Energy-Efficient SmallCell Deployment in Heterogeneous Cellular Networks (Postprint)

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Abstract

This paper investigates the energy efficiency of heterogeneous cellular networks under homogeneous Poisson point processes. First, heterogeneous cellular networks are modeled using homogeneous Poisson point processes; then, expressions for the system coverage probability and achievable rate are derived under Rayleigh fading channels, and a closed-form expression for energy efficiency is obtained; finally, the density of small base stations is optimized via convex optimization algorithms to maximize network energy efficiency. Simulation results demonstrate that the density of small base stations has a significant impact on system energy efficiency, and that proper configuration of small base station density can effectively improve system energy efficiency.

Full Text

Preamble

Title: Energy-Efficient Micro-Base Station Deployment in Heterogeneous Cellular Networks

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Abstract: This paper investigates the energy efficiency of heterogeneous cellular networks under homogeneous Poisson point processes. First, we model heterogeneous cellular networks using homogeneous Poisson point processes. Then, we derive expressions for system coverage probability and achievable rate under Rayleigh fading channels, and further obtain a closed-form expression for energy efficiency. Finally, we optimize the density of micro-base stations through convex optimization algorithms to maximize network energy efficiency. Simulation results demonstrate that micro-base station density significantly impacts system energy efficiency, and that reasonable configuration of micro-base station density can effectively improve system energy efficiency.

Keywords: heterogeneous cellular networks; homogeneous Poisson point process; energy efficiency; coverage probability; achievable rate

0 Introduction

Over the past decade, the explosive growth of mobile data traffic has posed numerous challenges to traditional cellular networks. While deploying large numbers of base stations can address the rapidly increasing service demand, this approach leads to substantial energy consumption that contradicts the requirements of green communications. Consequently, the concept of heterogeneous cellular networks has been proposed and has garnered widespread attention. Heterogeneous cellular networks comprise base station nodes with different transmission powers and coverage ranges. In addition to conventional macro base station deployments, various low-power base stations such as femto base stations and pico base stations are deployed within macro cells. Macro base stations, with their high transmission power, provide basic network coverage, while pico base stations are primarily deployed in hotspot areas to serve as supplements to macro base stations, improving signal quality for cell-edge users and enhancing capacity in hotspot regions.

Traditional modeling of heterogeneous cellular networks has primarily relied on hexagonal grid models, where macro base stations are regularly positioned at the centers of hexagonal cells and micro base stations are regularly deployed at the edges. Although intuitive, this grid-based model differs significantly from actual base station deployments and presents mathematical difficulties in analyzing interference characteristics. To overcome these limitations, Jeffrey G. Andrews pioneered the use of Poisson Point Processes (PPP) for modeling cellular network base stations. PPP models not only capture the random distribution characteristics of network nodes but also substantially simplify the analysis of cellular network performance, thus attracting considerable research interest. Leveraging the advantages of PPP models, this paper analyzes heterogeneous cellular networks based on PPP while comprehensively considering base station biasing and spectrum reuse schemes.

Existing literature on improving energy efficiency primarily employs methods such as radio resource management, base station sleeping, and deployment strategies. Reference [4] studied the lower bound of user rates and transformed a non-convex optimization problem into a convex one, proposing a two-step algorithm for optimal power and channel allocation to minimize system power consumption. Reference [5] used the criterion of whether switching micro base station users to macro base stations reduces power consumption to determine micro base station sleeping strategies, thereby reducing system power consumption through base station sleeping. Reference [6] utilized stochastic geometry theory to investigate optimal base station densities in heterogeneous cellular networks to minimize system energy consumption. Reference [7] derived expressions for success probability and energy efficiency under different sleeping modes, particularly examining the impact of random and dynamic sleeping strategies on system power consumption. Reference [8] allocated power and backhaul bandwidth for small cells based on channel state information and circuit power consumption to maximize system energy efficiency. Reference [9] reduced energy consumption in heterogeneous cellular networks through joint partial frequency reuse and base station sleeping, first deriving user coverage rates across different base station layers and then minimizing power consumption by optimizing partial frequency reuse factors and the active probability ratios of two types of base stations. Reference [10] improved system energy efficiency by introducing an offset factor to expand cell range. Reference [11] optimized uplink energy efficiency through user association strategies and power control, proposing an iterative algorithm. Reference [12] minimized power consumption in heterogeneous cellular networks through joint design of radio resources, power, and base station sleeping. However, none of these studies have considered the impact of micro base station density on system energy efficiency.

