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Energy Efficiency and Load Optimization in Heterogeneous Networks through Dynamic Sleep Strategies: A Constraint-Based Optimization Approach

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Abstract: This research endeavors to advance energy efficiency (EE) within heterogeneous networks (HetNets) through a comprehensive approach. Initially, we establish a foundational framework by implementing a two-tier network architecture based on Poisson process distribution from stochastic geometry. Through this deployment, we develop a tailored EE model, meticulously analyzing the implications of random base station and user distributions on energy efficiency. We formulate joint base station and user densities that are optimized for EE while adhering to stringent quality-of-service (QoS) requirements. Subsequently, we introduce a novel dynamically distributed opportunistic sleep strategy (D-DOSS) to optimize EE. This strategy strategically clusters base stations throughout the network and dynamically adjusts their sleep patterns based on real-time traffic load thresholds. Employing Monte Carlo simulations with MATLAB, we rigorously evaluate the efficacy of the D-DOSS approach, quantifying improvements in critical QoS parameters, such as coverage probability, energy utilization efficiency (EUE), success probability, and data throughput. In conclusion, our research represents a significant step toward optimizing EE in HetNets, simultaneously addressing network architecture optimization and proposing an innovative sleep management strategy, offering practical solutions to maximize energy efficiency in future wireless networks.

Keywords: energy efficiency; HetNets; energy utilization efficiency (EUE); network performance; wireless communication; optimization algorithms; stochastic geometry



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1. Introduction

The proliferation of high-speed devices, such as tablets, smartphones, laptops, and machine-to-machine (M2M) communication devices, drives the demand for high-data-rate networks. According to the 2022 annual report from Ericsson, mobile data traffic volume is projected to more than double between 2023 and 2027, with mobile video traffic expected to grow by nearly 30% annually until 2027 [1]. Researchers from academia and industries have reached a consensus that existing progress in the field of communication fails to meet the explosive data requirements of the foreseeable future.

Consequently, there is a growing recognition of the need for a paradigm shift in future 5G cellular networks [2–7]. The expectations from 5G are broad, encompassing a high data rate, high capacity, high energy efficiency, low latency, seamless connectivity, a secure network, and support for a wide range of applications.

Figure 1 illustrates the key demands of 5G networks, which include high data rates, high capacity, seamless connectivity, high energy efficiency, security, support for a wide range of applications, and low latency. These elements ensure that 5G can handle more devices, provide faster and more reliable connections, and support diverse applications while maintaining energy efficiency and strong security measures. Together, these demands enable the advanced capabilities and improved performance of 5G technology [8–10].

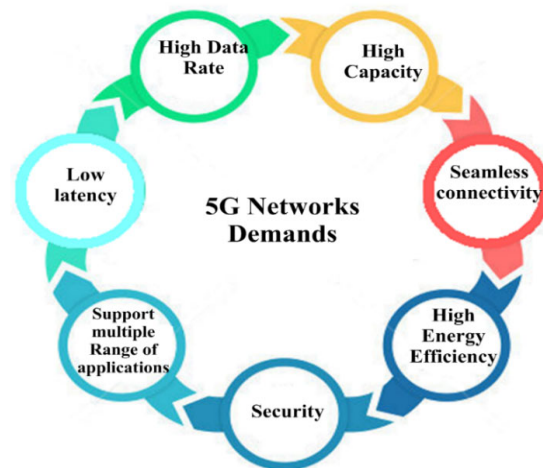


Figure 1. 5G network demands.

The “Big Five” key enabling technologies for 5G networks, illustrated in Figure 2, directly support the key demands outlined here. High data rates and capacity are achieved through the use of mmWave and small-cell base stations, addressing the need for high-speed and high-capacity connectivity. Massive MIMO enhances spectral efficiency and capacity, ensuring seamless connectivity and robust performance even with numerous simultaneous connections. M2M communication supports a wide range of applications, including the internet of things (IoT), by enabling direct device interactions without human intervention. D2D communication reduces latency by facilitating direct device-to-device connections, meeting the demand for low latency essential for real-time applications.

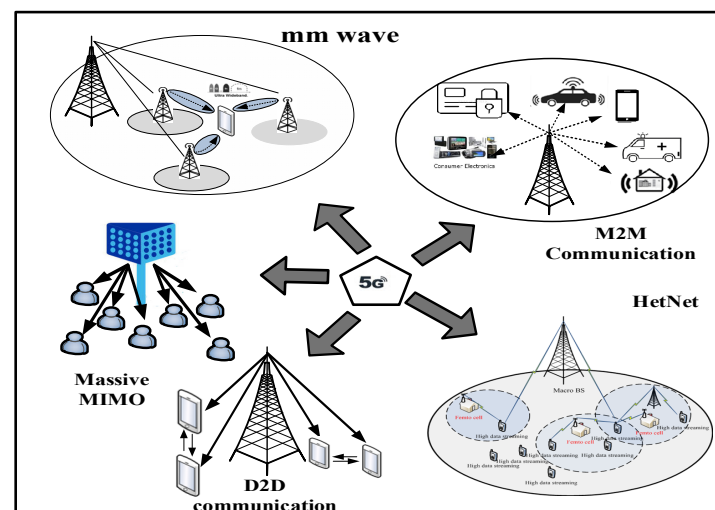


Figure 2. The ‘Big Five’ fundamental technologies for 5G networks.

Finally, heterogeneous networks (HetNets) integrate various types of base stations to ensure comprehensive coverage and high energy efficiency, optimizing network performance and reliability [11,12].

Among these technologies, massive MIMO (m-MIMO) and HetNets stand out as particularly promising. Both are comparable in terms of data rate and implementation aspects, yet HetNets emerges as the more powerful solution.

Table 1 further supports the potential of HetNets as a cost-effective method for achieving the prime objectives of 5G networks. Conversely, m-MIMO lags behind HetNets in terms of coverage and implementation cost, facing additional challenges such as complex network analysis, channel estimation, pilot contamination, and high deployment costs.

Table 1. Key enabling technologies for 5G.

Technology	Enabling Solutions					Ref.
	High Data Rate	High Capacity	Low Energy Consumption	High Coverage	High Implementation Cost	
HetNets	✓	✓	✓	✓	×	[13–17]
m-MIMO	✓	✓	✓	×	✓	

In this research work, we are also focusing on improving energy efficiency (EE) in HetNets. Given their potential and viability, HetNets can be considered the most potent solution to meet the primary demands of 5G networks, and enhancing their energy efficiency further strengthens their suitability for widespread adoption.

2. Literature Review

It has been now globally acknowledged that energy-related issues will have a greater impact in the coming years on wireless communication networks. Energy consumption by wireless networks can be minimized in various ways. Broadly, these approaches can be classified into five different categories, listed in Figure 3. Each technique has its benefits and limitations. Upgrading hardware equipment, e.g., power amplifiers, BS site relocation, and reselection, can provide maximum energy saving but requires costly solutions for hardware replacements [18].

