( n = 1, \cdots, N \).

Then, our optimization problem is divided by two steps. The first problem we need to solve is rewritten as
\[ \max_{L,M,L,M} \frac{\sum_{n=1}^N R_n}{L \sum_{i=1}^L P_{BS,i} + \sum_{j=1}^M P_{BS,j}} \quad \text{for the given } L, M. \]

We now develop an iterative algorithm that guarantees convergence to a local maximum of the above optimization problem. That is, our iterative algorithm solves this problem numerically.

This algorithm has two major parts, namely the Assignment and Positioning Steps. For every possible pair of numbers \( L \) and \( M \), we apply our algorithm, which finds the assignments of users to base-stations and the positions of the base-stations that maximize the energy-normalized throughput, and then find the optimal values \( L^* \) and \( M^* \) in terms of maximizing the energy-normalized throughput, which corresponds to our second optimization problem. For each instance of pair of numbers \( L \) and \( M \), the following two steps are repeated until convergence is achieved.

The Main Algorithm (Algorithm 1) is described below.
Algorithm 1 Main Algorithm

Inputs: $L$, $M$, and $x_n$ ($n = 1, \ldots, N$)
Outputs: $I_i, I_{i,j}$ ($i = 1, \ldots, L$), $m_j$, and $I_{m,j}$ ($j = 1, \ldots, M$)

1: repeat
2: Assignment Step (Algorithm 2)
3: Positioning Step (Algorithm 3)
4: until convergence is achieved

A. Assignment Step

In the Assignment Step, the spatial configuration of the base-stations is given, where in the $k$th step, the macro and micro base-stations are located at $l_i^{(k)}$ for $i = 1, \ldots, L$ and $m_j^{(k)}$ for $j = 1, \ldots, M$, respectively, for every step. The location of the end-users is also given, where the users are placed at $x_n$ ($n = 1, \ldots, N$) for every step. Then, we need to find the sets $I_{i,j}$, $i = 1, \ldots, L$ and $I_{m,j}$, $j = 1, \ldots, M$ in order to maximize the downlink sum-rate normalized to the total energy. To select an initial condition for the two sets $I_{i,j}$ and $I_{m,j}$ (i.e., $I_{i,j}^{(0)}$ and $I_{m,j}^{(0)}$), we assume that each end-user is initially served by its closest BS. Let $R(n,i)$ and $R(n,j)$ denote the energy-normalized throughput when user $n$ is associated with macro BS $I_i$ and micro BS $I_m$, respectively. We then develop Algorithm 2 that finds the best possible assignment of users to both macro and micro base-stations iteratively. We show the following algorithm for the Assignment Step.

Algorithm 2 Assignment Step

Inputs: $l_i^{(k)}, i = 1, \ldots, L$, $m_j^{(k)}, j = 1, \ldots, M$, and $x_n$, $n = 1, \ldots, N$
Outputs: $I_{i,j}^{(k+1)}$, $i = 1, \ldots, L$ and $I_{m,j}^{(k+1)}$, $j = 1, \ldots, M$

1: repeat
2: for all user $x_n$ do
3: for all $l_i^{(k)}$ (or $m_j^{(k)}$) do
4: Calculate $R(n,i)$ (or $R(n,j)$)
5: if $R(n,i) \leq R(n,j)$ (or $R(n,j) \leq R(n,b)$) then
6: $b \leftarrow i$ (or $b \leftarrow j$)
7: end if
8: end for
9: Add the index $i$ (or $j$) to the set $I_{b}^{(k+1)}$
10: end for
11: until convergence is achieved

Note that the algorithm converges to a local maximum of end-user assignments for a given spatial configuration of base-stations.

B. Positioning Step

The goal of the Positioning Step is to update the positions of the macro base-stations, $I_i$ for $i = 1, \ldots, L$, and the micro base-stations, $m_j$ for $j = 1, \ldots, M$, in order to maximize the energy-normalized throughput, given a fixed assignment for the users. In the $k$th step, the two sets $I_{i,j}^{(k)}$, $i = 1, \ldots, L$ and $I_{m,j}^{(k)}$, $j = 1, \ldots, M$ are given.

