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Performance Analysis of Energy Efficient Heterogeneous Cellular Networks

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CERTIFICATE

This is to certify that the thesis titled **"Performance Analysis of Energy Efficient Heterogeneous Cellular Networks"** has been carried out by **Ms. Pushpa Kumari** under my supervision and guidance in partial fulfilment of the requirements for the award of degree of **"Master of Technology"** in Electronic Circuits and Systems at department of Electronics and Communication Engineering, Integral University, Lucknow, India.

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ABSTRACT

With the exponential increase in mobile internet traffic driven by a new generation of wireless devices, future cellular networks face a great challenge to meet this overwhelming demand of network capacity. At the same time, the demand for higher data rates and the ever-increasing number of wireless users led to rapid increases in power consumption and operating cost of cellular networks. One potential solution to address these issues is to overlay small cell networks with macrocell networks as a means to provide higher network capacity and better coverage. However, the dense and random deployment of small cells and their uncoordinated operation raise important questions about the energy efficiency implications of such multi-tier networks. Another technique to improve energy efficiency in cellular networks is to introduce active/sleep (on/off) modes in macrocell base stations. In this thesis, we investigate the design and the associated tradeoffs of energy efficient cellular networks through the deployment of sleeping strategies and small cells. Using a stochastic geometry based model, we derive the success probability and energy efficiency in homogeneous macrocell (single-tier) and heterogeneous K-tier wireless networks under different sleeping policies. In addition, we formulate the power consumption minimization and energy efficiency maximization problems, and determine the optimal operating regimes for macrocell base stations. Numerical results confirm the effectiveness of switching off base stations in homogeneous macrocell networks. Nevertheless, the gains in terms of energy efficiency depend on the type of sleeping strategy used. In addition, the deployment of small cells generally leads to higher energy efficiency but this gain saturates as the density of small cells increases. In a nutshell, our proposed framework provides an essential understanding on the deployment of future green heterogeneous networks.

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SYMBOLS AND ABBREVIATIONS

SINR	Signal-to interference-plus-noise ratio
RBS	Radio Base Station
R	Bit rate
B	Bandwidth
FLOPS	Floating point operations per second
DSP	digital signal processing
AWGN	additive white Gaussian noise
PDF	Probability density function
α	Light generated cell output voltage and current
QoS	Quality of service
E_{eff}	Energy efficiency
$\mathbb{P}_{SS}$	Diode reverse saturation current
BS	Base Station
MBS	Macrocell base stations
PPP	homogeneous Poisson point process
AP	access points
GSM	Global System for Mobile Communications
N_0	noise power spectral density
B	Bandwidth
E^3F	Energy efficiency evaluation framework
MIMO	Multiple-input multiple-output
Δ_M	load-dependent power consumption
$\mathbb{P}_{RS}$	coverage probability of Radom sleeping

CHAPTER 1

INTRODUCTION

A new wireless technology generation is introduced every decade and the standardization is guided by the International Telecommunication Union (ITU), which provides the minimum performance requirements. For example, 4G was designed to satisfy the IMT-Advanced requirements [1] on spectral efficiency, bandwidth, latency, and mobility. Similarly, the new 5G standard [2] is supposed to satisfy the minimum requirements of being an IMT-2020 radio interface [3]. In addition to more stringent requirements in the aforementioned four categories, a new metric has been included in [3]: energy efficiency (EE). A basic definition of the EE is [4], [5].

$$\mathrm{EE[bit/Joule]} = \frac{\text{Data rate [bit/s]}}{\text{Energy consumption [Joule/s]}}$$

This is a benefit-cost ratio and the energy consumption term includes transmit power and dissipation in the transceiver hardware and baseband processing [5], [6]. A general concern is that higher data rates can only be achieved by consuming more energy; if the EE is constant, then 100× higher data rate in 5G is associated with a 100× higher energy consumption. This is an environmental concern since wireless networks are generally not powered from renewable green sources. It is desirable to vastly increase the EE in 5G, but IMT-2020 provides no measurable targets for it, but claims that higher spectral efficiency will be sufficient. There are two main ways to improve the spectral efficiency: smaller cells [6], [7] and massive multiple-input multiple-output (MIMO) [8], [9]. The former gives substantially higher signal-to-noise ratios (SNRs) by reducing the propagation distances and the latter allows for spatial multiplexing of many users and/or higher SNRs. Since these gains are achieved by deploying more transceiver hardware per km^2, higher spectral efficiency will not necessarily improve the EE; the EE first grows with smaller cell sizes and more antennas, but there is an inflection point where it starts decaying instead [10]. The bandwidth is fixed in these prior works, but many other parameters are optimized for maximum EE. There are other non-trivial tradeoffs, such as the fact that transceiver hardware becomes more efficient with time [6], [11], so the energy consumption of a given network topology gradually reduces.

While the Shannon capacity [12] manifests the maximal spectral efficiency over a channel and the speed of light limits the latency, the corresponding upper limit on the EE is unknown. A comprehensive study of the EE of 4G base stations is found in [13]. It shows that a macro site delivering 28 Mbit/s has an energy consumption of 1.35kW, leading to an EE of 20 kbit/Joule. Recent papers report EE numbers in the order of 10 Mbit/Joule [5], [14], [15] when considering future 5G deployment scenarios and using estimates of current transceivers' energy consumption. There is also numerous papers that consider normalized setups (e.g., 1 Hz of bandwidth) that give no insights into the EE that can be achieved in practice. Finally, the channel capacity per unit cost was studied for additive white Gaussian noise (AWGN) channels in [16], which is a rigorous but normalized form of EE analysis.

The goal of this paper is to analyze the physical EE limits in a few different cases and, particularly, give practically relevant numbers on the maximum achievable EE. Existing cellular architectures are designed to cater to large coverage areas, which often fail to achieve the expected throughput to ensure seamless mobile broadband in the uplink as users move far away from the base station. This is mainly due to the increase in inter-cell interference, as well as constraints on the transmit power of the mobile devices. Another limitation of conventional macrocell approach is the poor indoor penetration and the presence of dead spots, which result in drastically reduced indoor coverage. In order to overcome these issues and provide a significant network performance leap, heterogeneous networks have been introduced in the LTE-Advanced standardization [1]–[3]. A heterogeneous network uses a mixture of macrocells and small cells such as microcells, picocells, and femtocells. These small cells can potentially improve spatial reuse and coverage by allowing future cellular systems to achieve higher data rates, while retaining seamless connectivity and mobility in cellular networks. Besides the issue of meeting overwhelming traffic demands, network operators around the world now realize the importance of managing their cellular networks in an energy efficient manner and reducing the amount of CO_2 emission levels simultaneously [4]–[7]. Current studies show that the amount of CO_2 emission levels due to information and communication technologies is already 2%. With the exponential increase in data traffic and mobile devices, this figure is projected to increase significantly. Improving energy efficiency also helps network operators reduce the operational cost as energy constitutes a significant part of their expenditure. As a result, the terminology of "green cellular network" has become very popular recently, showing the current sentiment of the telecom industries to place more emphasis on energy efficiency as one of the key performance indicators for cellular network design [7]. Although the deployment of small cell networks is seen to be a promising way of catering to the ever increasing traffic demands, the dense and random deployment of small cells and their uncoordinated operation raise important questions about the implication of energy efficiency in such multitier networks [8]–[11]. Besides introducing small cells into existing macrocell networks, another effective technique is to introduce sleep mode in macrocell base stations (MBSs) [12]–[15]. The main motivation is that current cellular networks usually assume that the traffic demand is always high and so the MBSs are always powered on at all times. However, studies have shown that there are high fluctuations in traffic demand over space and time in cellular networks [6]. For example, the traffic demands in urban and rural areas or traffic demands in day and night time are entirely different. From this perspective, there is potential in energy savings by adapting the sleeping mode of MBSs to the demanded traffic. Nevertheless, when we switch some MBSs off, certain users may need to connect to MBSs located further away while experiencing a lower amount of intercell interference. For the case of dense deployment of MBSs, we know that these two effects cancel out equally and the coverage probability is independent of the sleeping mode [16]. However, for sparse deployment of MBSs, it is expected that we need to maintain the coverage of the cellular networks when we implement sleeping mode in MBSs either through power control or open access small cells. Since both techniques consume power, it is unclear which technique is more energy efficient and how the energy efficiency depends on the intensity of small cells and access policy. On the other hand, one of the major challenges in small cell deployment is the incursion of inter-tier interference due to aggressive frequency reuse, which can deteriorate the effectiveness of small cell architecture [1]–[3]. As a result, there has been a significant amount of research on managing inter-tier and intra-tier interference in a two-tier small cell network, which consists of a macrocell network overlaid with small cells [17], [18]. In [17], the authors proposed a spectrum partitioning approach to avoid the inter-tier interference between the macrocell and small cell tiers by using orthogonal spectrum allocation. However, under a sparse small cell deployment setting, this approach is clearly inefficient and much higher area spectrum efficiency can be attained if spectrum sharing is allowed [18]. On the other hand, for spectrum sharing in two-tier small cell networks, it becomes imperative to properly manage the inter-tier interference using techniques such as access control [18], [19], power control [20], [21], multiple antennas

