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Enhancing Energy Sustainability in Two-Tier Heterogeneous Cellular Networks in 5G through Idle Mode Capabilities

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Abstract: The rise of 5G technology has led to increased data traffic on cellular networks, resulting in higher energy consumption and strain on backhaul lines. Two-tier heterogeneous cellular networks (HetNets) with idle mode capability (IMC) offer a solution. This research investigates the impact of transitioning from 2G to 5G and varying the pico to macro base station density ratio β on energy-efficient resource allocation in a two-tier HetNet with IMC. The study employs a 3D model considering user equipment (UE) distance and a practical 3GPP path loss model. Network performance is assessed based on the signal-to-interference ratio (SIR) derived from the average power. The results indicate that optimizing antenna height and gain, increasing pico base station (PBS) density, and reducing macro base station (MBS) density enhance energy efficiency (EE). IMC mode, which deactivates inactive BSs, further improves EE and reduces backhaul data volume. These findings emphasize the potential of IMC for efficient resource allocation in two-tier HetNets, mitigating energy consumption and backhaul challenges in modern cellular networks.

Keywords: energy sustainability, two-tier heterogeneous cellular network, idle mode capability, energy efficiency, energy saving strategies.

通过空闲模式功能增强 5G 中两层异构蜂窝网络的能源可持续性

摘要: 5G 技术的兴起导致蜂窝网络上的数据流量增加，从而导致更高的能源消耗和回程线路的压力。具有空闲模式功能 (整合管理委员会) 的两层异构蜂窝网络 (异构网络) 提供了一种解决方案。本研究调查了从 2G 过渡到 5G 以及改变微微基站与宏基站密度比β对具有整合管理委员会的两层异构网络中节能资源分配的影响。该研究采用考虑用户设备(UE)距离的 3D 模型和实用的 3 总计划路径损耗模型。网络性能是根据平均功率得出的信号干扰比(先生)进行评估的。结果表明，优化天线高度和增益、增加微微基站(公共广播公司)密度和降低宏基站(MBS)密度可提高能源效率(电子工程)。整合管理委员会模式可停用不活动的学士，进一步提高电子工程并减少回程数据量。这些发现强调了整合管理委员会在两层异构网络中实现

高效资源分配、减轻现代蜂窝网络中的能耗和回程挑战的潜力。

关键词：能源可持续性、两层异构蜂窝网络、空闲模式能力、能源效率、节能策略。

1. Introduction

In response to the escalating challenge of mounting energy consumption within cellular networks, the emergence of two-tier heterogeneous cellular networks (HetNets) has cast a promising light on the horizon. This innovative approach has the potential to revolutionize the landscape of wireless communication by proactively addressing the energy quandary. At its core, HetNets harmoniously combine the prowess of macro base stations (MBSs) and pico base stations (PBSs) within two-tier architecture, propelling network performance and energy efficiency (EE) to new heights of achievement [1]. A cornerstone of this transformative strategy lies in the distinct characteristics that PBSs embody. Tailored to embrace smaller coverage areas, PBSs adeptly wield the power of localized wireless connectivity. This strategic localization functions as a conduit for the deft offloading of traffic from their MBS counterparts, orchestrating an energy conservation symphony that reverberates across the network expanse. The ramifications of this symbiotic partnership ripple further, culminating in a tangible alleviation of pressure on the intricate backhaul lines. As these vital conduits of data transmission encounter reduced strain, the symphony continues its crescendo, producing a harmonious convergence of energy conservation and heightened network performance [2]. It is within the densely woven tapestry of PBS deployment that the orchestra's most intricate melodies are woven. The ubiquity of PBSs ushers in a new era of data offloading efficiency, where the requirement for extensive data transmission over the backhaul network is appreciably diminished. Through this intricate dance of data, energy consumption wanes, and the network remains resolute and primed for the demands of an ever-evolving digital epoch. Yet, the symphony of HetNets is further enriched by avirtuoso technique—the idle mode capability (IMC)—a power-saving concerto that orchestrates base stations into a harmonious choreography of activity and repose. By seamlessly transitioning dormant base stations into states of minimal power consumption during quiescence, IMC emerges as a beacon of energy frugality. Through this artful modulation of energy usage, base stations balance their vital role in signal propagation with prudent energy stewardship. Thus, the symphony of HetNets fuses with the cadence of IMC, offering a harmonious solution to the growing symphony of energy consumption that resonates through the cellular network sphere. In the pursuit of synergy and strategic advancement, the research horizon beckons forth with a dual-fold objective. The first refrain resounds in the quest to optimize the deployment of MBSs and PBSs, a melody aimed at elevating network EE. A second crescendo arises in the study of the impact of IMC on the twilight slumber of inactive base stations, a performance art poised to elevate EE further while diminishing the voluminous data load that courses through the backhaul. These research motifs, intertwined in harmonious progression, compose a sonata of innovation and practical application. In summary, HetNets are a triumphant ode to the challenges posed by escalating energy consumption in cellular networks [3]. Through the artful interplay of MBSs and PBSs, augmented by the deft choreography of IMC, cellular networks emerge emboldened, their energy consumption mitigated, and their performance elevated to crescendos previously unattainable. As network operators weave the threads of resource allocation and energy-conscious techniques, they are poised to conduct a symphony of sustainability—a harmonious composition of energy savings, operational frugality, and seamless wireless connectivity.