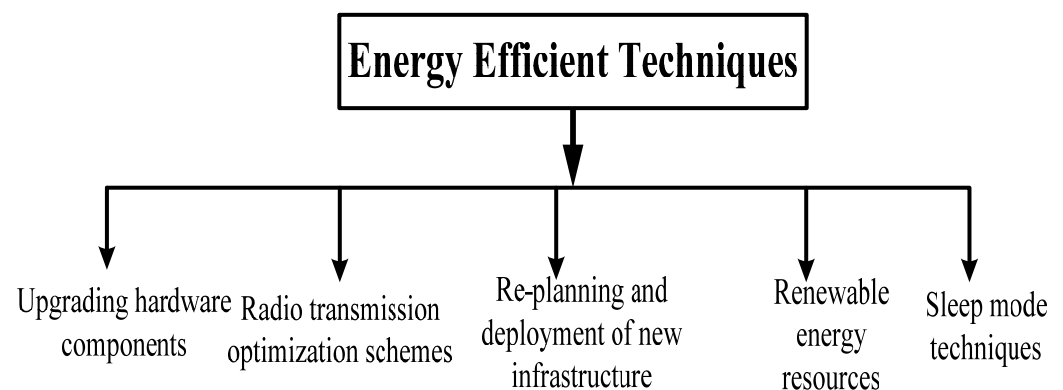


Figure 3. EE techniques in cellular network.

Radio transmission optimization techniques, e.g., cooperative relays, cognitive radios, signal resource allocation, and channel coding schemes are comparatively cheaper solutions, but these techniques have high chances of error due to uncertainty and have trade-offs between energy saving and system performance. Re-planning and deployment of new infrastructure like integrated macro and small cells will introduce new challenges to the radio interface. Adoption of renewable resources like solar, hydro, and wind power can serve as a long-term solution but it will come with a high replacement cost, and for current BS, there are limited gains [19].

Last but not least is the sleep mode techniques, e.g., turning on/off underutilized BS can provide much easier implementations and low-cost solutions for energy efficiency improvements. However, its network modeling will be a difficult task. It can be noticed that out of many EE techniques, sleep mode schemes seem to be the most viable option for cellular networks, as sleep mode schemes do not require any hardware replacement. This makes it a cost-effective and potentially viable solution for making current HetNets more EE [20,21]. In addition, it is also imperative to notice that before enabling the sleep mode in particular BSs, the intended sleep-enabled BSs must coordinate with other BSs and release its channel resources to active neighboring BSs. The active BS must provide extended data rate services and coverage to users located inside sleeping BSs [22].

The exchange of traffic information between BSs is usually managed by the BS Controller. However, switching a BS to sleep mode will eventually result in an increase in outage probability and call-blocking events, which will result in a deteriorating QoS experienced by users [23]. To improve the energy efficiency of cellular networks, researchers have identified the following categorical sleep-enabling techniques: Figure 3 shows the state-of-the-art small-cell sleep-enabling methods. During sleep mode, appropriate UA can be used to increase network performance. For example, when a BS enters sleep mode, users impacted by this should link to other BSs that have available resources. It means that the affected users should not automatically connect to the BS that provides high SINR if they can obtain BS connectivity with more bandwidth (capacity), low SINR, or a larger distance [2,24]. Hence, an optimal UA method that maximizes BS cooperation is desired for maintaining acceptable QoS with maximum energy savings.

In traditional UA schemes, users tend to associate with the BS that provides the best SINR levels. With this understanding, all the BS will be fully loaded, and this strategy is used to maximize the network throughput. However, HetNets, where small-cell BS is underlaid by macro BS, have much lower transmit power as compared to macro BSs. This results in a significant difference in the coverage areas of macro and small-cell BS, ultimately making user association more difficult in EE HetNets. For example, if UA is based on the received signals from BSs, macro BS is more prone to be fully occupied due to its high coverage, antenna gain and transmit power. On the other hand, small-cell BSs will have few users due to their smaller transmit power, antenna gain, and coverage. This is an extremely undesirable situation because the user connected with macro parent BSs will have reduced capacity (bandwidth) compared to the users in the tier of small cells. This situation leads to an inequitable distribution of resources among users and may decrease the network's total sum rate and spectral efficiency [25]. Hence in energy-efficient HetNet UA is one of the major features that may affect many other key performance indicators like QoS, load balancing, interference, etc. [26]. To cater to this issue in HetNets, artificial cell biasing methods are used to maximize load balancing and manipulate UA. In this technique, users are artificially biased to favor small-cell BS over macro cell. However, it is worth mentioning that when a user is artificially inclined to link to a small cell, it will receive strong interference from macro BS.

This situation will lead to increased aggregate interference, which certainly affects the QoS parameter experienced by the biased user. Therefore UA biasing has a tradeoff performance with average rate and coverage probability in HetNets [27]. Extensive efforts have been made in the last few years for UA optimization in HetNets [2,26]. In this research work minimum, biased transmission distance (m-BTD) scheme presented in [26] is adopted. In this method, a user already knows the location of nearby BSs from all tiers along with its location. The user is responsible for computing the relative distance to the nearest BS from each tier. A biasing system is defined which has real numbers [8].

Self-organizing networks (SON) were proposed in 3GPP standards. Later on, it was implemented in 4G standards including WiMAX and LTE. Robust network management is provided by SON. Cell breathing or cell zooming has the same features as SON but offers greater adaptability. It is a network layer technique in which the size of a small cell is dynamically modified based on data traffic conditions. by changing BS antenna

transmission power, tilt angle, or height. From an implementation point of view, it is simple as compared to turning off/on BS. However, small-cell deployment is considered the most recent and robust method to improve EE in wireless cellular networks [22,25,28–30]. This research work is also based on adapting EE in HetNets through a small-cell sleep deployment technique. Figure 4 represents the existing sleep-enabling techniques.

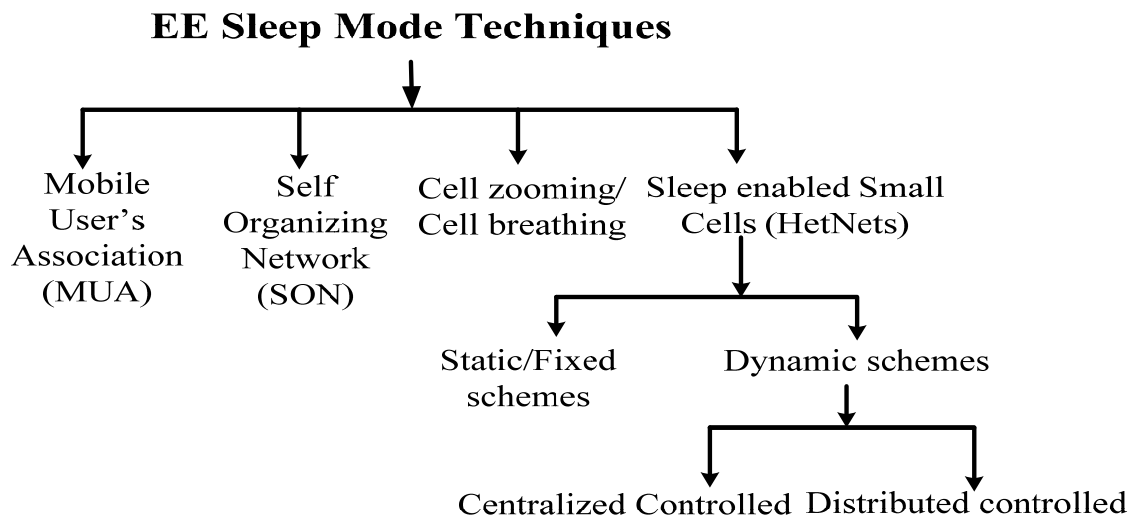


Figure 4. Sleep enabling techniques.