[22], or cognitive radio [23]–[25]. Besides interference management techniques, interference modeling in two-tier networks using stochastic geometry has also gathered considerable attention due to its accuracy and tractability [26]–[28]. The spatial distribution of MBSs in the network is usually modeled by lattices or hexagonal cells since their deployment is considered well-planned, centralized, and hence regular. Nevertheless, it has been recently shown that modeling MBSs by a homogeneous Poisson point process (PPP) and associating macrocell users to their closest MBSs is a tractable yet accurate macrocell network model [16]. On the other hand, femtocell access points (FAPs) are extensively modeled as PPP as well, mainly due to uncoordinated and random deployment and operation. In this work, we apply the tools from stochastic geometry to analyze the energy efficiency of cellular networks through the deployment of sleeping strategy as well as small cells. By assuming that the network operators have some information of the traffic usage patterns, they can employ a coordinated sleeping mode, where certain MBSs will be shut off while others increase their coverage areas to avoid coverage hole. In particular, we model the sleeping mode at each MBS as a Bernoulli random variable, where q denotes the probability that a MBS remains in operation and the underlying spatial distribution of MBSs is modeled as a PPP. In practice the network operators will have a predetermined policy of sending MBSs to sleep that ensures reasonable coverage over the entire network, i.e., such as spacing out sleeping MBSs regularly. We nevertheless adopt a marked PPP to model the dynamics of the sleeping mode (which is a random process) for its tractability in order to come up with reasonable design guidelines of green cellular network design. To maintain similar network coverage after some MBSs have been switched off, we need to perform some form of power control. Given no knowledge of the channel state information, we will employ fixed power control. One question we will explore is the effect that q has on the energy efficiency when we shut some MBSs off.

While we will reduce the interference from some MBSs, this will cause certain macrocell users to connect to MBSs which are even further away. Besides homogeneous macrocell networks with sleeping strategy, we will also investigate the energy efficiency in heterogeneous K-tier networks with open access small cells. In addition, we formulate optimization problems in the form of power consumption minimization and energy efficiency maximization and determine the optimal operating frequency of the macrocell base station. Numerical results confirm that the effectiveness of sleeping strategy in homogeneous macrocell networks but the gain in energy efficiency depends on the type of sleeping strategy used. In addition, the deployment of small cells generally lead to higher energy efficiency but this gain saturates as the density of small cells increases.

The mobile industry faces a critical energy consumption challenge. Anticipated by Gartner [1],by 2013 smartphones will exceed 1.82 billion units and surpass PCs as the most common web access devices. Consequently, more wireless infrastructures have to be deployed with large demands on energy. Meanwhile, data-intensive services are beginning to dominate mobile services. The network data volume is expected to increase by a factor of 10 every five years, associated with a 16–20 percent increase of energy consumption [2]. Applying this rate to mobile communications, which contribute 15–20 percent of the entire information and communications technologies (ICT) energy footprint and 0.3–0.4 percent of global CO_2 emissions [2], the mobile industry faces a great sustainable development problem in energy consumption. It is crucial to develop energy-efficient wireless technologies to meet this challenge. We study in this thesis the energy efficiency (EE) of the wireless access network, which is broadly defined as any wireless system using radio base stations (RBSs) or access points (AP) to interface mobile devices with the core network or Internet. The reasons to focus on wireless access networks are following. First, since wireless access networks are the most widely deployed wireless networks in the world, energy-efficient solutions designed for wireless access networks are expected to significantly improve EE in the ICT sector. Second, as a long tradition, the standards of wireless access networks are mainly focused on throughput performance. Only recently has EE been receiving increasing attention. Significant studies are needed to balance performance and EE. Third, the demand from mobile users for EE is urgent in order to enjoy better mobile services. As shown in Fig.1.1, statistics indicate that the RBS is the main source of energy consumption in the network of a mobile operator [3]. Energy efficient solutions for wireless access networks are mainly concentrated on RBSs. Among all components in an RBS, power amplifiers (PAs) drain the most energy. Energy is also dissipated in alternating current/direct current (AC/DC) converting, cabling, and cooling. Various solutions have been proposed to improve EE of the RBS, such as increasing PA efficiency, using non-active cooling techniques, employing masthead PA to reduce feeder loss, exploiting energy efficient backhaul solutions, applying energy-efficient deployment strategies, and introducing energy-efficient protocols. This thesis overviews soft methods to improve EE of RBSs, with an emphasis on Long Term Evolution

(LTE) sys tems. Soft methods do not upgrade hardware, but tune parameters in protocols, and apply enhanced architecture and deployment strategies for EE improvement. They enable flexible and cost-efficient solutions with minimum impact on hardware implementation.

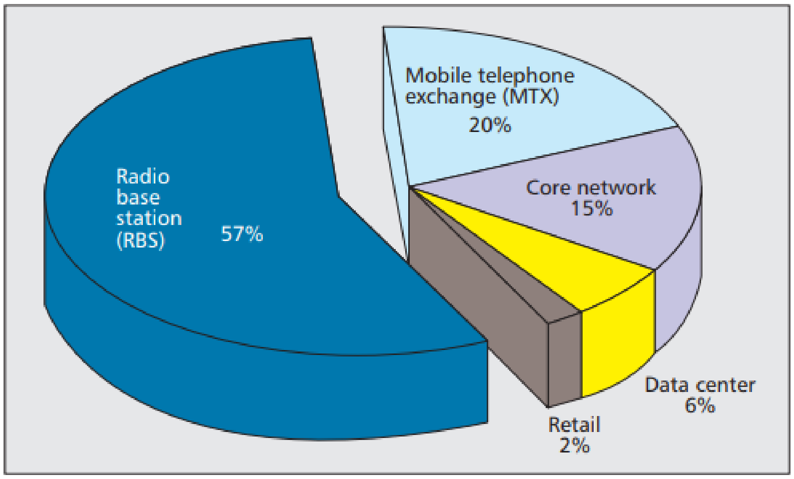

Figure 1.1 Energy consumption composition of a mobile operator [3].

1.1 UNDERSTANDING ENERGY EFFICIENCY:

It is worth understanding EE before introducing energy saving techniques. In the field of engineering, a system is usually designed to transform energy to useful work. EE can therefore be defined as the ratio of useful work to the total supplied energy. The useful work in a communication system refers to the effort to deliver modulated signals for information exchange. The definition of EE varies according to measured objects. There are two basic methods to measure EE. One way is to define EE as the ratio of efficient output power/energy to total input power/energy. This definition is widely used by systems and components such as power supply, PAs, and antennas. The other way defines EE as the performance per unit of energy consumption. This is referred to as floating point operations per second (FLOPS) in digital signal processing (DSP), million instructions per second (MIPS) in computer systems, and throughput (bits per second) in communication systems.

In a communication system information is transmitted in the form of modulated electrical, electromagnetic, or optical waveforms. Due to the imperfection of electronic components, a significant part of energy turns into heat. Moreover, in a wireless system, due to the open nature of the wireless medium, only part of the radiated energy reaches the receiver. Measurements show a Global System for Mobile Communications (GSM) RBS may only have EE of 3.1 percent [4]. It renders a prominent challenge to improve the EE of wireless systems.

EE in a communication system is not a simple problem. Information theory reveals some insights on the complexity. According to the Shannon formula, the EE of a communication system based on the additive white Gaussian noise (AWGN) channel can be written as

$$\eta_{\mathrm{EE}} = \frac{R}{P} = \frac{B}{P} log_2\left(1 + \frac{P}{BN_0}\right) \quad (1.1)$$

where R is the bit rate of information, P is the received power, B is the bandwidth, and N_0 is the noise power spectral density. The unit of the EE metric is then bits per joule, which indicates the information units transmitted per one energy unit. Equation 1.1 shows that if N_0 is fixed, EE is the function of power density P/B. There are several observations from Eq. 1.1:

- ηEE does not monotonically increase with B or P. In a practical system where the bandwidth is a less flexible parameter, the maximum EE of a system is hard to achieve.
- For a given rate R, using more bandwidth requires less power. If the bandwidth is infinite, the required power is fixed to $P = N_0 R \ln 2$. This gives a hint to trade bandwidth with energy.
- The objective to optimize throughput performance is normally conflict with that to maximize EE. Balancing these two objectives complicates the system design.

Note that Eq. 1.1 gives an EE model for a generic communication system. For a wireless system, EE also depends on distance, carrier frequency, efficiency of antennas, and so on. Moreover, interference and fading make EE of a wireless system vary according to the radio environment. It should be also remarked that Eq. 1.1 is an ideal model without considering the hardware implementation of a system. In reality, the circuits of a system will turn a significant amount of energy into heat. Therefore P in Eq. 1.1 should be replaced by the sum of the supplied power of the RBS and user terminals. Indeed, in a RBS the energy transforming to heat dominates the energy consumption of the RBS. Reducing energy wasted by RBSs becomes the main concern of energy saving in a wireless access system.