2. Literature Review

This literature review focuses on the use of stochastic geometry, particularly the Poisson point process (PPP), in the analysis of heterogeneous cellular networks. It also explores the challenges and alternatives introduced by non-Poisson point processes to overcome limitations in modeling real-world cellular network deployments. The review touches upon various methodologies, including the Ginibre point process (GPP) [4], the Matérn hard-core point process (MHCPP) [5], the Poisson cluster process (PCP) [6], the Matern cluster process (MCP) [6], the Poisson hole process (PHP) [8], [9], and the PPP-based approximate SIR analysis (ASPPP) method [10]–[12]. The Poisson point process (PPP) has emerged as a widely used modeling tool in the study of cellular networks because of its mathematical simplicity and ability to capture the random distribution of base stations. By representing base station locations as a set of random points distributed according to a Poisson distribution, researchers can analyze cellular networks under various conditions and configurations, such as different base station densities, antenna heights, and transmit powers. The PPP enables investigations into network performance metrics such as coverage, capacity, and energy efficiency (EE), leading to the development of optimization techniques to enhance network effectiveness. However, the assumption of independent base stations in the PPP model diverges from the reality of network implementation, potentially limiting the accuracy of the analysis. To address this limitation, non-Poisson point processes have been suggested as alternatives. Notably, the Ginibre point process (GPP) and the Matérn hard-core point process (MHCPP) have been proposed to model realistic heterogeneous networks with spatial exclusion or aggregation of base stations. These alternatives introduce more complex geometrical considerations, leading to more accurate representations of real-world deployments. Estimating the signal-to-interference ratio (SIR) distribution becomes more intricate when using non-Poisson point processes. Researchers have turned to approaches such as the PCP and MCP to capture the clustering properties of small base stations in heterogeneous networks. In addition, the PHP has been utilized to explain the attraction between MBSs and PBSs, contributing to a more comprehensive modeling framework. Despite the challenges posed by non-Poisson point processes, the literature introduces methods such as the PPP-based approximate SIR analysis (ASPPP) to bridge the gap. This method leverages the SIR distribution of PPP networks to approximate the SIR distribution of non-PPP networks accurately. Thus, it provides a practical tool for evaluating network effectiveness under different non-Poisson point process scenarios. In conclusion, the use of stochastic geometry, particularly the Poisson point process, has been instrumental in analyzing and optimizing heterogeneous cellular networks. Non-Poisson point processes, such as the GPP and MHCPP, offer more accurate modeling alternatives, while methodologies such as the PCP, MCP, and PHP further enrich the modeling landscape. The PPP-based approximate SIR analysis method serves as a valuable tool for evaluating network effectiveness across diverse deployment scenarios, addressing the challenges posed by non-Poisson point processes. Research on network topologies and transmission techniques continues to captivate both academic and industrial realms as a fundamental pursuit in enhancing energy efficiency (EE) and consumption in future mobile communication systems [13]–[16]. This section provides an in-depth overview of the current landscape of EE improvement in networks, focusing on base station (BS) deployment, BS sleep strategies, and power allocation. Factors such as the number of BSs, their inter-distance, and the transmit power of the MBS all intricately influence the system's EE, as demonstrated in [17]. Notably, optimizing these factors can yield substantial energy savings. In a similar vein, the exploration by [18] into the potential of pico cells (PBSs) to enhance system capacity and reduce energy consumption underscores the multifaceted considerations inherent in EE improvement strategies. The findings of [19] underscore the pivotal role of spectral efficiency enhancement through the addition of PBSs to mega cells, leading to tangible improvements in EE, particularly when the PBS density is judiciously optimized. The interplay between local delay and EE in heterogeneous networks was scrutinized in [20] employing the PPP and PCP to model BSs. The results of the study were the predictions made by the PCP, revealing heightened local latency and EE due to intra-cluster interference. In addition, [21] introduced a comprehensive formula to estimate the lower bound of the average reachability rate for the Matern cluster process (MCP), while concurrently investigating the optimal number of cell clusters that maximize EE. Energy-efficient strategies involving BS sleep mechanisms have demonstrated substantial potential. The contributions of [22]–[24] underscore how EE improvement can be realized through transmission power scaling and strategic on/off switching of BSs. Similarly, the groundbreaking work of [25] showcases a significant reduction in network power consumption through the utilization of the sleep strategy for small base stations (SBSs), anchored on system throughput considerations. Collaborative sleep strategies were explored by [26] leveraging the parameters $\lambda_{M\ BS}$ and λ_{SBS} to optimize energy consumption. The optimization model unveiled in [27] tactfully organizes the four operational states of base stations, ensuring that the minimum level of service for consumers is maintained while achieving a substantial reduction in power consumption, up to 10%. An additional practical avenue for bolstering the EE of heterogeneous cellular networks (HCNs) involves the optimization of base station transmission power. This is exemplified by [28], where a novel simultaneous interference and power management technique effectively minimized signal interference, bolstered LTE-A performance, and optimized energy use. Game theory made its mark in addressing the complexities of uplink power regulation and appropriate unit selection in open-access, two-tier femtocell networks, as documented in [29]. The analysis of [30] meticulously scrutinized the impact of BS transmit power on EE, leveraging a PPP model and presenting a formula for determining the optimal transmit power for maximizing EE. Meanwhile, a symbiotic approach to network EE enhancement was highlighted by [31], advocating a harmonious adjustment of PBS density and transmit power. Finally, [32] delved into the realm of two-tier HetNets, exploring the EE implications stemming from the spatial repulsion of BSs within the same tier. This comprehensive examination culminated in a novel EE improvement strategy, further enriching the landscape of strategies for bolstering the energy efficiency of future mobile communication systems.