The above-mentioned techniques are applied to optimize EE in a single-tier network, i.e., macro only. However, adding a small BS will change the network infrastructure from a homogenous to a heterogeneous network. The main focus of this research is on enhancing energy efficiency in a HetNet environment, comprising small-cell BSs alongside macro BSs. Table 2 represents the summary of BS sleep mode techniques in a cellular network. The majority of research efforts have concentrated on enhancing data throughput, coverage, resource efficiency, and other aspects not directly related to energy efficiency. The performance analysis of HetNet has not been investigated to its full potential from an energy point of view. Within HetNets, when small cells are expected to enter the sleep phase, they typically adopt two main types of sleep methods which are fixed, static, and dynamic sleep methods. Fixed and static sleep methods use a predetermined number of state switches over a set period. In contrast, dynamic sleep mode schemes permit BSs to adjust their states flexibly, responding to parameters such as traffic and channel conditions [7,20,31].

Dynamic sleep mode scheme performs better than fixed schemes but due to an increase in the number of switching operations, its computation complexities are also higher [32]. The dynamic scheme is further divided into two subcategories named, centralized schemes (CS) and distributed schemes (DS). DS approach provides more ease in terms of its implementation and manageability but has some trade-off in terms of its performance as CS have knowledge of all BS in the entire network, so their impacts are high when compared with distributed ones. Moreover, introducing sleep mode in small cells can minimize the overall consumption when compared to a macro-only network [33]. However, sleeping mode also introduced some fundamental limitations on some important factors like optimum QoS, outage, coverage, and throughput.

Consequently, only certain privileged users of macro-cell cancer can have a high data rate, while others may suffer from outages. In [34], optimized UA was used through total data rate and energy consumption ratio maximization. However, this approach does not provide an improvement in the energy efficiency of the network and ignores the negative impact on QoS parameters [2].

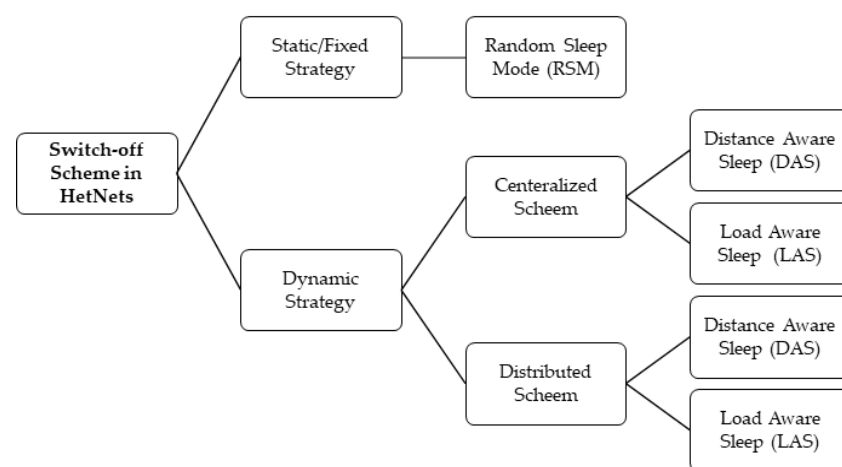
Table 2. Summary of BS sleeping techniques.

BS Sleeping Techniques	Approach	Key Points/Description
Mobile User Association (MUA)	Mobile users transfer themselves from sleeping BS to the nearest BS	Maximum energy efficiency is dependent on the channel state information and access conditions of the nearest BS
Self-Organizing Network (SON)	BSs shared their traffic conditions with other BSs and then automatically configured themselves for sleep/active modes	While preserving QoS requirements, this technique aims to minimize the active BSs through collaboration among multiple small cells.
Cell Breathing/Cell Zooming	BSs continuously monitor the traffic conditions and adaptively change their coverage regions concerning traffic requirements	EE can be optimized by taking computationally complex zooming algorithms for BS cooperation
Small Cells Deployment or HetNets	Macrocells should remain in active mode while small BSs can go asleep	Optimal density deployment of both macro and small-cell BS is desired

Numerous valuable contributions have been published on energy efficiency for HetNets by considering the few QoS parameters and the effect of traffic variations [35,36]. Nevertheless, the common problem is that they have considered the traditional homogeneous hexagonal grid (HHG) model for the network topology design. The authors in [37–41] have to use stochastic geometry for performance analysis of HetNets. In particular, the authors in [37,38] have designed a k-tier HetNet using stochastic geometry and defined outage probabilities and average data throughput for the multi-tier network.

State-of-the-Art Sleep Mode Strategies

Random sleep mode (RSM) and load-aware sleep mode (LSM) currently represent the state-of-the-art BS switch-off strategies within contemporary HetNets [22,28,30,42], as shown in Figure 5. However, they come up with their own limitations and challenges. The most straightforward method for switching off small BSs involves independently turning them on or off based on a specified probability. The authors in [43,44] have explored algorithms based on random sleep mode (RSM). These schemes utilize probabilistic models such as the Bernoulli processes [45], the exponential process [46], the uniform process [47], the Poisson process [48], etc., which have been extensively investigated.

**Figure 5.** State-of-the-art switch-off methods for small-cell BS.

Moreover, in practical networks, data traffic loads vary across different geographical areas and are not uniform. These fluctuations in non-uniform traffic loads present an opportunity to reduce energy consumption by powering down less-utilized small-cell BSs.

These strategies are commonly referred to as load-aware strategies (LAS). In [49], authors suggested a LAS-based adaptive strategy for reducing cumulative energy consumption, which varies over time due to non-uniform data traffic. Both complete channel state information (CSI) and incomplete CSI are used to drive switch-off strategies.

In [50], researchers introduced a load-aware approach that optimizes a utility function considering interference and throughput. The model employs progressive and heuristic methodologies to dynamically deactivate unnecessary BSs, but it is worth mentioning that both [49,50] focus on the fixed data traffic profile.

Though the RSM- and LSM-based algorithms have fewer computational complexities and a comparatively low operational cost, these techniques lack adaptability to unpredictable factors such as the distance between small-cell and macro BSs relative to mobile users or traffic conditions in actual wireless networks [21,51]. Nonetheless, RSM-based algorithms harm the overall network energy efficiency rather than benefit, as the amount of energy efficiency achieved is insufficient to compensate for the decrease in average throughput and coverage [22].