CHAPTER 2

LITERATURE SURVEY

Aleksandar damnjanovic et.al.(2011) In this paper heterogeneous deployment is seen as a pragmatic and cost-effective way to significantly enhance the capacity of LTE cellular networks. Macro nodes are used to ensure broad coverage, and low-power nodes may be located close to places with increased demand for data. Interference management represents the first crucial component of this strategy as severe interference from the macro nodes significantly limits the offloading potential of low-power nodes. Cell range expansion enabled through resource partitioning is necessary as it creates the potential for traffic load balancing, which improves the trunking efficiency of the network. The interference cancellation receiver at the UE ensures that cell acquisition channels of weak cells can be detected and CRS interference removed, fully exploiting the potential of heterogeneous network deployments. All three components are necessary to achieve the full potential of heterogeneous deployments.

D.Lopez-Perez et.al.(2011) HetNets have the potential to significantly boost network performance, benefiting from transmit-ter-to-receiver distance reduction and enabling better spatial reuse of the spectrum. This paper has identified the major advantages of HetNets, as well as their technical challenges and research problems. Particular attention has been given to the avoidance of cross tier interference due to its crucial role in proper operation of multi-tier networks. Furthermore, the main eICIC techniques currently under discussion in 3GPP have been evaluated through realistic system-level simulations.

A.Ghosh et.al. (2012): In this paper, a theoretical framework of a multi-tier cellular network based on random spatial models was developed and it was shown that essential intuition of these mathematical results hold in practice. The technical arguments for adding heterogeneous elements to the existing cellular network appear to be very strong. Simulation results show that there is a 4X improvement in user experience with the deployment of picocells in a multi-tier network even without any ICIC techniques. Applying TDM based e-ICIC and cell range extension increases the number of users connected to the underlay network and improves the overall user experience compared to a macro cell network. A PoC system, where the picos were mounted on street poles was deployed in Europe and initial results show ~3–4X user-experience improvement over a single-tier macro system.

A.Fehske et.al.(2011): This paper quantifies the global carbon footprint of mobile communications, and discusses its ecological and economic implications. We predict an increase of emissions by a factor of three between 2007 and 2020 rising to about 235 Mto CO2e. Production of mobile devices and global RAN operation will remain the major contributors, accompanied by an increasing share of emissions due to data transfer in the backbone. Energy consumption of RANs will play an increasing role in mobile operators' business models. Technologies to reduce energy consumption of global RANs are a key enabler for the spread of mobile communications in developing countries. Conditioned on quick implementation and alongside other “classical” improvements of the spectral efficiency of mobile networks, green mobile communication technologies offer the potential to serve three orders of magnitude more traffic with three times the number of sites but the same overall energy consumption as of today.

Y. Chen et.al.(2011): In this paper, Traditional mobile wireless network mainly design focuses on ubiquitous access and large capacity. However, as energy saving and environmental protection become global demands and inevitable trends, wireless researchers and engineers need to shift their focus to energy-efficiency-oriented design, that is, green radio. In this article, we propose a framework for green radio research and integrate the fundamental issues that are currently scattered. The skeleton of the framework consists of four fundamental tradeoffs: deployment efficiency-energy efficiency, spectrum efficiency-energy efficiency, bandwidth-power, and delay-power. With the help of the four fundamental trade-offs, we demonstrate that key network performance/cost indicators are all strung together.

G. Auer et.al.(2011): In order to quantify the energy efficiency of a wireless network, the power consumption of the entire system needs to be captured. In this article, the necessary extensions with respect to existing performance evaluation frameworks are discussed. The most important addenda of the proposed energy efficiency evaluation framework (E^3F) are a sophisticated power model for various base station types, as well as large-scale long-term traffic models. The BS power model maps the RF output power radiated at the antenna elements to the total supply power of a BS site. The proposed traffic model emulates the spatial distribution of the traffic demands over large geographical regions, including urban and rural areas, as well as temporal variations between peak and off-peak hours. Finally, the E^3F is applied to quantify the energy efficiency of the downlink of a 3GPP LTE radio access network.

Z. Hasan et.al.(2011): Energy efficiency in cellular networks is a growing concern for cellular operators to not only maintain profitability, but also to reduce the overall environment effects. This emerging trend of achieving energy efficiency in cellular networks is motivating the standardization authorities and network operators to continuously explore future technologies in order to bring improvements in the entire network infrastructure. In this article, we present a brief survey of methods to improve the power efficiency of cellular networks, explore some research issues and challenges and suggest some techniques to enable an energy efficient or "green" cellular network. Since base stations consume a maximum portion of the total energy used in a cellular system, we will first provide a comprehensive survey on techniques to obtain energy savings in base stations. Next, we discuss how heterogenous network deployment based on micro, pico and femtocells can be used to achieve this goal. Since cognitive radio and cooperative relaying are undisputed future technologies in this regard, we propose a research vision to make these technologies more energy efficient. Lastly, we explore some broader perspectives in realizing a "green" cellular network technology.

S. Parkvall et.al.(2017): This paper provides an overview of the technology components and capabilities of the New Radio (NR) radio interface standard currently under development by 3GPP. NR will enable new use cases, requiring further enhanced data rates, latency, coverage, capacity, and reliability. This needs to be accomplished with improved network energy performance and the ability to exploit spectrum in very high frequency bands. Key technology components to reach these targets include flexible numerology, latency-optimized frame structure, massive MIMO, interworking between high and low frequency bands, and ultra-lean transmissions. Preliminary evaluations indicate that, with these technology components, NR can reach the 5G targets.

A. Mammela and A. Anttonen(2017): In this tutorial particular attention is given to the computing power in the physical layer of wireless devices, which are energy and power limited. Communication uses the power in the analog radio frequency parts and computation uses power in the signal processing and other tasks required during communication, both in the transmitter and in the receiver. Example applications include sensor networks and mobile devices in ultradense small cell networks where the link distances are below about 10 m, and the computing power is larger than the communication power. The computation-communication tradeoff means that if one of the powers is increased, the other one must be decreased, otherwise the total power increases. Energy efficiency is a challenging multidisciplinary topic, and the consequences of the interrelated fundamental limits are not well understood. The link bit rates are increasing exponentially each year, which implies that there must be a corresponding exponential trend in improving energy efficiency, defined as number of bits per energy unit, both in computation and communication. It is well known that for communications, due to noise, the Shannon limit forms the fundamental limit for the received energy per bit, but in computation there is a similar limit called Landauer limit for the switching energy of a transistor. Near the two fundamental limits the energy efficiency cannot be improved any more exponentially. Our main contribution is to elaborate the connections between the various technology predictions, different fundamental limits and possible design trade-offs. Specifically, we show that because of the aforementioned fundamental limits, the exponential trends in bit rates cannot continue without a compensating exponential trend in energy efficiency. We also revisit the concept of crossover distance and derive it from the fundamental limits to give some further system-level insight on the energy consumption bottlenecks.

Fredrik Rusek et. al.(2013) :Multiple-input multiple-output (MIMO) technology is maturing and is being incorporated into emerging wireless broadband standards like long-term evolution (LTE) [1]. For example, the LTE standard allows for up to eight antenna ports at the base station. Basically, the more antennas the transmitter/receiver is equipped with, and the more degrees of freedom that the propagation channel can provide, the better the performance in terms of data rate or link reliability. More precisely, on a quasi static channel where a code word spans across only one time and frequency coherence interval, the reliability of a point-to-point MIMO link scales according to Prob(link outage) SNR-ntnr where nt and nr are the numbers of transmit and receive antennas, respectively, and signal-to-noise ratio is denoted by SNR. On a channel that varies rapidly as a function of time and frequency, and where circumstances permit coding across many channel coherence intervals, the achievable rate scales as min(nt, nr) log(1 + SNR). The gains in multiuser systems are even more impressive, because such systems offer the possibility to transmit simultaneously to several users and the flexibility to select what users to schedule for reception at any given point in time .

B. Debaillie et.al(2015): The power efficiency of cellular base stations is a crucial element to maintain sustainability of future mobile networks. To investigate future network concepts, a good power model is required which is highly flexible to evaluate the diversity of power saving options. This paper presents an advanced power model which supports a broad range of network scenarios and base station types, features and configurations. In addition to the power consumption, the model also provides values on the hardware sleep capabilities (sleep depths, transition times, power savings). The paper also discusses the technology trends and scaling factors which are used to predict the power consumption of base stations up to the year 2020. Two use cases are described, illustrating the power savings over different sleep depths, and quantifying the power consumption evolution over different technology generations.