The work most closely related to this paper is reference [6], which only addresses optimization of system energy consumption, whereas our work directly optimizes system energy efficiency. We derive the expression for system energy efficiency and achieve its optimization through convex optimization methods. Simulation results validate the correctness of our theoretical analysis.

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1 Heterogeneous Cellular Network Model

We consider a two-tier heterogeneous cellular network scenario as shown in [Figure 1: see original paper]. The network consists of macro base stations and pico base stations, with pico base stations deployed within macro cell coverage areas following a Poisson point distribution. Different tiers have different transmission powers, densities, and supported data rates. We assume that base stations in tier i follow a homogeneous Poisson point process (HPPP) with density , where i = 1, 2. The base station distribution is illustrated in [Figure 2: see original paper]. For analytical tractability, we assume complete independence between tiers. Each tier has transmission power P , and all base stations within the same tier have identical transmission power. The signal-to-interference-plus-noise ratio (SINR) threshold for each tier is , and the path loss exponent for each tier is . User locations also follow an HPPP with density , independent of the base station distribution.

From statistical theory [13][14], all users in a randomly distributed heterogeneous network have identical statistical characteristics. Therefore, without loss of generality, we analyze the performance of a typical user located at the origin. We consider full frequency reuse, where the channel fading loss between a base station at location r and the typical user at the origin is h . Assuming Rayleigh fading, h follows an independent and identically distributed exponential distribution. The path loss function is L(r) = ||r|| . Thus, the signal power received by the typical user from a base station in tier k at location r is P h ||r|| . If this user connects to that base station, its SINR is:

$$\mathrm{SINR}_k = \frac{P_k h_r ||r||^{-\alpha}}{\sum_{j\in\Phi_k\setminus\{r\}} P_k h_j ||j||^{-\alpha} + \sigma^2}$$

where the denominator' s first term represents the total interference from other base stations, and ^{2} is the constant additive noise power. In typical heterogeneous cellular networks, the dominant interference source is inter-cell interference, which is generally much larger than additive noise. Therefore, we neglect the noise term, as justified in reference [15]. We assume users employ SINR-based association, meaning a user connects to tier k if that tier can provide SINR greater than . Since this may result in a user being able to connect to multiple tiers simultaneously, we assume 1 for analytical convenience, ensuring that at most one base station can provide SINR greater than at any given time. In other words, a user can connect to at most one base station.

2 Performance Analysis of Heterogeneous Cellular Networks

2.1 Coverage Analysis

Coverage probability is a crucial quality-of-service metric in wireless communications, typically represented by the complementary cumulative distribution function (CCDF) of the received SINR—i.e., the probability that SINR exceeds a certain threshold. Mathematically, user coverage probability is defined as:

$$\mathcal{C} = \mathbb{P}(\mathrm{SINR} > \beta)$$

We assume base stations operate in open access mode, meaning target users can connect to any tier. In our system model, this implies users select the base station providing the maximum SINR. According to Corollary 1 in reference [15], for an interference-limited two-tier heterogeneous cellular network (neglecting noise), coverage probability can be expressed as:

$$\mathcal{C} = \sum_{k=1}^{2} \lambda_k P_k^{2/\alpha} \int_0^\infty \exp\left(-\pi \sum_{j=1}^{2} \lambda_j P_j^{2/\alpha} r^{2/\alpha} \left(1 + \beta_j^{2/\alpha} \int_{\beta_j^{-2/\alpha}}^\infty \frac{1}{1+u^{\alpha/2}} du \right) \right) dr$$

From equation (3), we observe that coverage probability depends on base station density, transmission power, and SINR thresholds. However, among these three factors, base station density plays the most decisive role. If the SINR threshold values are identical across tiers (= =), coverage probability simplifies to:

$$\mathcal{C} = \frac{1}{1 + \beta^{2/\alpha} \int_{\beta^{-2/\alpha}}^{\infty} \frac{1}{1+u^{\alpha/2}} du}$$

This reveals that coverage becomes independent of base station density, transmission power, and the number of network tiers. Consequently, increasing base station density or power does not affect coverage. This occurs because the useful signal power and interference power received by users follow similar trends, keeping the SINR approximately constant. Since users select base stations based on SINR relative to the threshold, coverage remains essentially unchanged.