Under the assumption that end-user $n$ is served by macro BS $I_i$ and micro BS $I_m$, Algorithm 3 basically solves the following equation with respect to $l_i$ (for $i = 1, \ldots, L$) and $m_j$ (for $j = 1, \ldots, M$):

$$\max_{l_i,m_j} \frac{\sum_{n=1}^{N} R_n}{\sum_{i=1}^{L} P_{BS,i} + \sum_{j=1}^{M} P_{BS,j}},$$

which is described in Section III. More specifically, for every BS, we solve (7) numerically assuming that the other base-stations are fixed, and repeat in an iterative manner until convergence is achieved.

For this purpose, we first pick a sufficiently large number of points in $[0, D]$ for each BS, and then use an efficient numerical method to find the updated position of the BS up to a desired accuracy. We continue in an iterative manner. We assume random BS positions, uniformly and independently distributed on the line, as an initial condition for the two sets $l_i^{(0)}$ and $m_j^{(0)}$ (i.e., $I_i^{(0)}$ and $I_m^{(0)}$). The following algorithm provides the Positioning Step.

Algorithm 3 Positioning Step

Inputs: $l_i^{(k)}$ and $I_{i,j}^{(k)}$, $i = 1, \ldots, L$, $m_j^{(k)}$ and $I_{m,j}^{(k)}$, $j = 1, \ldots, M$, and $x_n$, $n = 1, \ldots, N$, and accuracy $\delta > 0$
Outputs: $l_i^{(k+1)}$, $i = 1, \ldots, L$ and $m_j^{(k+1)}$, $j = 1, \ldots, M$

1: repeat
2: for all base-stations $b$ (or $b_m$) do
3: for all points picked in $[0, D]$ do
4: Calculate $\sum_{i=1}^{N} R_n / \sum_{j=1}^{M} P_{BS,j}$
5: end for
6: end for
7: Set $l_i^{(k+1)}$ (or $m_j^{(k+1)}$) to the point such that $\sum_{i=1}^{N} R_n / \sum_{j=1}^{M} P_{BS,j}$ is maximized
8: end for
9: until the change in $l_i^{(k+1)}$ (or $m_j^{(k+1)}$) is less than $\delta$ for all $i = 1, \ldots, L$ (or $j = 1, \ldots, M$)

Given an arbitrarily small $\delta > 0$, Algorithm 3 converges along with a sufficiently large number of points for each BS, because $\{l_i^{(k)}\}$ and $\{m_j^{(k)}\}$ are Cauchy sequences. That is, the algorithm converges to a local maximum of BS positions for a fixed assignment for the users.


<table>
<thead>
<tr>
<th>Notation</th>
<th>Value</th>
<th>Notation</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_1$</td>
<td>21.45</td>
<td>$b_i$</td>
<td>354.44 W</td>
</tr>
<tr>
<td>$a_m$</td>
<td>7.84</td>
<td>$b_m$</td>
<td>71.50 W</td>
</tr>
<tr>
<td>$P_{t,i}$</td>
<td>20 W</td>
<td>$P_{t,m}$</td>
<td>4 W</td>
</tr>
<tr>
<td>$N_0$</td>
<td>$-134$ dB ($-174$ dBm/Hz)</td>
<td>$B$</td>
<td>5 MHz</td>
</tr>
<tr>
<td>$P_{th}$</td>
<td>2000 W</td>
<td>$N$</td>
<td>60</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>3</td>
<td>$D$</td>
<td>1 km</td>
</tr>
</tbody>
</table>

### Table I

**System Parameters**

C. Discussion

In each cycle of the Main Algorithm, the energy-normalized throughput is increased. It easily follows that the Main Algorithm converges to a local maximum of the optimization problem. In order to obtain a better result, we can run the algorithm several times with different initial conditions $t_i^{(0)}$, $t_i^{(0)} (i = 1, \cdots, L)$, $t_{m,j}^{(0)}$, and $m_{i,j}^{(0)} (j = 1, \cdots, M)$, thus yielding different local maxima. Among the local maxima, we can choose the one closest to the global maximum.