Luca Venturino et.al.(2015): This paper addresses the problem of energy-efficient resource allocation in the downlink of a cellular orthogonal frequency division multiple access system. Three definitions of energy efficiency are considered for system design, accounting for both the radiated and the circuit power. User scheduling and power allocation are optimized across a cluster of coordinated base stations with a constraint on the maximum transmit power (either per subcarrier or per base station). The asymptotic noise-limited regime is discussed as a special case. Results show that the maximization of the energy efficiency is approximately equivalent to the maximization of the spectral efficiency for small values of the maximum transmit power, while there is a wide range of values of the maximum transmit power for which a moderate reduction of the data rate provides large savings in terms of dissipated energy. In addition, the performance gap among the considered resource allocation strategies is reduced as the out-of-cluster interference increases.

CHAPTER 3

SYSTEM MODEL

3.1 Network Model :

We consider a wireless cellular network consisting of MBSs located according to a homogeneous PPP Θ_M of intensity λ_M in the Euclidean plane. Users are distributed according to a different independent stationary point process of intensity μ. Each macrocell user is associated with its geographically closest MBS and the analysis is performed for a randomly selected typical user. Since Θ_M is a stationary process, the distribution of distance R_M between a macrocell user and its designated MBS remains the same regardless of the exact locations, and its probability density function (pdf) is given by $f_{R_M}(r) = 2\pi\lambda_M r exp(-\lambda_M \pi r^2)$. We assume universal frequency reuse among base stations and that each MBS serves only one user. If there are multiple users in a Poisson-Voronoi cell, some form of orthogonal resource sharing (e.g. frequency or time division multiple access) is performed.

3.2. Signal-to-Interference-plus-Noise Ratio:

For notational convenience, we denote a base station by its location while the user is at the origin 0. For downlink transmission of a MBS x to the typical user 0, the signal-to interference-plus-noise ratio (SINR) experienced by a macrocell user is given by

$$SINR_M(x \to u) = \frac{P_{t,i} h_x g(x)}{\sum_{y \in \Theta_M} P_{t,y} h_y g(y) + \sigma^2} \quad (3.1)$$

where $\Theta_{(x)}$ denotes the set of nodes interfering with x, $P_{t,i}$ denotes the transmit power at tier i, and h_x,h_y are the channel power gain due to small-scale fading from x, y respectively. In the following, we assume that $h_x \sim \exp(1)$ and $h_y \sim \exp(1)$ (Rayleigh fading). The background noise is assumed to be additive white Gaussian with variance σ^2 and the path loss function is denoted by $g(x) = \|x\|^{-\alpha}$, with α being the path loss exponent.

3.3. Performance Metrics:

Using (3.1) we can define the success probability from x to u as $\mathbb{P}(SINR_M(x \to u) > \gamma)$, where γ is a prescribed quality-of-service (QoS) threshold. By averaging the success probability over the distance to the nearest node, we obtain the coverage probability of a typical macrocell user given by $\mathbb{P}_M(\gamma)$. The throughput attained at a given BS-user link is given by $\mathbb{P}(\text{SINR} > \gamma)\log 2(1+\gamma)$ and the area spectral efficiency (network throughput) is taken over all the links in the network, where for a homogeneous network scenario is defined as $\text{Ʈ}_M = \lambda_M \mathbb{P}_M(\gamma)\log_2(1+\gamma)$. Lastly, we define the energy efficiency E_{eff} as follows:

$$\mathrm{E}_{eff} = \frac{\text{Area Spectral Efficiency}}{\text{Average Network Power Consumption}} = \frac{\text{Ʈ}}{\lambda_M P_{tot}} \quad (3.2)$$

where P_{tot} denotes the MBS power consumption.

3.4. Power Consumption Model:

3.4.1 Homogeneous (Single-tier) Network model:

The power consumption at each MBS is given by $P_{tot} = P_{M0} + \beta\Delta_M P_M$ where P_{M0} is the static power expenditure of the MBS, βP_M is the RF output power of the MBS, and Δ_M is the slope of the load-dependent power consumption in MBS [6]. A fixed power control policy is adopted here in order to avoid creating coverage holes or areas where the target SINR is below an acceptable level due to switching off MBS. To ensure a similar level of coverage as before sleeping, we assume that all awake MBS transmit with power βP_M, where β is a ratio that represents power control. It is assumed that β is the same for all MBSs.

3.4.2 K-tier Heterogeneous Network model:

We also consider a general K-tier heterogeneous network model, where the base stations in each tier are modeled as independent homogeneous PPP Θ_i with intensity λ_i. We will always use Θ_1 for the macro tier Θ_M. In addition, we consider again that all base stations in the K tiers share the same bandwidth. Without employing any sleeping mode at each base station in the i-th tier, the average power consumption of the i-th tier heterogeneous networks is given by

$$P_{Het,i} = \lambda_i(P_{i0} + \Delta_i P_i) \quad (3.3)$$

where P_{i0} is the static power expenditure of the base station in the i-th tier, P_i is the RF output power of the i-th tier base station, and Δ_i is the slope of the load-dependent power consumption the base station in the i-th tier.

3.5. Base Station Sleep Mode Strategies:

In this chapter, we present the two main policies that we propose and analyze in order to optimize the power consumption at each MBS. We investigate policies of dynamically switching off MBS, where the power consumed by a switched off MBS in sleep mode is P_{sleep}. Note that we consider that $P_{sleep} < P_{M0}$ which is a valid assumption for future base stations with sleeping mode capabilities. To maintain similar network coverage after some MBSs having been switched off, we employ power control by selecting $P_{t,M} = \beta P_{t_0,M,}$ where β denotes the uniform increase in transmission power for MBS. The attractiveness of fixed power control is that it compensates for the sleeping activity without the need for obtaining instantaneous channel state information for the macrocell users.

3.5.1 Random Sleeping:

In random sleeping, we model the sleeping strategy as a Bernoulli trial such that each station continues to operate with probability q and sleeps (is turned off) with probability 1−q, independently of all the other base stations. Therefore, after applying random sleeping at the macro tier, the average total power consumption of the macrocell network is given by

$$P_{RS} = \lambda_{Mq}(P_{M0} + \Delta_M \beta P_M) + \lambda_M(1 - q)P_{sleep} \quad (3.4)$$

3.5.2 Strategic Sleeping:

Instead of randomly switching MBSs off, we can also switch off MBSs when their activity levels are low, e.g. when load or traffic demands are low. Specifically, we model this strategic sleeping as a function s : [0, 1] → [0, 1] which says that if the activity level of the coverage area associated with the MBS has activity level x, then it operates with probability s(x) and sleeps with probability 1−s(x), independently. This sleep mode strategy can be seen as a load-aware policy and it can incorporate traffic profile in the optimization problem. As a result, the average power consumption of the macrocell network after employing strategic sleeping is given by

$$P_{SS} = \lambda_M E\{s\}(P_{M0}+\beta\Delta_M P_M)+\lambda_M(1-E\{s\})P_{sleep}, \quad (3.5)$$

where $E\{s\} = \int_0^1 s(x) f_A(x) dx$ and $f_A(x)$ is the pdf of A and A denotes the random activity within a cell and takes values in [0, 1]. The rationale behind the proposed strategic sleeping is the following: while random sleeping models a network that is adaptive to the fluctuating activity levels during the day, strategic sleeping goes one step further and models a network that is adaptive to the fluctuating activity levels within the location. Furthermore, the strategic sleeping model may be used as a method of measuring the impact of cooperation among MBSs. Let us illustrate this with an example. Suppose that we have a pair of cooperating MBSs. If the activity level in the combined coverage area is expected to be below half of the full capacity, then the pair may choose to keep only one of them awake. Then, the awake MBS may serve both coverage areas or the coverage areas can be reassigned among all remaining awake MBSs. The above cooperation model can be modeled by strategic sleeping by having, say, both MBS to stay awake with probability $s = 0.5$. While an explicit association between neighboring MBSs is technically absent, this model may nevertheless be seen as a way to measure the energy savings by introducing cooperation within the network.

CHAPTER 4

HOMOGENEOUS MACROCELL NETWORK

In this chapter, we study the effect of switching off MBSs based on the aforementioned sleeping policies, i.e. randomly and dynamically. The performance measure is the coverage probability and the effect of noise is taken into account, i.e. $\sigma^2 > 0$. In recent work analyzing coverage in macro cellular networks, it is shown that the coverage probability is independent of the intensity of the base stations in the interference-limited regime ($\sigma^2 \rightarrow 0$) [16]. This also holds true in heterogeneous K-tier networks [18], [29]. The main reason behind this is the fact that in dense networks, the improvement in received signal power by adding more MBSs and bringing the transmitters closer to the receivers is equally canceled out by the increased interference from more MBSs (interferers). Nevertheless, when MBS sleeping policies are applied, the effect of noise is noticeable and cannot be ignored as the number of interferers may be significantly decreased. Therefore, in this work we also consider the case where $\sigma^2 > 0$.