According to Corollary 2 in reference [15], the probability that a user connects to tier k can be expressed as:

$$\mathcal{A}_k = \frac{\lambda_k P_k^{2/\alpha} \beta_k^{-2/\alpha}}{\sum_{j=1}^{2} \lambda_j P_j^{2/\alpha} \beta_j^{-2/\alpha}}$$

Examining equation (5), we find that users preferentially connect to tiers with higher density, greater transmission power, and lower SINR thresholds. Similar to the coverage analysis, base station density is more decisive than transmission power or SINR thresholds for association probability.

2.2 Minimum Achievable Rate Analysis

In heterogeneous cellular networks with equal resource allocation, all base stations assign identical bandwidth resources to their served users. According to Shannon' s formula, when a target user connects to a tier k base station, its minimum achievable rate can be expressed as:

$$R_k = \frac{B}{N_k} \log_2(1 + \beta_k)$$

where B represents system bandwidth and N denotes the average number of users served per base station in tier k. For analytical simplicity, we assume N and are independent, which does not affect result accuracy [16]. Thus, R can be expressed as:

$$R_k = \mathbb{E}\left[\frac{B}{N_k}\right] \log_2(1 + \beta_k)$$

In heterogeneous cellular networks, macro base station density is typically fixed. Therefore, the total minimum achievable rate in the system is:

$$R_{\text{total}} = \sum_{k=1}^{2} \lambda_k \mathcal{A}_k R_k$$

where $\mathcal{A}_k$ represents the coverage probability of tier k.

2.3 Energy Efficiency Analysis

Base station power consumption generally consists of two components: static power consumption and dynamic power consumption. Static power consumption includes power amplifiers, cooling systems, signal processing units, antennas, backup batteries, etc. Dynamic power consumption is generated by base station transmission power. A base station' s total power consumption can be expressed as:

$$P_k = P_k^{\text{static}} + w_k P_k^{\text{tx}}$$

where P_k^{static} is the static power consumption of tier k base stations, w_k is the power scaling factor related to transmission power, and P_k^{tx} is the base station transmission power. Since static and dynamic power consumption are generally independent, system energy efficiency is defined as the ratio of total system throughput to total power consumption per unit time. In this paper, system energy efficiency is expressed as:

$$\eta_{EE} = \frac{R_{\text{total}}}{P_{\text{total}}}$$

where P_{total} is the total power consumption of all base stations in the network, which depends on both base station power and density. Based on the expressions for coverage probability and throughput, system energy efficiency can be expressed as:

$$\eta_{EE} = \frac{\sum_{k=1}^{2} \lambda_k \mathcal{A}_k R_k}{\sum_{k=1}^{2} \lambda_k (P_k^{\text{static}} + w_k P_k^{\text{tx}})}$$

Since R_k is linearly related to the load of serving base stations, we assume $\mathbb{E}[w_k/N_k] = w_k \mathbb{E}[1/N_k]$ for simplicity. Through a series of algebraic simplifications, the energy efficiency expression becomes:

$$\eta_{EE} = \frac{B \log_2(1+\beta_1)\lambda_1 \mathcal{A}_1/(1.28\lambda_u + \lambda_1 \mathcal{A}_1) + B \log_2(1+\beta_2)\lambda_2 \mathcal{A}_2/(1.28\lambda_u + \lambda_2 \mathcal{A}_2)}{\lambda_1(P_1^{\text{static}} + w_1 P_1) + \lambda_2(P_2^{\text{static}} + w_2 P_2)}$$

3 Energy Efficiency Optimization

This section focuses exclusively on optimizing micro base station density. It can be readily shown that the objective function in optimization problem (13) is concave. To facilitate solution using convex optimization algorithms, we negate equation (13), transforming optimization problem (14) into a convex optimization problem. Since the first derivative of the objective function in problem (14) is nonlinear, the optimal solution cannot be obtained by simply setting the derivative to zero. We employ the golden section method to find the minimum value of the objective function.