2.1. Contributions

- [33] suggests that increasing the antenna gain of macro or macro and pico BSs can result in extended coverage areas, but this can also cause increased interference between cells, leading to reduced network performance and higher energy consumption.

• [34] achieved EE of 0.0018 bps/Hz/W with PPP and $\alpha = 4$, while in this study, EE of 0.6834 Mbps/W or 341.7 bps/Hz/W was achieved using a realistic 3GPP path loss model.

• This study examines the impact of macro and pico BS antenna height on EE in a two-tier heterogeneous cellular network using IMC. The results indicate that optimal antenna height can significantly improve EE, and the study highlights the importance of adjusting antenna height to maximize network efficiency.

3. System Model

The system model, which comprises a two-tier HetNet
with MBSs and PBSs with different β, is examined in the study, as illustrated in Fig. 1. The energy-efficient distribution of resources is achieved through IMC, which enables the user equipment (UE) to remain connected to the network while consuming minimum power. We have adopted a specific model that considers the 3D distance between UEs and BSs and involves a limited number of UEs. The 3D distance between a UE and a BS can significantly impact the quality of service and overall performance of a cellular network. The distance between the UE and BS affects the signal strength, SIR, and PL, all of which are critical factors in determining the signal quality. The signal strength between the UE and BS decreases as the distance between them increases because of the attenuation of the radio signal. The radio signal power diminishes with distance as it propagates through the air, and the signal may also be absorbed or reflected by obstacles such as buildings, trees, or other structures. This results in a weaker signal, leading to lower data rates, higher packet loss, and poorer call quality. As the distance between the UE and BS increases, the PL also increases. Factors such as the frequency of the signal, the environment where it travels, and the distance between the UE and BS can affect PL, which is the attenuation of the signal as it travels through the air. PL is a significant factor in determining the range of a wireless network and can be affected by the terrain, obstacles, and other factors in the environment. The impact of 3D distance between the UE and BS on the SIR cannot be overstated. With increasing distance, the strength of the signal weakens, while the noise level remains unchanged, leading to a reduction in the SIR. This can result in lower data rates, higher error rates, and poor signal quality. The network's performance is evaluated based on the SIR calculated using average power. Calculating the SIR on the basis of the average power has some positive effects as well. One advantage is that it is a simple and practical approach that can be easily implemented in practical systems. It does not require complex algorithms or hardware and can be used in real time to estimate the signal quality at a UE. Another advantage of using average power to calculate the SIR is that it is less sensitive to noise and interference than other methods. By averaging the power over time and frequency, it can reduce the impact of short-term interference or fluctuations in signal power. Improved overall system performance can be achieved by achieving more stable and reliable SIR values. Additionally, using average power to calculate SIR can provide a fairer and uniform representation of the network conditions. By averaging the power over time and frequency, it can smooth out any variations in signal strength or interference levels, which can help ensure that all UEs are treated equally in terms of signal quality. This can lead to better overall network performance and user experience. Overall, calculating the SIR on the basis of average power can be a practical and effective approach for many cellular network scenarios. In certain scenarios, it can be advantageous to use a straightforward and reliable estimation of signal quality, despite any potential limitations. Optimizing the antenna height and gain of BSs can improve the EE of the network. The research indicates that enhancing the network's EE is possible by increasing λ_P BS while decreasing λ_M BS and by using IMC to turn off inactive BSs, thereby reducing the backhaul data volume traffic load. On the whole, the system model improves EE in two-tier HetNets through the efficient distribution of resources. The HCN, which has two layers of BSs with distinct coverage areas and transmit powers, is shown in Fig. 1. In this network, the BSs and UE are represented using a Poisson point process, which is a probabilistic model used to depict random point patterns in space. The PPP assumes that the locations of the BSs and UEs are distributed randomly and independently of each other. MBSs have a large coverage area and high transmit power, whereas SBSs have a smaller coverage area and lower transmit power. At the location of a UE, the choice of a BS to connect to depends on which BS can provide a better SIR. This can be either an MBS or an SBS. The SIR is a metric that gages the quality of the received signal in relation to interference from other BSs. In this network, the SIR can be computed by averaging the power received from all BSs located within a certain distance of the UE. This is due to the random placement of the BSs, which allows the UE to receive signals from multiple BSs. To model this network, the authors have used symbols to represent the different components. Let Nm and Ns be the number of MBSs and PBSs or SBSs, respectively. Consider the coordinates of the ith BS denoted by Xi and Yi, where i = 1, 2, ..., Nm + Ns. In addition, let Pi represent the transmit power of the i − th BS, while hi indicates the channel gain between the i − th BS and the UE. The UE can be located at any point (x,y) in the network, which is represented by symbols. Let S be the

set of all BSs within a certain distance r of the UE. Then, the SIR at the UE's location can be calculated as follows:

$$SIR = \frac{(H_i * P_i)}{\left(\sigma^2 + \sum_{j=0}^{\infty}(H_j * P_j)\right)}, \quad i,j \in S, j \neq i \qquad (1)$$

Here, σ^2 is the noise power at the UE receiver, and the sum is taken over j of all BSs within a certain distance r of the UE, excluding the i–th BS. In conclusion, a two-tier HetNet with PPP can be modeled using symbols to represent the different components. The SIR at the UE's location can be calculated using the average power received from the BSs within a certain distance of the UE. Efficient distribution of resources and enhanced EE in the network are made possible using this approach. The system model comprises a multi-slope 3GPP PL model, two distinct types of BSs with varying power levels, and a restricted amount of user equipment.