4 .1 Random Sleeping :

As explained in Chapter 3, the random sleeping strategy is simply equivalent to modeling the active MBSs as a marked PPP with intensity $q\lambda_M$ and increasing the transmission power of the active MBSs to βP_M.

4.1.1 Theorem 1. In homogeneous macrocell networks with random sleeping, the coverage probability of a randomly located macrocell user is given by

$$\mathbb{P}_{RS}(\beta,\gamma) = 2\pi q\lambda_M \int_{r=0}^{\infty} r exp(-\pi r^2 q\lambda_M\left(1+\rho(\gamma,\alpha)\right)) \times \exp\left(-r^{\alpha}\,\gamma\sigma^2/\beta P_{t,m}\right)dr \quad (4.1)$$

Where $\rho(\gamma,\alpha) = \gamma^{2/\alpha}\int_{\gamma^{-2/\alpha}}^{\infty}\frac{1}{1+u^{\alpha/2}}du$

Furthermore, for $\sigma^2 = 0$, $\mathbb{P}_{RS}(\beta, \gamma)$ can be simplified as

$$\mathbb{P}_{RS}(\beta,\gamma) = \frac{1}{1+\rho(\gamma,\alpha)} \quad (4.2)$$

- Proof of Theorem 1

The coverage probability is defined as

$$\int_{r=0}^{\infty} \mathcal{L}_I(r)\mathcal{L}_N(r) f_{\lambda_M}(r)dr \quad (4.3)$$

where the probability density function of the MBS $f_{\lambda_M}(r)$ is $2\pi\lambda_M r \exp(-\pi\lambda_M r^2)$ (without sleeping) and $2\pi q\lambda_M r \exp(-\pi q\lambda_M r^2)$ (with sleeping).

We can see that the coverage probability is completely independent of the sleeping policy, the density of MBSs λ_M, as well as the power control β when $\sigma^2 = 0$.The only parameter that affects the coverage probability is the target SINR threshold γ. In the case of $\sigma^2 > 0$, numerical integration is required to calculate the coverage probability.

4.2 Strategic Sleeping:

Here we analyze the strategic MBS switching off that is based on the activity of macrocell users in each cell. We assign i.i.d. random variables $A_i \sim A$ to each MBS $i \in \Theta_M$, such that A takes values in [0, 1]. A_i represents user activity within the Poisson-Voronoi cell that the MBS covers. That is to say, for any user located in a Poisson-Voronoi cell of a MBS with activity level a, the user is active with probability a, i.e. it is actually connected to the MBS with probability a. Therefore, we can model the sleeping strategy as a function s :[0, 1] → [0, 1], which implies that if the activity level of the MBS has activity level x, then it operates with probability s(x) and sleeps with probability 1 − s(x). In addition, we impose that s(x) is increasing. Using this model, the active MBSs are distributed accordingly to a homogeneous PPP with intensity $\lambda_M E\{s\} = \lambda_M \int_0^1 s(x) f_A(x)dx$. Therefore, the coverage probability that captures the activity of the macrocell user is provided in the next theorem.

4.2.1 Theorem 2. The coverage probability of the active macrocell user2 is given by

$$\mathbb{P}_{SS}(\beta,\gamma) = \frac{1}{E\{a\}}\Big\{\int_0^1 xs(x)\, f_A(x)dx \int_{r=0}^{\infty} exp(-\pi r^2 \lambda_M E\{s\}\big(\rho(\gamma,\alpha)\big) \times \exp\,(-r^{\alpha}\,\gamma\sigma^2/$$
$$\beta P_{t,m})g_1 r dr + \int_0^1 x(1-s(x))f_A(x)dx \sum_{i=2}^{\infty} \int_{r=0}^{\infty} exp(-\pi r^2 \lambda_M E\{s\}\big(\rho(\gamma,\alpha)\big) \times$$
$$\exp\,(-r^{\alpha}\,\gamma\sigma^2/\beta P_{t,M})g_i r dr \quad (4.4)$$

where $g_i(r)$ is the pdf of the i-th nearest point from a PPP, such that $g_i(r) = \frac{2\pi^i r^{2i-1}\lambda_M^i}{(i-1)!} exp(-\pi r^2 \lambda_M)$. For $\sigma^2 = 0$, $\mathbb{P}_{SS}(\beta,\gamma)$ can be simplified as

$$\mathbb{P}_{SS}(\beta,\gamma)=\frac{1+\rho(\gamma,\alpha)E\{as(a)\}/E\{a\}}{1+E\{s\}\rho(\gamma,\alpha)(1+\rho(\gamma,\alpha))} \quad (4.5)$$

- Proof: The first step is to condition on the activity of a typical cell a(x). Next, we enumerate all the MBSs in increasing order of distance from the user, starting from the distance of each MBS from the user is almost surely distinct. Nord denotes the order of the MBS the user connects to and $f_A(x)$ denotes the pdf of A. The success probability per link is thus given by

$$\mathbb{P}_{SS} \overset{(a)}{\triangleq} \frac{1}{E\{a\}}\int_0^1 x\mathbb{P}(SINR > \gamma|x)\, f_A(x)dx$$

$$\overset{(b)}{\triangleq} \frac{1}{E\{a\}}\int_0^1 \{x\mathbb{P}(N_{ord} = 1)\mathbb{P}(SINR > \gamma|N_{ord} = 1) + x\mathbb{P}(N_{ord} > 1)\mathbb{P}(SINR > \gamma|N_{ord} > 1)\}f_A(x)dx$$

$$\overset{(c)}{\triangleq} \frac{1}{E\{a\}}\Big\{\int_0^1 xs(x)\int_{r=0}^{\infty} \exp\left(-\pi r^2 \lambda_M E\{s\}\rho\right) exp(-\pi r^2\lambda_M) \exp\left(-r^{\alpha}\gamma\sigma^2/\beta P_{t,M}\right)dr + x(1-s(x))\mathbb{P}(SINR > \gamma|N_{ord} > 1)\Big\}f_A(x)dx \quad (4.6)$$

where (a) is by definition of a coverage probability weighted over the active user links, (b) partitions into the event of the nearest MBS being awake and the event of the nearest MBS being asleep, and (c) is from the Laplace transform of the remaining active interferers, distributed as a PPP with intensity $E\{s\}\lambda_M$, and the pdf of the nearest MBS. This leads us to $\mathbb{P}(\text{SINR} > \gamma|N_{\text{ord}} > 1)$, which is given by

$$\mathbb{P}_{SS}(\rightarrow|N_{ord} > 1) \overset{(a)}{\triangleq} \sum_{i=2}^{\infty} \mathbb{P}(N_{ord} = i|N_{ord} > 1)\mathbb{P}_{SS}(\rightarrow|N_{ord} = i)$$

$$\overset{(a)}{\triangleq} \sum_{i=2}^{\infty} E\{s\}(1-E\{s\})^{i-2}\int_{r=0}^{\infty} exp\left(-\frac{r^{\alpha}\gamma\sigma^2}{\beta P_{t,M}}\right)\exp\left(-\pi r^2\lambda_M E\{s\}(1+\rho)\right)2(\lambda_M\pi)^i r^{2i-1}dr \quad (4.7)$$

where (a) splits into the events “connect to the i-th MBS”,(b) is the Laplace transform of the interference term and the pdf of the i-th MBS.

In the case where $\sigma^2 = 0$, the term $P(\text{SINR} > \gamma|N_{\text{ord}} > 1)$ simplifies to

$\sum_{i=2}^{\infty} \frac{E\{s\}(1-E\{s\})^{i-2}}{(1+E\{s\}\rho)^{i}} = \frac{1}{1+\rho}\frac{1}{1+E\{s\}\rho}$ which,combined with (4.6), leads to (4.5).

For the case of $\sigma^2 = 0$, we can see that the coverage probability is independent of the intensity of MBSs and the transmit power. Unlike the case of random sleeping, the strategic sleeping has an effect on the coverage probability even in the interference-limited regime (σ^2=0). Using (4.5),which corresponds to the interference-limited regime, we can show an interesting property of the strategic sleeping: the coverage probability of the active macrocell user is at least as good as in the case where no sleeping mode is employed.

4.2.2 Lemma 1. When $\sigma^2 = 0$, the sleeping strategy s improves the coverage probability of the active macrocell user if it satisfies the following inequality

$$E\{as(a)\} > E\{s\}E\{a\} \quad (4.8)$$

- Proof: The proof is omitted as it follows after standard algebraic manipulations. The consequence of Lemma 1 is that, for fixed E{s}, if we want to maximize E{as(a)}, we need to match large values of s with high activity. Thus, by assuming that s(x) is increasing,this guarantees that strategic sleeping cannot result in worse performance than the case of no switching off as stated in the following lemma.

4.2.3 Lemma 2:When $\sigma^2 = 0$, if s(x) is increasing in x, the coverage probability of the active macrocell user in the strategic sleeping case is at least as good as the non sleeping case.