The proposed dynamic DOSS considers realistic network models; accounts for random spatial network impact, user density variation, and diverse traffic conditions; and mitigates negative QoS impacts from sleep mechanisms. It provides computationally efficient solutions for energy-efficient HetNets while adhering to QoS requirements. These solutions are derived through stochastic geometry, optimizing the balance between energy efficiency and average throughput while meeting coverage probability and average wake-up time delay constraints.

3. Proposed Dynamical DOSS Model

The proposed model aims to maximize the EE of the HetNet using the D-DOSS approach. This approach involves a strategic algorithm that forms small clusters throughout the network by dividing it into N_C equal-sized squares, each representing a cluster region. These cluster boundaries help identify the cluster each BS belongs to but do not affect UA, as users will still connect to the BS providing the maximum SINR β_{max} . Compared to CS, the decentralized D-DOSS approach offers better ease of implementation and manageability, though it may have some performance trade-offs since CS has comprehensive knowledge of all BSs in the network, resulting in higher impact. The optimization problem is formulated considering various constraints such as delay constraints, coverage probability constraints, and SINR threshold constraints. The goal is to ensure efficient network operation while maintaining the required QoS for users.

The D-DOSS approach forms clusters within the network, with each cluster managed to balance load and performance. This decentralized management scheme optimizes power consumption and resource allocation, enhancing the overall EE of the network. Table 3 lists all the parameters used in the equations for implementing D-DOSS and problem formulation.

Table 3. Parameters definition for equations.

Parameter	Description
N	Total number of users in the network
n	Specific value that N can take
$P(N = n)$	Probability of having n users
λ_u	User density or arrival rate
λ_{BS}	Base station density or arrival rate
ρ	Constant used in cell size distribution, typically $\rho = 3.575$
Γ	Gamma function for factorial generalization
$P(N \leq n)$	Cumulative probability of having fewer users

Table 3. Cont.

Parameter	Description
K	Number of tiers in the network
$P(N = 1)$	The probability of having exactly one user
$P(N = 0)$	The probability of having no users
P_a	The probability of a BS being active
p_s	Probability of a BS transitioning to sleep mode
q_{ON}	Power consumption in the ON state
$q_{standby}$	Power consumption in the standby state
q_{sleep}	Power consumption in the sleep state
q_{swoff}	Power consumption in the switch-off state
P_f	Transmit power of the Femto-tier base station
P_T	Total power consumption
P_i	Transmit power of the i -th tier base station
α	Exponent of path loss
$A(\alpha, \beta_i, \beta_{min})$	A function involving SINR and path loss exponent
β_i	SINR threshold for the i -th tier
β_{min}	Minimum threshold of SINR
β_f	SINR threshold for the Femto-tier
P_{CON}	Probability of coverage when the BSs are in the ON state
β_{Th}	SINR threshold for QoS maintenance
d_{min}	Delay constraint
P_s	Probability to go into sleep mode
λ_f	Small Base Station density or arrival rate of small BS
$F_{X(A)}$	Probability density function of X
EE	Energy efficiency Function
β_f	SINR threshold for the small-cell tier
β_{macro}	SINR threshold for the macro BS tier

If $N_c = 1$, the CS and DS both will be identical. In a K-tier network which contains N total numbers of users. At any point X in VT, within an area of A , the probability of a BS to serve a user for three different cases is given as follows:

Case (i): $N = n$,

$$P(N = n) = \int_0^\infty P[N = n|X = A]f_x(A)dA$$

$$\cong \frac{\lambda_u^n (\rho\lambda_{BS})^K \Gamma(n+\rho)}{\Gamma(\rho)n!(\lambda_u + \rho\lambda_{BS})^{n+\rho}}$$
(1)

where N is the random variable, n is a specific value that N can take, $P(N = n) = \int_0^\infty P[N = n|X = A]f_x(A)dA$ is the conditional probability, $f_x(A)$ is the probability density function of X , and λ_u and λ_{BS} are user and small BS density, respectively. Further ρ is a constant used in cell size distribution here? $\rho = 3.575$, and (Γ) is a gamma function for factorial generalization. The above integral can be solved using identity [52] for the general case when a BS has few or fewer users, i.e., $(N \leq n)$,

$$(N \leq n) = \sum_{i=1}^K \sum_{j=1}^N \frac{\lambda_{u_j}^K (\rho \lambda_{BS_i})^\rho \Gamma(i + \rho)}{\Gamma(\rho) K! (\lambda_{u_j} + \rho \lambda_{BS_i})^{i+\rho}} \quad (2)$$

Equation (2) represents the cumulative probability of the number of users being less than or equal to n in a multi-tier network, incorporating user densities and base station densities, along with their respective system parameters. $(N \leq n)$ is the probability that the number of users N is less than or equal to n , K is the number of tiers in the network, N is the total number of users in the network, $\lambda_{\{u_j\}}$ is user density or arrival rate for the J th user, $\lambda_{\{BS_i\}}$ is the density or arrival rate of BSs for the i th BS.

In a special case (ii), when $N = 1$ or $N = 0$, i.e., when BS has at least a single user or it has no user, it can be represented as follows:

$$(N = 1) = \sum_{i=1}^K \left(1 + \frac{\lambda_u / \lambda_{BS_i}}{\rho}\right)^{-(\rho+1)} \frac{\lambda_u}{\lambda_{BS_i}} \quad (3)$$

$$(N = 0) = \sum_{i=1}^K \left(1 + \frac{\lambda_u / \lambda_{BS_i}}{\rho}\right)^{-\rho} \quad (4)$$

The probability of an active BS with at least one user can be written as follows:

$$p_a = 1 - [P(N = 0)] = 1 - \sum_{i=1}^K \left(1 + \frac{\lambda_u / \lambda_{BS_i}}{\rho}\right)^{-\rho} \quad (5)$$

The above equations indicate that the probability of a BS staying in active mode depends upon the user–BS density ratio denoted as $\vartheta = \lambda_u / \lambda_{BS_i}$, when $\lambda_u \gg \lambda_{BS_i}$, then $P(N = 0) \approx 0$ and $p_a \approx 1$ representing a situation when the BS density is sufficiently high to ensure at least a single user per BS.

The probability of BS to turn into the sleep mode will be p_s , which can be written as follows:

$$p_s = 1 - p_a \quad (6)$$

p_s represents the combined probability of BS to turn into the sleep mode in different modes, as per its activity level, i.e., each cluster has a fraction on $1 - p_s$ off total BS, which is in an active state.