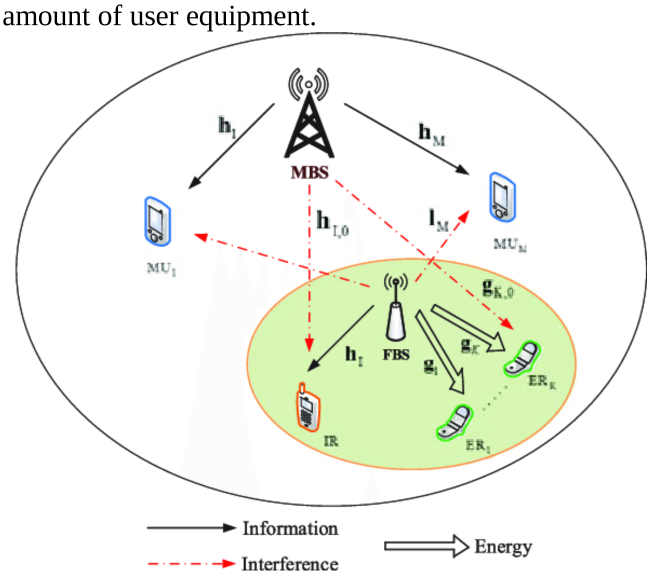

Fig. 1 Two-tier HCN includes macro cell BSs, pico cell BSs, and user equipment (UE)

In the system model depicted in Fig. 1, it is assumed that the UE is positioned at the origin of the coordinate axis (0, 0). According to this model, the UE can connect to any BS of either the macro or pico tier as long as it satisfies the specified average receive power. To establish a connection with a BS of any tier, the study uses a coupling association technique in which the UE connects to the same BS in both the uplink and downlink transmissions. To establish a connection, the following steps are taken. This approach ensures that the UE selects the BS that can provide the highest average received power, regardless of its location. Furthermore, it allows the network to achieve efficient resource utilization and enhanced EE.

Every other MBS and PBS in the network will cause interference for a user connected to an MBS, as per the system model depicted in Fig. 1. The intended signal is represented by a solid line, and the interference signals are represented by dashed lines. Previous research has typically assumed that users are infinite, which ensures that at least one user is connected to each BS and that no BS remains empty. However, due to the limited power of BSs, it is not feasible in practice. Therefore, our model considers a finite number of users per BS, which results in some BSs not serving any users and thus not contributing to interference power. The algorithm defined in 2 connects a UE to a BS of either tier. To calculate the PL model according to 3GPP for the two-tier heterogeneous cellular network depicted in Fig. 1, the scenario illustrated in Fig. 3 should be referred to. The PL model is used to estimate the attenuation of the radio signal as it propagates from the base station to the UE. The 3GPP model takes into account various factors that affect the PL, including the distance between the base station and the UE, the frequency of the signal, the environment, and the characteristics of the antenna. In the scenario shown in Fig. 3, the MBS is located at the center of the cluster, and the SBSs are distributed around it. The UEs are also distributed randomly within the cluster. According to [35], the PL model is calculated by measuring the 3D distance between the UE and the base station and recording the received signal strength. Below is presented the resulting model. One can calculate the PL model for a two-tier HetNet according to [35] as follows:

The maximum PL is given by the maximum path losses for line-of-sight (LOS) and non-LOS (nLOS) scenarios. For the LOS scenario, two PL formulas, PL_1 and PL_2, are used depending on the distance between the UE and the base station (BS). If the 2D distance, d_{2D}, is between 10 m and a breakpoint distance, d'_{BP}, PL_1 is used; otherwise, PL_2 is used.