- Proof: The result is a consequence of a more general result that states that, given two increasing measurable functions on a random variable, the covariance is non-negative. The proof can be found in [30]. Therefore, from Lemma 1, we conclude that a strategic, load-aware sleeping policy suggests the intuitive policy that a high fraction of MBSs is switched off when the activity is low. This means that users in areas with low activity are heavily penalized. However, Lemma 2 assures us that the benefits for the majority of the users outweighs the decreased performance for the minority.

The above results can be easily extended to the case where base stations and users have multiple antennas. The main technical challenge is the fact that the small-scale fading variables will be in general distributed according to gamma distribution (chi-squared) with different shape and scale parameters, depending on the multi-antenna scheme used. Briefly, using properties of the

Laplace transform, we can show that this will make appear higher order derivatives of the Laplace transform of the interference in the above expressions for the success probability and throughput. Detailed investigation on the effect of multiple antennas on the energy efficiency is left for future work.

4.3. Constrained Optimization Framework:

In the following, we use the results from the previous heading to solve several energy efficiency related optimization problems under different sleeping policies:

4.3.1 Power Consumption Minimization with Random Sleeping:

In the first problem, we minimize the power consumption subject to a coverage probability constraint, which can be interpreted as a QoS constraint. In the case of random sleeping, the problem is formulated as follows

$$P_{RS}:\begin{cases}\underbrace{min}_{q} \quad \lambda_M q(P_{M0}+\Delta_M \beta P_M) \\ \qquad +\lambda_M(1-q)P_{sleep} \\ \quad s.t. \quad \mathbb{P}_{RS}(\beta,\gamma)\geq\epsilon\end{cases} \tag{4.9}$$

where q is the fraction of MBSs that are still operating. In order to solve the above problem, we first show that the coverage probability is an increasing function of a certain variable x. Then, we find the value x^* that satisfies the constraint tightly, and finally, we solve the minimization problem subject to the condition x^* .Therefore, rewriting $q\lambda_M = S$ in Theorem 1,we have

4.3.1.1 Lemma 3. For $\sigma^2 > 0$ and $\alpha > 2$, the coverage probability $\mathbb{P}_{RS}$ increases with increasing S.

- Proof: By rewriting the success probability, we have

$$S\int_{r=0}^{\infty} 2\pi r exp(-r^2 S c_1)\exp(-r^{\alpha}2c_2)\,dr = S\int_{r=0}^{\infty} 2\pi r exp(-r^2 S c_1)\exp\left(-x^{\alpha/2}2c_2\right)dx$$

Let T > S and by substituting y = xT/S, we obtain

$$T\int_{x=0}^{\infty} 2\pi exp(-xTc_1)\exp\left(-x^{\alpha/2}c_2\right)dx = S\int_{y=0}^{\infty} 2\pi exp(-ySc_1)\exp\left(-y^{\alpha/2}(S/T)^{\alpha/2}c_2\right)dx >$$

$S\int_{y=0}^{\infty} 2\pi exp(-ySc_1)\exp\left(-y^{\alpha/2}c_2\right)dx$ .The last step makes use of the fact $\alpha > 2$ and $c_2 = \sigma^2\gamma > 0$. Hence, we $\mathbb{P}_{\mathrm{RS}}$ have increases with S. From Lemma 3, we may conclude that the minimum power consumption occurs when $q\lambda_M$ satisfies the constraint tightly.

Hence, $q^*_{\mathrm{PC,RS}}$ is given by

$$\epsilon = 2\pi q^*_{\mathrm{PC,RS}}\lambda_M \int_{r=0}^{\infty} \exp\left(-\pi r^2\lambda_M q^*_{\mathrm{PC,RS}}\left(1+\rho(\gamma,\alpha)\right)\right)\exp\left(-r^{\alpha}\,\gamma\sigma^2/\beta P_{t,M}\right)dr \quad (4.10)$$

4.3.2. Power Consumption Minimization with Strategic Sleeping:

The minimization problem in the case of strategic sleeping is formulated similarly as

$$P_{SS}:\begin{cases} \underbrace{min}_{s} \quad \lambda_M(E\{s\})(P_{M0}+\Delta_M\beta P_M) \\ \qquad\quad +\lambda_M(1-E\{s\})P_{sleep} \\ \qquad\quad s.t. \quad \mathbb{P}_{SS}(\beta,\gamma)\geq\epsilon \end{cases} \quad (4.11)$$

Solving the above optimization problem is more challenging in the case of strategic sleeping since before stating that the constraint is satisfied by equality, we first need to compute the optimal strategy as shown in the following lemma.

4.3.2.1 Lemma 4. For a fixed E{s}, the strategy that optimizes the success probability per active user is to have $s(a) = 1_{\{a\geq a0\}}(a)$ for some a_0. That is to say, the strategy takes a form of a threshold function where the MBS is switched on if the activity exceeds a_0.

- Proof: Once again, we use the notation Nord to denote the order of the MBS that the user is connected to. In addition, we impose that all strategies are measurable functions. Firstly, note that $\mathbb{P}$(SINR > γ|Nord = 1) is more than $\mathbb{P}$(SINR >γ|Nord > 1) or in other words, the success probability when the nearest active MBS is the nearest MBS than if not. This is intuitively evident. Next, note that the optimal S*(a) is completely characterized by a*. Now, suppose we have a strategy $S_1(a)$ that is not (almost surely) S*(a). Then, by definition of being different, there exists a > 0 such that the set B = {x, x ≥ a*, $S_1(x) < 1-\epsilon$} has measure > 0.Roughly speaking, we just find a set where the strategy is not 1. Next, we construct another strategy $S_2(a)$ from $S_1(a)$ while retaining E{s}. Roughly, we part from the function $S_1(x)$ for x < a* and $S_1(x) > 0$ and "fill" up the set B. Then, using $\mathbb{P}$(SINR > γ|Nord = 1) and by the notion that "we serve more people by switching on in areas with higher activity than in areas with lesser activity", we arrive at the conclusion that S_2 has a higher coverage rate per active user than S_1. Lastly, the only function where we cannot do this sort of procedure is precisely the one characterized by S*.Therefore, the optimal solution s*(a) can be characterized by a single variable a_0, which we denote as a*. The optimization problem is solved using equality for the QoS constraint, in which case, the solution is characterized based on a*.

4.3.2.2 Theorem 3. The optimal s*(a), denoted as a*, satisfies

$$\epsilon = \frac{1}{E\{a\}} \mathbb{P}(SINR > \gamma | N_{ord} = 1) \int_{a^*}^{1} x f_A(x)\ dx + \ \mathbb{P}(SINR > \gamma | N_{ord} > 1) \int_{0}^{a^*} x f_A(x) dx\} \quad (4.12)$$

Where

$$\mathbb{P}(SINR > \gamma | N_{ord} = 1) = \int_{r=0}^{\infty} e^{\left(-\pi r^2 \lambda_M E\{s\} \rho(\gamma,\alpha)\right)} e^{-\frac{r^\alpha \gamma \sigma^2}{\beta P_{t,M}}} g_1 r dr,$$

and

$$\mathbb{P}(SINR > \gamma | N_{ord} > 1) = \sum_{i=2}^{\infty} \int_{r=0}^{\infty} e^{\left(-\pi r^2 \lambda_M E\{s\} \rho(\gamma,\alpha)\right)} e^{-\frac{r^\alpha \gamma \sigma^2}{\beta P_{t,M}}} g_i r dr,$$

N_{ord} = i denotes the event the user is connected to the i-th nearest MBS.

Despite the simple form of the optimal strategy, which is to switch on MBSs when the activity level exceeds a threshold, it may be realistic to assume a probabilistic decision making function taking probabilities that are not in {0, 1}.This is because operators may choose to shut down MBSs in a coordinated fashion according to the activity in a certain location. While this does not model coordination between neighboring cells, we can use intermediate probabilities to model the effect of coordination with a neighboring MBS which the current MBS hands traffic over to.

CHAPTER 5

HETEROGENEOUS K-TIER NETWORKS

5.1 Introduction:

In this chapter, we consider that all base stations in the heterogeneous networks operate in open access, i.e. any user is allowed to connect to access points (called below as BSs) from any tier [29]. We consider three different user association schemes, namely location based scheme, average signal based scheme, and instantaneous SINR based scheme. Specifically, we have

- **Location based scheme:** Assume that a user knows the locations of nearby access points from all tiers and its own location. The user computes the relative distance to the nearest access points from each tier, which we denote as $\{r_i\}$. Define a biasing system, which are real numbers $\{\kappa_i\}$. The user then connects to the BS corresponding to $\min(\{\kappa_i r_i\})$.
- **Average signal based scheme:** Assume that users are able to associate with the BS based on the perceived average SINR. Denote $\{Q_i\}$ as the highest perceived average signal from each tier. Similarly define a biasing system $\{\tau_i\}$. The user connects to the BS corresponding to $\max(\{\tau_i Q_i\})$.
- **Instantaneous SINR based scheme:** This model is based on [29]. The user connects to tier i if the instantaneous SINR exceeds γ_i. We assume that $\gamma_i > 1$ so at most one tier will provide a signal exceeding the threshold, in which case we say that the user is connected.