4. Problem Formulation

Here, the goal is to optimize the EE of HetNet under the dynamically DOSS approach; therefore, the optimization problem can be formulated using the aforementioned constraints, i.e., delay constraints, the constraint of coverage probability, and SINR threshold constraints. Hence our goal is to maximize

$$\begin{aligned} & EE_{(q_{ON}, q_{standby}, q_{sleep}, q_{swoff})} \\ &= \left[\frac{1}{\lambda_f(q_{on} + 0.5q_{standby} + 0.15q_{sleep}) \frac{P_f}{P_T} + \sum_{i=2}^K \left(\frac{\lambda_i P_i}{P_T} \right)} \right] \\ & * \left[\frac{\lambda_f q_{ON} P_f^{2/\alpha} \mathcal{A}(\alpha, \beta_i, \beta_{min}) + \sum_{k=2}^K \lambda_k P_k^{2/\alpha} \mathcal{A}(\alpha, \beta_k, \beta_{min})}{\lambda_f q_{ON} P_f^{-2/\alpha} \beta_f^{-2/\alpha} + \sum_{k=1}^K \lambda_k P_k^{2/\alpha} \beta_k^{-2/\alpha}} + \log(1 + \beta_{min}) \right] \end{aligned} \quad (7)$$

Subject to

$$0 \leq q_{on} + q_{standby} + q_{sleep} \leq 1 \quad (8)$$

$$q_{on} + 0.5q_{standby} + 30q_{sleep} \leq d_{min} \quad (9)$$

$$P_{CON} = \frac{\lambda_f q_{ON} P_f^{\frac{2}{\alpha}} \beta_f^{-\frac{2}{\alpha}} + \sum_{j=2}^K \lambda_i P_i^{\frac{2}{\alpha}} \beta_i^{-\frac{2}{\alpha}}}{\lambda_f P_f^{\frac{2}{\alpha}} + \sum_{j=2}^K \lambda_i P_i^{\frac{2}{\alpha}}} \frac{1}{2\pi \csc(\frac{2\pi}{\alpha}) \alpha^{-1}} > \beta_{Th}$$

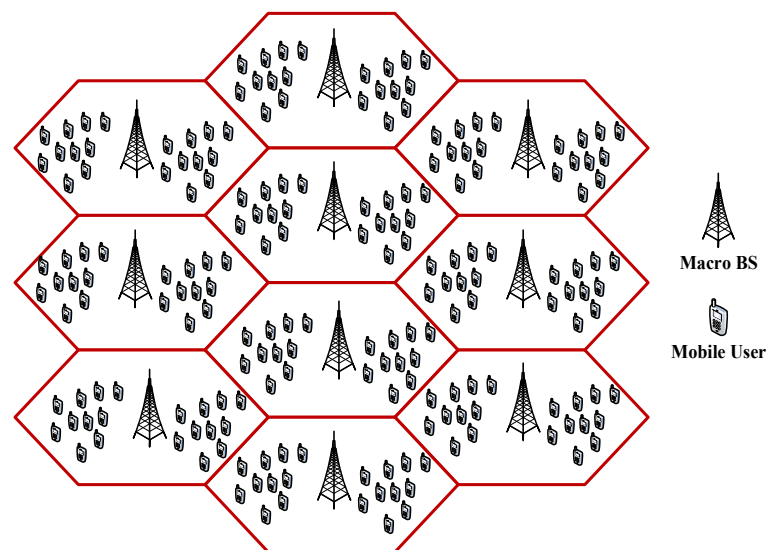
$$\begin{cases} \beta_{faverage} < \beta_{Th} \\ \beta_{macro} > 1 \end{cases} \quad (10)$$

Here, variables of interest include q_{sleep} , q_{on} , $q_{stand\ by}$, and the optimal solution would be the maximized EE, while the QoS requirement is satisfied. The variables related to problem formulation are defined as P_{CON} is the coverage when the BS is On state, λ_f is the arrival rate or density of femto-tier BS, $q_{\{ON\}}$ is power consumption in the ON state, $q_{\{standby\}}$ is power consumption in the standby state, $q_{\{sleep\}}$ is power consumption in the sleep state, $q_{\{swoff\}}$ is power consumption in the switch-off state, P_f is transmit power of the femto tier base station, P_T is the total power consumption, P_i is the transmit power of the i th tier base station, α is the Path loss exponent, $A(\alpha, \beta_i, \beta_{min})$ is a function involving the path loss exponent and SINR, β_i is SINR threshold for the i th tier, β_{min} is minimum SINR threshold, and β_f is the SINR threshold for the femto-tier.

5. Results and Analysis

HetNets will have an entirely different network topology than the traditional homogeneous network as represented in Figure 6. In a traditional network, all BSs space-out (single type-macro only) have distinct areas of coverage with a ubiquitous model for macro BSs locations. However, in HetNets, which has a nested combination of macro cells overlaid by small-cells design, the BSs are placed randomly according to the desired metric (like coverage requirement, high data rate requirements, etc.). Therefore, the nested BS locations need to be modeled by using some random process that corresponds to an entirely different network topology as compared to the traditional macro-only network.

HetNet comprises collections of multiple/single channels, which are also known as wireless links, sharing both frequency and space. Each channel has its own set of transmitters and receivers. In communication networks, channels can be simple or complicated. Point-to-point (p2P) is known as the simplest one, in which a single transmitter transmits data to only one receiver (like device to device). The broadcasting downlink channel sends information from a single transmitter to multiple receivers. The multiple access channels transmit information from many receivers to a single receiver (e.g., uplink channel), with multiple users transmitting data to associated BS. Figure 7 represents the model for the wireless channel.



(a) Homogenous Traditional Network

Figure 6. Cont.

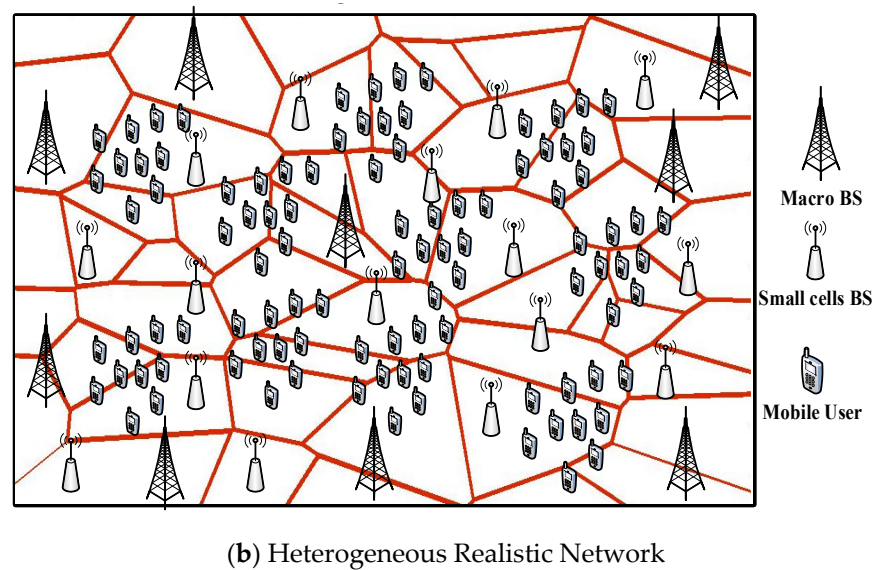


Figure 6. Traditional network topology (a) Vs. Real HetNet topology (b).