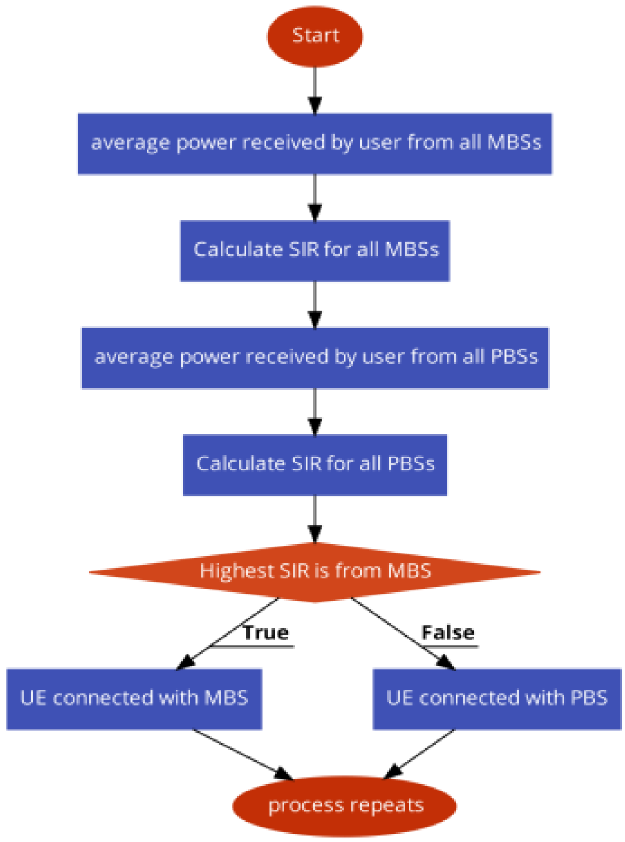

Fig. 2 Steps to follow for successful connection establishment

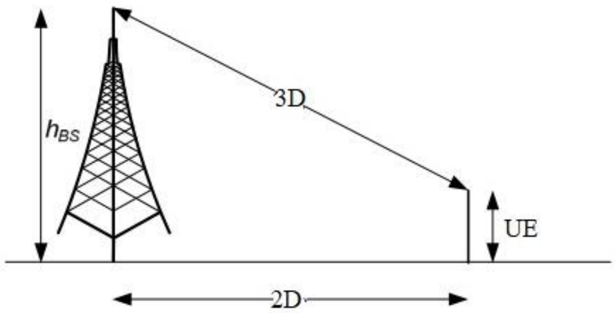

Fig. 3 Scenario for calculating the PL model

The formula for PL_1 is

$28.0 + \alpha M_{1LOS} \times 10 \log_{10} d_{3D} + 20 \log_{10} f_c$,

where M_1LOS is the median PL at 1 meter, α is the PL exponent, d_{3D} is the 3D distance between the UE and BS, and f_c is the carrier frequency.

The formula for PL_2 is

$28.0 + \alpha M_{2LOS} \times 10 \log_{10} d_{3D} + 20 \log_{10} f_c - 9\log_{10}[(d'_{BP})^2 + (H_{BS} - H_{UT})^2]$,

where M_{2LOS} is the median PL at the breakpoint distance, H_{BS} and H_{UT} are the heights of the BS and UE, respectively.

For the nLOS scenario, the PL formula is

$13.54 + \alpha M_n LOS \times 10 \log_{10} d_{3D} + 20 \log_{10} (f_c) - 0.6(H_{UT} - 1.5)$

The PL model for PBSs, which considers the distance of users from these BSs, is calculated according to [35] and presented below:

The maximum PL is chosen between the PL for line-of-sight (LOS) and non-LOS (NLOS) scenarios.

$$P L = \max(PL_{LOS}, PL_{nLOS}) \quad (2)$$

The PL model for line-of-sight (LOS) propagation PL_{LOS} is defined as follows:

$$PL_{LOS} = PL_1 \text{ for } 10 \text{ m} \leq d_{2D} \leq d'_{BP}, \text{ and } PL_{LOS} = PL_2 \text{ for } d'_{BP} \leq d_{2D} \leq 5 \text{ Km} \quad (3)$$

where d_{2D} is the two-dimensional distance between the UE and BS, d3D is the corresponding three-dimensional distance, f_c is the carrier frequency, and H_{BS} and H_{UT} are the heights of the BS and UE, respectively.

PL_1 and PL_2 are the PL coefficients, which are given by

$$PL_1 = 32.4 + \alpha P_1 LOS \times 10\log_{10}(d_{3D}) + 20\log_{10}(f_c) \quad (4)$$

$$PL_2 = 32.4 + \alpha P_2 LOS \times 10\log_{10}(d_{3D}) + 20\log_{10}(f_c) - 9.5\log_{10}[(d'_{BP})^2 + (H_{BS} - H_{UT})^2)] \quad (5)$$

The PL coefficient for non-line-of-sight (nLOS) propagation, PL_{nLOS}, is given by

$$PL_{nLOS} = 22.4 + \alpha P_{nLOS} \times 10\log_{10}(d_{3D}) + 20\log_{10}(f_c) - 0.3(H_{UT} - 1.5) \quad (6)$$

where P_{1LOS}, P_{2LOS}, and P_{nLOS} are constants, and α is the PL exponent, as shown in Table 2.

Rewritten:

$$d'_{BP} = 4*H'_{BS}*H'_{UT}*fc/c \quad (7)$$

The effective antenna height at the base station, denoted as H'_{BS}, and at the user equipment, denoted as H'_{UT}, can be computed using Equations 8 and 9. Equation 7 defines d'_{BP}, where f_c represents the center frequency normalized by 1×10^9 Hz, and all distance-related values are normalized by 1 m. The speed of electromagnetic waves is denoted as $c = 3\times10^8$ m/s.

$$H'_{BS} = H_{BS} - H_E \quad (8)$$

$$H'_{UT} = H_{UT} - H_E \quad (9)$$

where H_{BS} and H_{UT} are the actual antenna heights, and H_E is the effective environment height equal to 1 m. Table 1 shows the cellular generations based on the BS density ratio (β). Table 2 lists the simulation parameters used in the study.

Table 1 Classification of cellular network generations based on base station density ratio (*β*) [33]

β	Cellular Generations
$\beta \leq 10$	2nd Generation ~ 3rd Generation
$10 < \beta < 60$	4th Generation
$60 < \beta < 2500$	5th Generation
B > 2500	Ultra-Dense Network (UDN) – Beyond 5G

Table 2 Parameters used in the simulation [33]

Parameters	Values in units
Pico-to-Macro BS density ratio (*β*)	{10, 15, 30, 50, 65, 80, 333, 500, 1000, 1500, 2500} [7]
Pico BS density (λ_p)	{0.1, 1, 10, 50, 65.065, 100, 500, 1000, 2500, 5000, 10000 (BSs/km^2)} [7]
Tier BS Power (T_M,T_P)	{46,24} dBm [7]
Gain of MBs (*min G_M*, *max G_M*)	{0,15} dB [7]
Gain of PBSs (*min GP*, *max GP*)	{0,5} dB [7]
Gain of UE antenna	0 dB [7]
min|*HM*|, *max*|*HM*|	{0,23.5} m [35]
min|*HP*|, *max*|*HP*|	{0,8.5} m [35]
PL slopes for MBS [*α*M1LOS, *α*M2LOS, *α*MnLOS]	{2.2,4,3.908} [35]
PL slopes for PBS [*α*P1LOS, *α*P2LOS, *α*PnLOS]	{2.1,4,3.53} [35]
Carrier Frequency (f_c)	2 GHz [35]
Band width (*BW*)	10 MHz [35]
Thermal Noise (N_o)	-104 dBm [35]