We first provide the coverage probability for the location based scheme:

5.1.1 Theorem 4. The coverage probability for the general mobile user operating under the location based scheme is given by

$$\mathbb{P}_{LOC} = \sum_{i=1}^{K} \int_{r=0}^{\infty} 2\lambda_i \pi r exp(-r^2 c_i) exp(-r^\alpha \alpha_i)\, dr \quad (5.1)$$

where $a_i = \gamma\sigma^2/P_{t,i}$ and $c_i = \pi\lambda_i(1+\rho(\gamma,\alpha)) + \frac{\pi}{\kappa_i^2}\sum_{j\neq i}\lambda_j \left(1+\rho\left(\gamma\frac{P_{t,j}\kappa_i^\alpha}{P_{t,i}\kappa_j^\alpha},\alpha\right)\right)$ when $\sigma^2 = 0$

we have

$$\mathbb{P}_{LOC,\sigma^2=0} = \sum_{i=1}^{K} \frac{\lambda_i \kappa_i^2}{\sum_j \lambda_j \kappa_i^2 \left(1+\rho\left(\gamma \frac{P_{t,j}\kappa_i^{\alpha}}{P_{t,i}\kappa_j^{\alpha}}, \alpha\right)\right)} dr \quad (5.2)$$

- Proof: Let $f_i(r) = 2\pi\lambda_i r\exp(-\pi\lambda_i r^2)$ denotes the pdf of the distance to the nearest BS in tier i. First, we compute the probability of connecting to tier i, i.e. $\mathbb{P}(\kappa_i r_i < \kappa_j r_j \forall_j \neq i)$ as follows:

$$\mathbb{P}(\kappa_i r_i < \kappa_j r_j \forall_j \neq i) = \int_{r=0}^{\infty} f_i\,(r)\mathbb{P}(\kappa_i r < \kappa_j r_j \forall_j \neq i)dr$$

$$= \int_{r=0}^{\infty} f_i\,(r)\left(\prod_{j\neq i} \int_{r_j = r^{\kappa_i}/_{\kappa_j}}^{\infty} f_j(r_j)\, dr_j\right)dr$$

$$= \int_{r=0}^{\infty} f_i\,(r)\left(\prod_{j\neq i} \exp\left(-\pi\lambda_i \left(r\,{}^{\kappa_i}/_{\kappa_j}\right)^2\right)\right)dr$$

$$= \frac{\lambda_i \kappa_i^2}{\sum_j \lambda_j \kappa_j^2} \quad (5.3)$$

Now, conditioned on the event that the user is connected to the i-th tier, we derive the probability of a successful transmission. This requires us to determine the Laplace Transform of the interference and noise terms. For the Laplace Transform of the noise term, it is given in (25). As such, we need to derive the generic Laplace transform due to interference I from transmitters from a general tier j (including i) [16], [18]:

$$\mathcal{L}_{I(j)}(s) = \mathbb{E}_{\Theta_j}[exp_{h}\left(sh_y P_{t,i} x_y^{-\alpha}\right)]]$$

$$= \mathbb{E}_{\Theta_j}\, {}^{1}/(1 + sP_{t,i}x_y^{-\alpha})]$$

$$= exp\left(-2\pi\lambda_i \int_{r^{\kappa_i}/_{\kappa_j}}^{\infty} \left(1 - \frac{1}{1+sv^{-\alpha}}\right) vdv\right) \quad (5.4)$$

where the last step follows from known results about the probability generating functional (PGFL) of PPPs. Following the definition of the success probability as $\mathbb{P}(\mathrm{SINR} > \gamma)$, we compute $\mathbb{E}_h[P_{t,i}hr^{-\alpha} > \gamma I(j)]$ and after some algebraic manipulations, we get $\mathcal{L}_{I(j)}(\gamma r^{\alpha}/\ P_{t,i}) = exp\left(-2\pi\lambda_i \int_{r^{\kappa_i}/_{\kappa_j}}^{\infty} \left(1 - \frac{1}{1+sv^{-\alpha}}\right) vdv\right) = \exp\left(-\pi\left(r\,{}^{\kappa_i}/_{\kappa_j}\right)^2 \lambda_i \rho\left(\frac{\gamma P_{t,i}\kappa_j^{\alpha}}{P_{t,j}\kappa_i^{\alpha}}, \alpha\right)\right)$.

The success probability is given by

$$\sum_i \frac{\lambda_i \kappa_i^2}{\sum_j \lambda_j \kappa_j^2} \int_{r_i=0}^{\infty} \left(\prod_j \mathcal{L}_{I(j)}\left(\frac{\gamma r^{\alpha}}{P_{t,i}}\right)\right) \mathcal{L}_N f_i(r) dr \quad (5.5)$$

and so the final step is to combine the previously obtained expressions and integrate w.r.t. r.

Instead of deriving the coverage probability for the average signal based scheme, we show that the location based and the average signal based schemes are equal with an appropriate choice of biasing factor. This is because the average signal is averaged over the fading effect so the remaining factors are the transmission power and path loss, being identical to the location based scheme. We formally state this in the following lemma.

5.1.2. Lemma 5. The average signal based user association scheme is equivalent to the location based scheme with $\tau_i = \kappa_i^{\alpha}/P_{t,i}, \forall_i$.

- Proof:First note that if we have two transmitters of the same type placed at distance x and y away where x < y, then the average signal from x is smaller than the average signal from y. Hence, we can assume that we always connect to the nearest BS from each tier i. To prove this result, we need to verify that, suppose $\tau_x = \kappa_x^{\alpha}/P_{t,x}$ for all x holds, whenever we have two tiers satisfying the relation $\kappa_i r_i = r_j \kappa_j$, then the relation $Q_i\tau_i = Q_j\tau_j$ holds as well (Q is the perceived average SINR signal).For a user connecting to tier *i*, the SINR is given by

$$\mathrm{SINR} = \frac{P_{t,i,1} h_{i,1} r_{i,1}^{-\alpha}}{\sigma^2 + P_A + P_B + P_C + P_D} \quad (5.6)$$

Where$P_A = P_{t,j,1} h_{j,1} r_{j,1}^{-\alpha}$, $P_B = \sum_{K\geq 2} P_{t,i,k} h_{i,k} r_{i,k}^{-\alpha}$, $P_C = \sum_{K\geq 2} P_{t,j,k} h_{j,k} r_{j,k}^{-\alpha}$, $P_D = \sum_{x\neq\{i,j\},K\geq 2} P_{t,x,k} h_{x,k} r_{x,k}^{-\alpha}$

As part of conditional probability, the term representing interference from tier *i* (and *j* also),$\sum_{K\geq 2} P_{t,i,k} h_{i,k} r_{i,k}^{-\alpha}$, is conditioned on that the transmitters index ≥ 2 are at r_i and beyond, while for tier x = {i, j}, all the transmitters are at r_x and beyond. By Slivnyak's Theorem, the transmitters are also distributed as homogeneous PPPs. Recalling the steps in (5.4) (and also, $\mathbb{E}_h[\exp(-P_{t,i} h_i r_i^{-\alpha})] = 1/(1 + P_{t,i,1} r_{i,1}^{-\alpha})$),we get the Laplace transform, hence success probability, for connecting to tier *i* as

$$\mathcal{L}_i\left(\frac{\gamma r^{\alpha}}{P_{t,i}}\right) = \frac{\exp\left(-\frac{\gamma r_i^{\alpha}\sigma^2}{P_{t,i,}}\right)}{1+-P_{t,j} r_i^{-\alpha}} \times \left\{\prod_k \exp\left(-\pi r_i^2 \kappa_k^2 \kappa_i^{-2} \lambda_k \rho\left(\frac{\gamma P_{t,k} \kappa_i^{\alpha}}{P_{t,i} \kappa_k^{\alpha}, \alpha}\right)\right)\right\} \quad (5.7)$$

Therefore, the relation $Q_i\tau_i = Q_j\tau_j$ is equivalent to the relation $\mathbb{P}_i(\tau_i \mathrm{SINR} > \gamma) = \mathbb{P}_j(\tau_j \mathrm{SINR} > \gamma)$ for all γ. Define $\gamma_i = \gamma/\tau_i$. To verify the relation $Q_i\tau_i = Q_j\tau_j$, replace γ with γ_i in (5.7). Continue by plugging in $r_i\kappa_i = r_j\kappa_j$ together with $\tau_x = \kappa_x^{\alpha}/P_{t,x}$ for all x and perform a series of algebraic manipulations to verify that the two success probabilities are indeed equal. This verifies that the relation $Q_i\tau_i = Q_j\tau_j$ also holds at the same time. Thus, the two schemes are equivalent with the relation $\tau_x = \kappa_x^{\alpha}/P_{t,x}$ for all x.