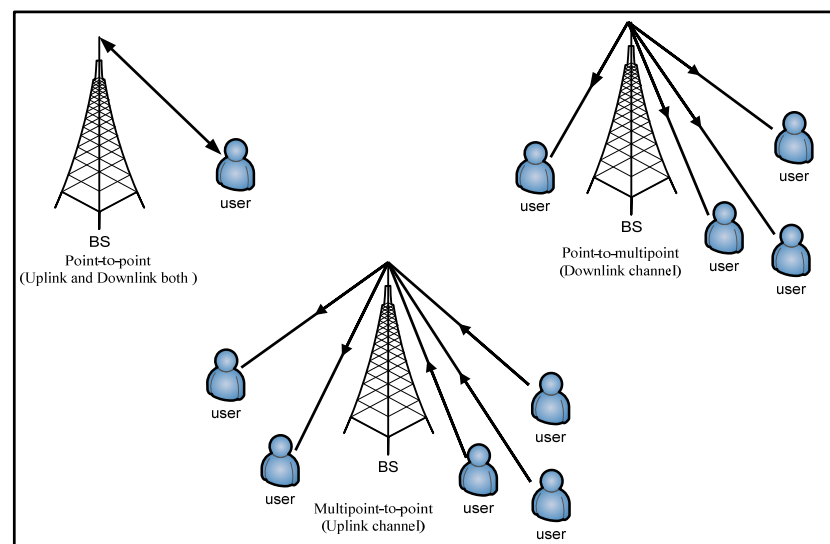


Figure 7. Wireless Network channel model.

5.1. Simulation Assumptions

The simulations were conducted using MATLAB, focusing on an interference-limited environment. In this study, we conducted 500 simulations per scenario to balance computational efficiency and result reliability. All the assumptions are justified and compared with the existing work with similar assumptions that have been referenced. All the simulation parameters are listed in Table 4. The following assumptions have been made for the assessment of the proposed dynamic DOSS EE strategy. Rayleigh fading channel is considered in this research which provides significant tractability and simplicity in the analysis of stochastic geometry-based HetNets.

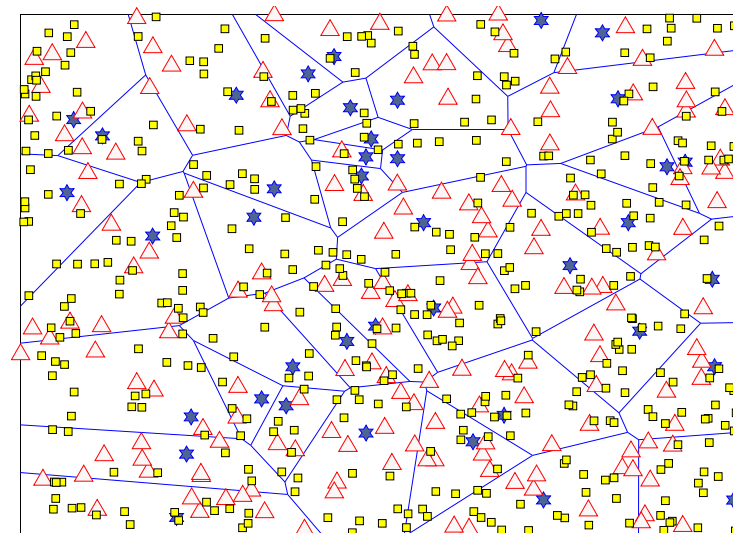
The effect of long-term shadowing has been ignored for the sake of reducing computational complexity. The long-term shadowing effect is usually ignored in much existing research [37,53]. However, authors in [54], showed that the accuracy of the long-term shadowing effect can be overcome by using Monte Carlo simulations. A universal frequency reuse pattern is adopted. It means that all BS in the entire network can access all the bandwidth available. Single Input Single Output antenna transmission is used. It should be noted that a lot of similar existing work of HetNets ignores the impact of MIMO [37].

Table 4. Parameters for Simulations.

BS Distribution	PPP
Number of simulations	500
Tier-1 (macro BSs) density	1/500 m ²
Tier-2 (femto BSs) density	4/500 m ²
The power consumption of macro BSs	400 W
The power consumption of femto BSs	40 W
SINR threshold of Femto β_f	1.1
SINR threshold for macro β_m	1.3
Path loss exponent	2
System bandwidth	10 MHz
Path loss model for macro	$L = 128.1 + 37.6\log_{10}(R)$ (R in km)
Path loss Model for small cell	$L = 140.7 + 36.7\log_{10}(R)$ (R in km)
MU rate requirement for macro BS	400 kbps
MU rate requirement for small-cell BS	400 kbps
The minimum distance between macro BS and MU	35 m
The minimum distance between macro BS and small-cell BS	75 m
The minimum distance between macro BS and MU	35 m
The minimum distance between small-cell BS and MU	10 m
The minimum distance between two small-cell BSs	40 m

5.2. Voronoi Tessellation Plot

A typical Voronoi tessellation plot from multi-tier HetNet is shown in Figure 8. The key idea behind the use of stochastic geometry research is that it can fairly capture the randomness and unpredictable nature of both TRX ends.

**Figure 8.** Voronoi tessellation plot for multi-tier network (★Macro, ▲Pico and ■MU).

It enables us to derive expressions in closed and semi-closed forms for critical performance metrics such as Signal-to-Interference Ratio (SIR), data throughput, channel capacity, and coverage probabilities without utilizing traditional deterministic models. Sleep mode strategies involve turning off or putting a few components or the entire BS or network into sleep mode when the network is underutilized [55].

Figure 9 represents the average daily traffic profile [56], which indicates the potential of energy saving by turning off a few or all BS components to sleep mode when the network load is comparatively low.

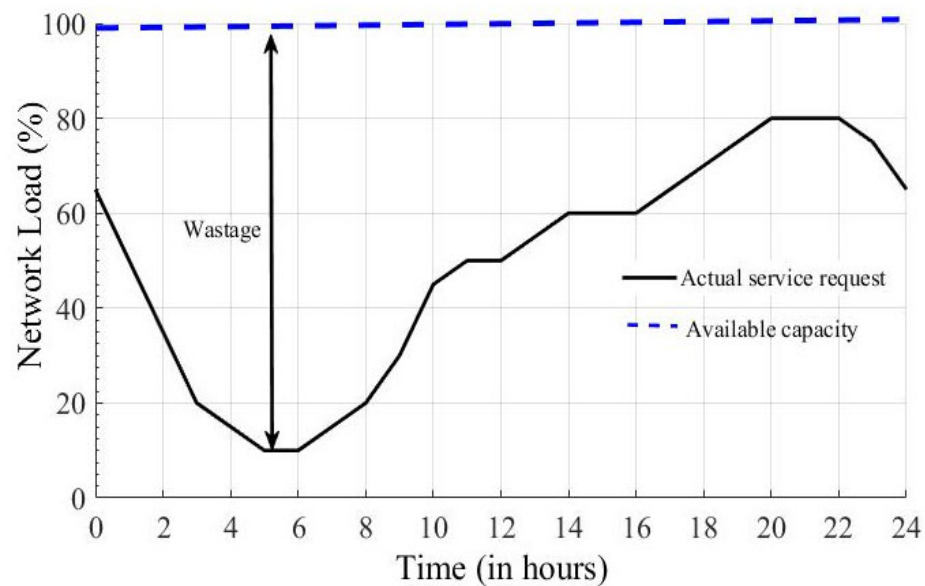


Figure 9. Daily data traffic profile.