4. Performance Metrics

EE is an important performance metric in two-tier HetNets and refers to the amount of energy used to transmit a certain amount of data. It is calculated as the ratio of the total data rate transmitted in the network to the total power consumption of the network. In HetNets, the power consumption includes both the transmit power of the BSs and the backhaul power required to transport data between the BSs and the core network. The EE metric is critical for network operators because it directly impacts their operational costs. Improving EE can help network operators reduce their energy consumption, which can result in lower operational costs and a reduced carbon footprint. Moreover, EE is also critical for meeting the growing demand for wireless connectivity, as it allows network operators to provide better coverage and capacity without increasing their energy consumption. In HetNets, EE is affected by various factors such as the density and location of BSs, number of users, modulation and coding schemes used for data transmission, and distribution of resources strategies employed. Therefore, optimizing these factors can significantly improve EE in HetNets. To improve EE, network operators can deploy a mix of MBSs and PBSs to achieve better network coverage, capacity, and resource utilization. In addition, techniques such as IMC can be used to reduce power consumption during periods of low traffic by shutting down idle BSs. Furthermore, network operators can employ resource distribution strategies, such as dynamic power allocation and user association, to ensure that the network resources are efficiently used while minimizing power consumption. In summary, improving EE is essential for network operators to reduce their operational costs and meet the growing demand for wireless connectivity while minimizing their environmental impact. A vital aspect to evaluate in two-tier heterogeneous cellular networks is EE, which can be measured using specific performance metrics.

4.1. Energy Efficiency Ratio (EER)

The EE of a heterogeneous cellular network consisting of macro and pico BSs can be measured using a metric called the energy efficiency ratio (EER). This metric indicates how much data can be transmitted per unit of energy consumed in the network.

To calculate the EER of a two-tier macro and pico BS network, the following formula is used:

EER = System Throughput/Total Energy Consumption (10)

4.2. Energy per Bit (EPB)

Another performance metric used to assess EE is energy per bit (EPB), which indicates the amount of energy required to transmit a single bit of data. The EPB of a two-tier macro and pico BS heterogeneous cellular network can be calculated as follows:

EPB = (Total Energy Consumption)/(Total Number of Bits Transmitted) (11)

Optimizing EE involves reducing the total energy consumption while maximizing the system throughput and total bits transmitted. Achieving this can involve adjusting traffic loads, optimizing transmit power, and carefully placing PBSs to avoid interference with MBSs. Improved EE has benefits such as better service provision, reduced carbon footprint, and improved business sustainability.

5. Results and Discussion

The ratio of MBSs to PBSs (β) is critical in the EE of a 5G HetNet. The deployment of more PBSs than MBSs can result in improved EE. This is due to the lower power consumption of PBSs compared with that of MBSs. Furthermore, PBSs can be placed closer to users, which reduces the distance the data must travel and energy consumption. PBSs can also be powered by alternative energy sources such as solar or wind power, which makes them more sustainable and improves EE. In contrast, having more MBSs than PBSs can negatively impact EE. MBSs consume more power and are usually located further away from users, which increases the distance data has to travel, leading to higher energy consumption. In addition, MBSs have a larger coverage area, which can result in a higher number of users served by a single base station. This, in turn, can lead to inefficient resource utilization, which increases energy consumption. Therefore, it is important to carefully consider the ratio of MBSs to PBSs when designing and deploying a HetNet. By deploying more PBSs, operators can improve EE, reduce their carbon footprint, and improve sustainability of their businesses. In this paper, we have considered EER in Mbps/W.

5.1. Simulation Tool

In this study, calculating EE as a function of β using Matlab involves several steps.

1) The values can be initialized by referring to Table 2, and random locations can be generated for both the BSs and UEs using the built-in rand command;

2) Next, the path loss (PL) between each BS and UE can be calculated using the PL model described in Section III, along with the Rayleigh fading model;

3) Once the path loss model is calculated, a random UE can be selected using the randi command, and the received signal-to-interference-plus-noise ratio (SINR) can be computed for each UE;

4) Because the noise is negligible, as shown in Table 2, the SINR is equivalent to the signal-to-interference ratio (SIR);

5) Using the SIR, the data rate for each UE can be calculated using the Shannon capacity formula, which relates the data rate to the SINR and channel bandwidth, as demonstrated in Equation 12.

Data Rate = (BW/Load) $\log_2(1 + \text{SIR})$ (12)

6) In the last step, the energy consumption for each UE can be calculated by applying a power consumption model that links the energy consumption to both the data rate and the circuit power consumption.

7) With the energy consumption computed, the EE can be determined for each UE using Equation 13.

EE = Data Rate/(Total Power/Load) (13)

8) Aggregate the EE values for all the UEs in each tier and calculate the total EE for the HetNet.

9) Vary the parameter β and repeat the steps above to obtain the EE as a function of β.

10) Plot the results using Matlab to visualize the relationship between EE and β.