V. Numerical Results

Under the above simplified network model, we evaluate energy-normalized throughput through computer simulation. Our system parameters are listed in Table I, where we use the LTE-based link budget for $N_0$ and $B$. Note that simulation results will depend heavily on the power model parameters $a_1$, $a_m$, $b_i$, and $b_m$, and thus the optimal $L^*, M^*$, and $m_{i,j}^*$ $(j = 1, \cdots, M)$ will vary according to the four parameters. In this work, we use the values suggested by [8], [9], [15]. The accuracy of the numerical calculations, $\delta$, is set to $10^{-4}$. Even if our algorithm converges to a local maximum of the optimization problem, we run the algorithm 100 times with different random initial BS positions in order to approach the global maximum as much as possible.

Figure 1 shows the energy-normalized throughput for the number of iterations when $L = 1$ and $M = 6$. As observed from the figure, the energy-normalized throughput increases for each iteration, converging to a local maximum. It is also seen that there is a sharp change in the energy-normalized throughput after the first iteration, and that the energy-normalized throughput rapidly converges to a final value without any oscillations. For comparison, the energy-normalized throughput behavior of the case assuming no power control is also examined to see how much power-control is beneficial in terms of maximizing the energy-normalized throughput by decreasing the amount of out-of-cell interference and by decreasing the energy consumption.

Figure 2 shows the maximum energy-normalized throughput for the number of trials of random initial BS positions when $L = 1$ and $M = 6$. As seen in the figure, the energy-normalized throughput increases with number of trials of initial BS positions, while closely approaching the global maximum.

Fig. 1. The energy-normalized throughput with respect to the number of iterations. The system with $L = 1$ and $M = 6$ is considered.

Fig. 2. The energy-normalized throughput with respect to the number of trials of random initial BS positions. The system with $L = 1$ and $M = 6$ is considered.
respect to the energy-normalized throughput for all \((L,M)\) pairs over no power control case. As shown in the figure, the energy-normalized throughput gets reduced beyond a certain number of base-stations (e.g., \(M = 11\) for power control and \(M = 6\) for no power control). This is because increasing the number of micro base-stations increases the downlink sum-rate with minimum out-of-cell interference and minimum power consumption with power control.

For all the parameters \(L\) and \(M\), the corresponding values \(L^*\) and \(M^*\) for \(L\) and \(M\) that maximize the energy-normalized throughput are given by \((L^*,M^*) = (0,11)\). It thus turns out that utilizing the macro base-stations in the line network is not helpful in terms of energy efficiency.\(^3\) We note that the \(L^*\) and \(M^*\) can be numerically decided off-line by the system designer.

### VI. Conclusion

We developed a two-step iterative algorithm to solve the problem of energy efficient BS planning in a green heterogeneous network. Simulation results were provided, and for various scenarios, the optimal number of base-stations and their corresponding positions that maximizes the energy-normalized throughput (i.e., energy efficiency) were computed. The convergence of our algorithm to a local maxima was shown to be guaranteed, and the possibility converging to the global maximum was also numerically verified by taking into account different random initial BS positions. Moreover, the energy-normalized throughput were shown for a variety of network scenarios. Future extensions include incorporating shadowing and short-term fading terms into our channel models.

### Acknowledgement

This work was supported by the Chief Technology Office, TELUS Corporation and by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2012R1A1A1044151).

### References


\(^3\)We have confirmed that the proposed iterative algorithm shows a similar converging behavior for a two-dimensional network. The extension to multi-dimensional networks is rather straightforward.