In addition to that it is also important to note that before enabling the sleep mode in particular BSs, the intended sleep-enabled BSs must coordinate with other BSs and release its channel resources to active neighboring BSs. The active BS must be able to provide extended coverage and data rate services to users located inside sleeping BSs. The exchange of traffic information between BSs is usually managed by the BS Controller. However, switching a BS to sleep mode will eventually result in an increase in outages which eventually leads to a reduction in coverage probability.

5.3. Probability of Coverage

Figure 10 represents the probability of coverage in terms of small-cell BS active rate versus time. It evaluates the effectiveness of the proposed strategy against other cutting-edge techniques during the lowest (5 hours) to highest busiest (22 hours) duration as observed from the plot. It can be observed D-DOSS strategy outperforms other techniques, particularly during periods of low traffic density, thus preventing mobile users from experiencing outage regions.

In load-aware strategies, the association between small-cell BSs and any mobile users is determined only by the static data traffic profile which may vary from the realistic values, the aware strategy has the lower active rate whereas, for RSM, all small-cell BSs are switch on/off according to some probability distributions which leads towards the lowest BS active rate as shown in the plot. This phenomenon does not happen in the proposed strategy especially during low to medium traffic hours due to the dynamic on/off mechanism of femto BSs. Therefore, the small-cell BSs in the D-DOSS strategy are 60% to 80% more active than the other two strategies.

5.4. Energy Utilization Efficiency (EUE)

EUE of the wireless network is defined as the ratio of the energy saved in sleep mode by all small or femto BSs to the energy drained during active mode, multiplied by the number of users assisted during peak hours. Mathematically, EUE can be expressed as:

$$EUE = \left(\frac{\text{Energy saved during sleep mode}}{\text{Energy consumed in Active mode}} \right) \times (\text{no of serverd users}) \quad (11)$$

Certainly, a higher EUE value indicates more efficient energy utilization within the network. [57]. From Figure 11, it can be observed that proposed dynamically DOSS strategies make a much better utilization of energy than other sleep strategies, mostly when the throughput requirements are high i-e when the number of mobile users per small cell increases after 20 to onwards, the EUE ratio increases with increasing number of mobile users for the proposed dynamically DOSS strategy. The rationale behind this is as follows, although LAS strategies follow static data traffic profile the actual traffic condition varies daily, therefore using static profile may reduce network performance by turning on unnecessary small BSs in active mode when the actual traffic load is low.

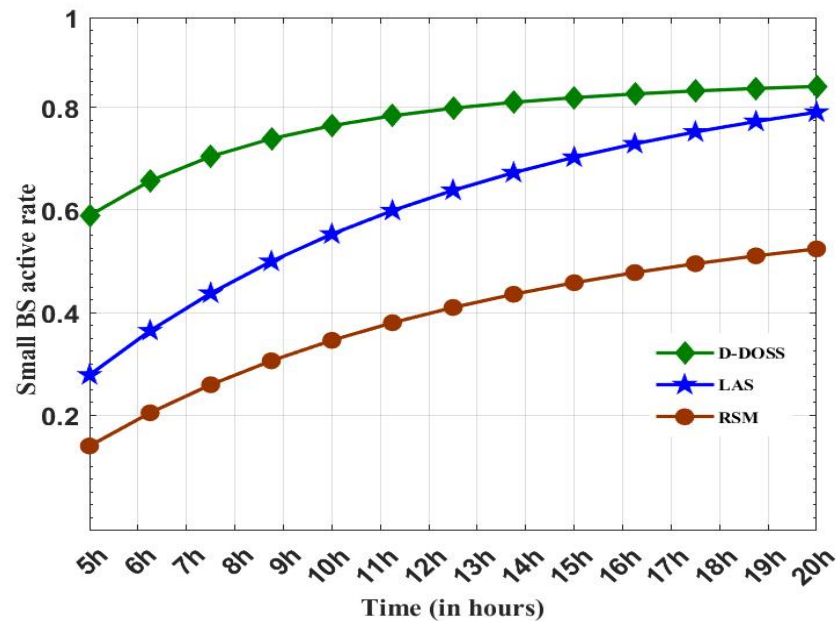


Figure 10. Small-cell BS active rate versus time.

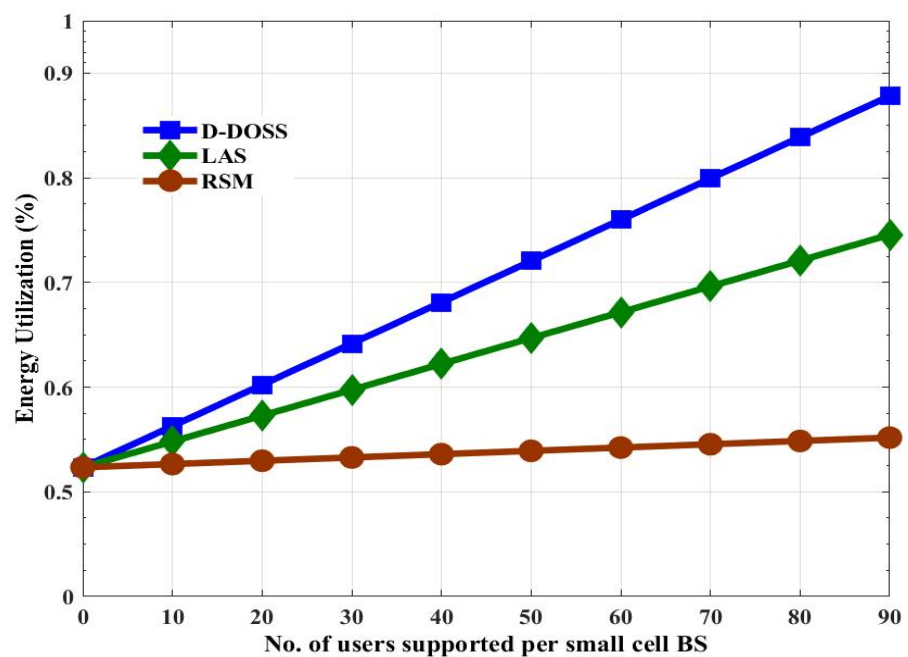


Figure 11. Energy utilization of network.

However, in dynamically DOSS strategies the small-cell BS adaptively update their activity status (ON/OFF) as per traffic variations so it will not only save energy but also serve a larger number of users as compared to LAS, thus it will lead towards improved EUE of the network.

5.5. Success Probability

For a randomly selected user located at the center of BS, Figure 12, shows the probability of success, with respect to q_{ON} . The simulated results show that the probability of mobile users receiving service when all the femto BSs are in off state is around 10%. Whereas with random sleep mode selection, this probability will increase to a level of 30% to 40%.