The algorithm is described as follows:

Algorithm Input: Micro base station density range
Algorithm Output: Optimal micro base station density and minimum value of the negated energy efficiency

1. Given initial interval [m, n] and precision > 0
2. Step 1: Set x = m + 0.618(n - m), f = f(x), go to Step 2
3. Step 2: Set x = m + 0.382(n - m), f = f(x), go to Step 3
4. Step 3: If |n - m| , then x* = (m + n)/2 and stop iteration. If |m - n| > , go to Step 4
5. Step 4: If f < f , then n = x , x = x , f = f , go to Step 2. If f = f , then m = x , n = x , go to Step 1. If f > f , then m = x , x = x , f = f , go to Step 5
6. Step 5: Set x = a + 0.618(n - m), f = f(x), go to Step 3

By setting the initial interval to [0,] and f(x) to - ( ), we can obtain the optimal micro base station density * using this algorithm. Substituting * into equation (13) yields the maximum energy efficiency.

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4 Simulation Analysis

This section validates the theoretical results through MATLAB Monte Carlo simulations, with results obtained from 5,000 random deployments in a square area. Unless otherwise specified, simulation parameters follow .

Table 1: System-Level Simulation Parameters for Two-Tier Heterogeneous Networks

Parameter	Value
Macro base station density	= 0.001 m ^{2}
User density	= 0.1 m ^{2}
Path loss exponent	= 4
SINR threshold (macro)	= 12 dB
SINR threshold (pico)	= 0 dB
Macro base station static power	1000 W

Parameter	Value
Macro base station transmit power	40 W
Pico base station static power	10 W
Pico base station transmit power	1 W
System bandwidth	10 MHz
Maximum pico base station density	0.35 m ^{2}

[Figure 4: see original paper] illustrates coverage probability versus macro base station threshold, with micro base station density set to twice that of macro base stations. The theoretical and simulation curves show good agreement, validating equation (8). Additionally, coverage probability decreases as the macro base station threshold increases. This occurs because users connect to base stations based on instantaneous SINR in our model; as the macro base station SINR threshold increases, the probability of users connecting to macro base stations decreases, leading to declining coverage.

[Figure 5: see original paper] shows the relationship between coverage probability and micro base station density, assuming a macro base station threshold $=$ 12 dB. Coverage probability increases with micro base station density but eventually converges to a stable value. This indicates that beyond a certain density, further increasing micro base stations does not improve coverage. When micro base station density is low, increasing density effectively serves edge users, gradually improving coverage. However, when density reaches a certain level, the increase in useful signal strength is offset by increased interference, establishing an equilibrium that prevents further coverage improvement.

[Figure 6: see original paper] depicts the relationship between micro base station density and energy efficiency for a fixed user density. Energy efficiency initially increases then decreases with growing micro base station density. The initial increase occurs because higher micro base station density offloads some users from macro base stations to micro base stations, which consume less power. However, since user density is fixed, when micro base station density exceeds a certain value, continuous increases in micro base stations raise total system power consumption, causing energy efficiency to decline. The figure also shows that increasing the macro base station SINR threshold improves system energy efficiency, as users become more likely to connect to micro base stations.

[Figure 7: see original paper] compares energy efficiency under optimal versus non-optimal micro base station densities for different user densities. The top curve represents system energy efficiency at optimal micro base station density, while the lower curves show efficiency at regular densities. The figure clearly demonstrates that reasonable adjustment of micro base station density can significantly improve system energy efficiency across various user density conditions.

5 Conclusion

This paper employs stochastic geometry theory to investigate the impact of micro base station deployment on system energy efficiency in heterogeneous cellular networks. We first derive the coverage probability expression for interference-limited scenarios, then construct a system energy efficiency mathematical model based on the derived minimum achievable capacity. For this model, we utilize convex optimization to obtain the optimal micro base station deployment under given configurations. Simulation results confirm the existence of an optimal micro base station density that yields higher energy efficiency than regular deployments. This research provides theoretical guidance for practical micro base station deployment.

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