5.2. Impact of Antenna Height on EE

In this paper, we examined how the EE of a 5G HetNet is affected by the ratio of MBSs to PBSs, which is represented by the symbol β. The focus of the investigation is on the height of the antennas. The authors have plotted the results in Fig. 4, which reveals the relationship between EE and antenna height. The blue line with square markers indicates the maximum EE achieved with the minimum antenna height for pico and macro cells. This is because lowering the antenna height reduces signal attenuation caused by PL and minimizes interference with neighboring cells, resulting in lower overall energy consumption and improved EE. Moreover, using lower antenna heights for pico cells can improve spectrum utilization by reducing interference between cells, which enhances network throughput and capacity. Overall, this study highlights the importance of selecting appropriate antenna heights and β values to optimize EE in HetNets.

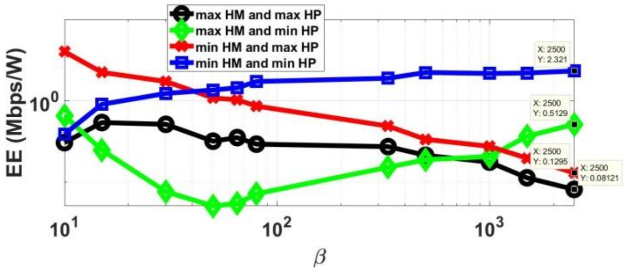

Fig. 4 Energy efficiency without IMC

5.3. Energy Efficiency with IMC

IMC is a crucial feature of 5G networks that enables devices to enter a low-power state when they are not actively transmitting or receiving data. This feature offers significant benefits to the EE and sustainability of wireless networks. With IMC, devices can conserve battery power during idle periods, which helps extend the lifespan of batteries and reduce e-waste. Moreover, this feature reduces the overall energy consumption of the network by allowing devices to enter a low-power state, which reduces the frequency of charging required for devices. IMC feature is particularly important for devices with limited battery life, such as smart phones, wearables, and IoT devices. By allowing these devices to enter into an idle mode during periods of inactivity, IMC helps reduce power consumption and prolong battery life. Furthermore, this feature helps reduce the number of devices competing for network resources, which improves the overall performance of the network. IMC feature in 5G networks enables devices to allocate resources more efficiently by entering an idle mode when they are not actively using the network. This not only reduces the overall energy consumption of the network but also contributes to the sustainability of wireless networks. By reducing the environmental impact of wireless communication technologies, IMC helps meet sustainability goals and reduce the carbon footprint of wireless networks. In summary, IMC is a critical feature in 5G networks that significantly improves the EE of the network, reduces the power consumption of devices, and enhances the sustainability of wireless networks. By allowing devices to enter into a low-power state during periods of inactivity, IMC reduces the frequency of charging required, prolongs battery life, and reduces the environmental impact of wireless communication technologies.

5.3.1. Antenna Height Impact on EE with IMC

The EE of a 5G network is a critical factor that impacts the sustainability and performance of the network. IMC is a feature that allows devices to enter a low-power state during idle periods, thereby significantly reducing power consumption and enhancing battery life. The benefits of IMC on EE are demonstrated in Fig. 5, which demonstrates that EE of the system improves when IMC mode is used. The black with 0 marker represents the maximum value of both |HM| and |HP|, and the EE improves from 0.0812 to 0.684 Mbps/W. The red with × marker represents the minimum |HM| and maximum |HP|, and the EE improves from 0.129 to 0.968 Mbps/W. The green color with marker represents the maximum |HM| and minimum |HP|, and the EE improves from 0.5129 to 4.142 Mbps/W. Finally, the blue color with marker represents the minimum value of both |HM| and |HP|, and the EE improves from 2.32 Mbps/W to 6.1 Mbps/W. Therefore, it can be concluded that IMC mode has a significant positive impact on the EE of the system, which is essential for the deployment of green wireless communication networks. While the authors of the paper found that the optimal EE is achieved with the minimum heights of the antenna, this may not be practical due to security and vandalism concerns. Therefore, the EE with the maximum absolute height difference between the macro and pico base stations (|HM|) and the minimum absolute height of the pico base station (|HP|) are considered optimal, resulting in EE of 4.142 Mbps/W. This finding suggests that while the optimal antenna height may not always be feasible, other design factors can be optimized to achieve the highest possible EE for a given network configuration.

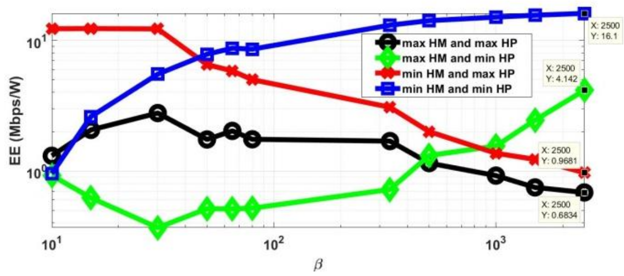

Fig. 5 Energy efficiency with IMC

5.3.2. Antenna Gain Impact on EE with IMC

In this section, the authors analyze the effect of gain on the optimal EE with max |HM| and min |HP|. Fig. 6 presents the results, showing that by applying gain on pico BS, the EE is improved from 4.142 Mbps/W to 5.783 Mbps/W. This improvement in EE is due to the fact that the gain increases the signal strength during the transmission, which leads to a more efficient use of the network resources. By enhancing the signal strength, the network can cover a wider area, thereby reducing the number of base stations required to maintain the coverage and capacity. This, in turn, reduces the energy consumption of the network and increases its overall EE. Therefore, the application of gain can significantly impact EE of the network, making it an important factor to consider in the optimization of HetNets. The impact of the antenna gain is shown in Fig. 6.