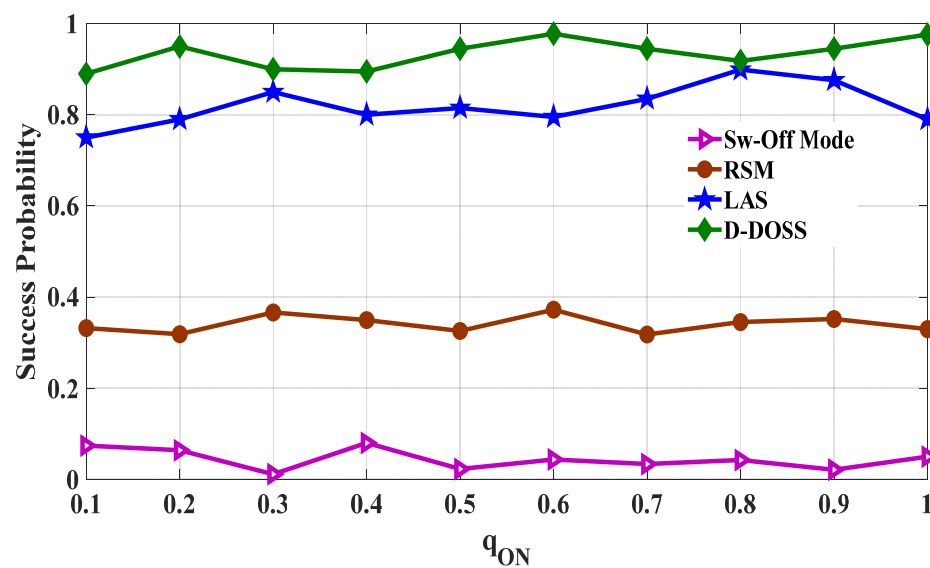


Figure 12. Probability of success.

In the load aware strategy, the chances of randomly selected mobile users obtaining the services can be raised up to 90%. However, simulated results indicate that dynamic DOSS outperforms all other techniques by ensuring the highest success probability. It means that dynamically DOSS strategy can provide a better QoS experience for the user along with the improved EE.

5.6. Data Throughput

Sleep mode strategies for energy efficiency significantly influence the average achievable data rate in the network. Figure 13 illustrates that in a network without sleep mode, both the average user rate and sum rate remain constant. This is due to the consistent number of active BS densities across the network. Furthermore, it establishes the upper limit on the maximum number of users served by BSs. However, with RSM, both the average sum rate and average user rate perform poorly due to its random selection of BSs to be turned off. In contrast, LAS and dynamically DOSS exhibit superior performance.

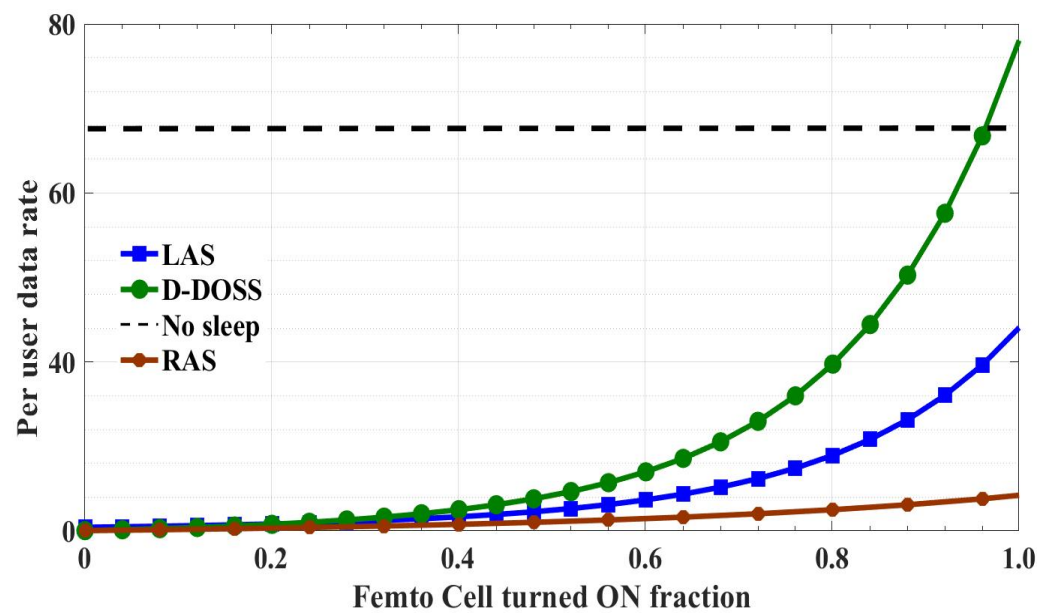


Figure 13. Average achievable per user throughput.

6. Conclusions

This research has achieved significant advancements in maximizing EE within HetNets to meet the growing demands of high-speed data networks. The study found that the proposed D-DOSS strategy resulted in a 60% to 80% increase in active small-cell BSs compared to state-of-the-art techniques during low to medium traffic densities [42]. Additionally, the EUE of the network showed substantial improvements, particularly with increasing numbers of mobile users, where the EUE ratio significantly rose. For instance, during high data traffic loads, the EUE under D-DOSS outperformed other sleep strategies, showcasing its ability to dynamically adapt to traffic variations and optimize energy utilization.

Despite the inherent trade-offs associated with distributed sleep approaches compared to centralized schemes, D-DOSS offers notable advantages in terms of implementation ease and manageability. By integrating D-DOSS and addressing diverse constraints, including delay, coverage probability, and SINR thresholds, this study represents a milestone in advancing HetNet technologies.

7. Limitation and Future Recommendations

While the adoption of the distributed dynamic on/off scheduling (D-DOSS) approach has shown promise in enhancing EE within HetNets, it is important to recognize inherent limitations. D-DOSS, by forming small clusters and evaluating key quality-of-service (QoS) parameters, offers ease of implementation and manageability. However, transitioning to a centralized system from distributed sleep approaches like D-DOSS may introduce higher computational demands and complexity. Moreover, simulations conducted in an interference-limited environment underscore D-DOSS's compatibility with distributed setups, but transitioning to a centralized system could amplify computational complexity and overhead.

In addressing these limitations, future research should prioritize real-world deployment and field trials to validate D-DOSS's efficacy in practical HetNet environments. Additionally, efforts should focus on enhancing D-DOSS's dynamic adaptation capabilities to enable it to respond more adeptly to evolving network conditions and traffic patterns. Development and refinement of optimization algorithms, considering factors like user mobility and varying environmental conditions, can further bolster D-DOSS's energy efficiency and performance. Integrating AI techniques, such as machine learning and reinforcement learning, holds promise for enhancing D-DOSS's intelligence and adaptability in optimizing HetNet energy efficiency. Lastly, standardizing and integrating D-DOSS into existing

network architectures will facilitate widespread adoption and deployment across diverse network environments, advancing the frontier of HetNet technologies and fostering the development of more sustainable wireless communication networks

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