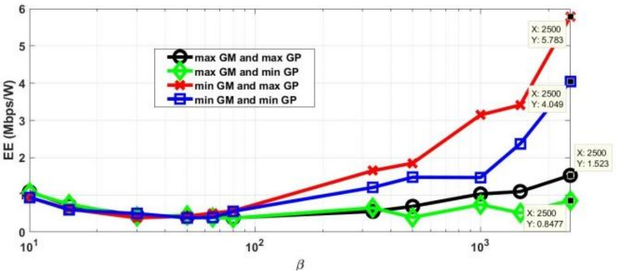

Fig. 6 The EE is plotted as a function of β for maximum |HM| and minimum |HP | under different antenna gain scenarios

EE has been explored in this section, and the results are illustrated in Fig. 6. The figure shows that increasing the antenna gain of pico BSs can lead to a significant improvement in EE. By increasing the antenna gain, pico BSs can cover a larger area while consuming the same amount of power. This means that fewer pico BSs are required to provide coverage, leading to lower overall energy consumption in the network. Another benefit of increasing the antenna gain of pico BSs is the reduction of interference between cells. When interference is minimized, devices can operate at a lower power level, which reduces the overall energy consumption of the network. This reduction in interference can also lead to higher throughput and capacity, as devices can communicate more efficiently with the network. Furthermore, the authors investigated the effect of antenna gain on EE in a practical scenario with maximum values of |HM |and |HP|, as depicted in Fig. 7. The results show that increasing the antenna gain of pico BSs can also lead to a significant improvement in EE in this scenario. By optimizing the antenna gain of pico BSs, the network can achieve a balance between the coverage area and power consumption, leading to improved EE and overall network performance. The study depicted in Fig. 7 analyzes the impact of applying antenna gain on the EE of a heterogeneous cellular network. This suggests that applying the gain only to macro or macro and pico BS antennas does not always improve EE. Increasing the antenna gain of macro or macro and pico BSs can extend their coverage area [33], resulting in increased interference between cells, negatively affecting network performance and increasing overall energy consumption. Another issue when applying antenna gain only to macro or macro and pico BSs is an imbalanced load distribution between BSs. Since pico cells have a smaller coverage area than macro cells, increasing the antenna gain of both types of cells equally can cause the coverage area of the macro cell to increase more than that of the pico cell, leading to an imbalanced load distribution. This can result in underutilization of pico BSs and overutilization of macro BSs, which can reduce EE. Moreover, increasing the antenna gain of macro or macro and pico BSs can also increase the cost of the network infrastructure. High-gain antennas are more expensive and require more complex installation than low-gain antennas, which can be a financial burden on network operators. Therefore, it is important to carefully consider the impact of antenna gain on network performance, load distribution, and cost before making any changes to the infrastructure.

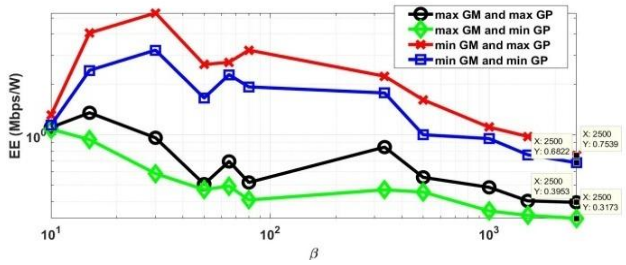

Fig. 7 The plot shows the EE with the maximum |HM| and maximum |HP| achieved by varying the antenna gain as a function of the BS density ratio (β)

However, increasing the gain on a Pico BS improves EE because it reduces the transmission power required to maintain a certain level of coverage and quality of service. This is because a higher gain antenna can transmit a signal over a greater distance with the same amount of power, which means that the BS can operate at a lower transmission power level. When a BS operates at a lower transmission power level, it consumes less energy and therefore has a lower carbon footprint. In addition, lower transmission power levels can reduce interference with other BSs, leading to more efficient use of spectrum and further energy savings. By reducing the transmission power required to maintain a certain level of coverage and quality of service, increasing the gain on a Pico BS can lead to significant energy savings for both the BS and the user’s device. This can result in lower energy costs, reduced greenhouse gas emissions, and a more sustainable wireless network.

6. Conclusion

EE of two-tier HetNets is strongly influenced by β. Optimizing the density of pico BSs while considering the coverage area and traffic load of each cell can improve the EE of the network. As the density of pico BSs increases, the coverage area of each cell decreases, which can lower the energy consumption of the network. This is because smaller coverage areas require less transmit power from the BSs to provide sufficient coverage, resulting in lower energy consumption. Furthermore, smaller coverage areas can reduce interference between cells, which can improve the overall EE of the network. The authors of the study also discovered that increasing the antenna height can result in an increase in the transmit power required to maintain a certain signal strength at the UE, which can increase the energy consumption of the BS. In addition, increasing the antenna gain of pico BSs can lower the interference between cells, which can further enhance the network's EE. When interference is reduced, devices can operate at a lower power level, resulting in lower overall energy consumption of the network. However, applying the gain only to macro or macro and pico BS antennas can reduce EE as extending the coverage area of these BSs can increase the interference between cells, thereby decreasing network performance and increasing overall energy consumption. While increasing the gain of a pico BS antenna can lead to significant energy savings and improved network efficiency, there are also potential disadvantages to consider, such as increased cost, complexity, and the possibility of narrower coverage areas. In this research, the authors improved the EE from 0.00181 to 341.7 bps/Hz/W, which is 99.995%, meaning that this HCN system has experienced substantial improvement of EE. This increase in EE can be interpreted as the ability of the HCN system to transmit a significantly higher amount of data per unit of power consumption compared with its previous performance.

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