5.1.3.Theorem 5: The coverage probabilities for the instantaneous SINR based scheme are

$$\mathbb{P}_{\text{INS}} = \sum_{i=1}^{k} \lambda_i \int_{r=0}^{\infty} 2\pi r exp(-(\sum_k \lambda_k P_{t,k}^{2/\alpha}) C(\alpha)(\gamma_i/P_{t,i})^{2/\alpha} r^2) \exp\left(-\left(\frac{\gamma_i}{P_{t,i}}\right)\sigma^2 r^{\alpha}\right) dr (5.8)$$

$$\mathbb{P}_{INS,\sigma^2=0} = \frac{\pi}{C(\alpha)} \frac{\sum_{i=1}^{k} \lambda_i P_i^{2/\alpha} \gamma_i^{-2/\alpha}}{\sum_{i=1}^{k} \lambda_i P_i^{2/\alpha}} dr \quad (5.8)$$

Where $C(\alpha) = \frac{2\pi^2}{\alpha} \csc (2\pi/\alpha)$

5.2. Constrained Optimization Framework:

Similar to the previous chapter, we investigate the problem of minimizing energy consumption subject to a QoS constraint in terms of coverage probability.

5.2.1 Power Consumption Minimization with Average Signal based Scheme:

In the following, we formulate an optimization problem that minimizes energy consumption across different tiers. Using Theorem 4 and Lemma 5, we obtain the following corollary.

5.2.2.1 Corollary 1. If we connect to the highest average SINR signal, the coverage probabilities are given by

$$\mathbb{P}_{\text{SIG}} = \sum_i \lambda_i P_i^{2/\alpha} \int_{r=0}^{\infty} 2\pi r exp(-r^{\alpha}\gamma\sigma^2)$$

$$\exp(-\pi r^2 \left(\sum_i \lambda_i P_i^{\frac{2}{\alpha}}\right)(1 + \rho(\gamma, \alpha)))\text{dr} \quad (5.9)$$

$$\mathbb{P}_{INS,\sigma^2=0} = \frac{1}{1+\rho(\gamma,\alpha)} \quad (5.10)$$

- Proof: Let $\kappa_i = P_{t,i}^{1/\alpha}$ in Theorem 4. The result is obtained after some algebraic manipulations.

We investigate now the following optimization problem:

$$P_{SIG}: \begin{Bmatrix} \underbrace{min}_{\lambda_i \forall_i} & \sum_i \lambda_i (P_{i0} + P_i \\ s.t. & \mathbb{P}_{OAP} \geq \epsilon \end{Bmatrix} \quad (5.11)$$

For our analysis, it is necessary to consider the cases $\sigma^2 = 0$ and $\sigma^2 > 0$ separately. When $\sigma^2 = 0$, the solution is to choose λ_i as small as possible, for all i. Hence, when the network is dense, it is beneficial to shut down as many access points as possible. However, this observation is no longer valid when the network is sparse as the assumption $\sigma^2 = 0$ is no longer valid. Now, suppose $\sigma^2 > 0$, we denote S $=\sum_i \lambda_i P_{t,i}^{2/\alpha}$ for notational convenience. As a consequence of Lemma 3, the optimal S* $=\sum_i \lambda_i^* P_{t,i}^{2/\alpha}$, satisfies

$$\epsilon = S^* \int_{r=0}^{\infty} 2\pi r exp(-r^2 \pi S^* (1 + \rho(\gamma, \alpha))) \exp\text{-}(r^\alpha \gamma \sigma^2) dr \quad (5.12)$$

This reduces the original minimization problem in (5.12) to

$$P_{SIG}^0: \begin{Bmatrix} \underbrace{min}_{\lambda_i, \forall_i} & \sum_i \lambda_i (P_{i0} + P_i) \\ s.t. & \sum_i \lambda_i P_{t,i}^{2/\alpha} = S^* \end{Bmatrix} \quad (5.13)$$

which is a linear program having as solution the tier that minimizes $(P_{i0} + P_i)\ P_{t,i}^{2/\alpha}$.This minimization problem can be further adapted to include certain constraints on λ_i and it still gives a linear program (for example, the macro tier structure is an existing infrastructure and this could be reflected by fixing λ_M). In a more general setting, one could include β_i representing power control as a decision variable (replace $P_{t,i}$ with $\beta_i P_{t,i}$) though the resulting minimization problem would require numerical computation.

5.2.2 Energy Efficiency Optimization with Instantaneous SINR based Scheme: In the following, we shall consider that the network has two tiers, a macro tier where random sleeping is implemented and a femto tier that does not implement any sleeping strategy. Given the density of the femtocell access points λ_F , we want to determine the value of q_{INS}^* that optimizes the energy efficiency. Since the equations are intractable in general, we assume that $\sigma^2 = 0$ as a means to obtain some insight. The problem formulation is given by

$$\mathrm{P_{INS}}: \begin{cases} \underbrace{max}_{q} \quad \frac{\pi}{C(\alpha)} \frac{q\lambda_{\mathrm{M}} P_{t,M}^{2/\alpha} {\gamma_i}^{-2/\alpha} + \lambda_{\mathrm{F}} P_{t,F}^{2/\alpha} {\gamma_i}^{-2/\alpha}}{q\lambda_{\mathrm{M}} P_{t,M}^{2/\alpha} + \lambda_{\mathrm{F}} P_{t,F}^{2/\alpha}} \times \frac{log_2(1+\gamma)(\lambda_{\mathrm{M}} q + \lambda_{\mathrm{F}})}{\lambda_{\mathrm{M}}\left(qP_{M0} + q\Delta_M P_M + (1-q)P_{sleep}\right) + \lambda_{\mathrm{F}}(P_{F0} + \Delta_F P_F)} \end{cases} \quad (5.14)$$

which is monotone decreasing in q and hence has optimal $q_{INS}^{*}= 0$.

CHAPTER 6

RESULTS AND DISCUSSION

In this chapter, we use the default values in Table-6.1 unless otherwise stated. The parameters concerning the power consumption are obtained from [6].

TABLE-6.1

PARAMETER VALUES USED RESULT

Parameter	Value
α	4
λ, μ	$10^{-4}\,m^{-2}$,$10^{-3}\,m^{-2}$
$P_{t,M}$, $P_{t,F}$	43 dBm, 10 dBm
σ^2	1
Γ	-10dB
P_{sleep}	75.0 W (Macro only)
P_{M0}, P_{F0}	130.0 W, 4.8 W
Δ_M,Δ_F	4.7, 8.0
P_M, P_F	20.0 W, 0.05 W

We shall consider two models of activity levels: binary where the activity level associated with each coverage area, which in turn is associated with a particular MBS is either 0 or 1 with probability 0.5 each, and uniform where the activity level is drawn from a uniform [0, 1] random variable. The sleeping strategy for both cases is identical: if the activity level in the coverage area associated with the MBS is a, then the MBS stays awake with probability a. We also calculate the coverage probability through Monte Carlo simulation. The locations of the MBSs are distributed according to a PPP in a 5000m×5000m grid, with 5000 trials. Fig.6.1 compares the analytical results versus the simulated results, verifying the validity of the expression (4.5) concerning the strategic sleeping strategy for $\sigma^2 = 0$. From henceforth, all figures are numerical plots of the expressions obtained previously. Fig. 6.2 shows the energy efficiency with random sleeping with respect to q for various values of β (expression (4.1) divided by expression (3.4)).

From this figure, we observe that the energy efficiency increases with q. This is because the network throughput decreases at a faster rate than the savings in power consumption when we decrease q. The figure also shows that the energy efficiency decreases with increasing β, which implies that the cost incurred from raising the power uniformly is not compensated by an increase in the data rate. Note that this result has not yet taken into account traffic demands and different operating power consumption parameters at the MBS. Therefore, it is likely that taking into account these additional parameters will give us new tradeoffs, which will be studied in future work. Nevertheless, our framework does give a simple tractable approach to study the effect of random sleeping in macrocell networks. Fig.6.3 plots the coverage probability versus noise σ^2 for different sleeping strategies (eq. (4.4)) while Fig. 4 plots the energy efficiency with respect to q for various sleeping strategies (eq. (4.4) divided by eq. (3.5)). For Fig. 6.3, the activity model for strategic sleeping is assumed to be 0 and 1 with equal probability 0.5. The sleeping strategy is modeled as 0 and 1, respectively. For random sleeping, MBSs are in sleep mode with probability 0.5. From the plots, we can see that the coverage probability per active user in strategic sleeping is only marginally better than no sleeping. We also see that strategic sleeping has a bigger margin of improvement over no sleeping when $\sigma^2 \rightarrow 0$. In this figure, we see that even for a contrived example, there is little improvement when noise is significant. On the other hand, our analytical results demonstrate that when $\sigma^2 = 0$, any increasing strategy S(a) would suffice. This implies that the presence of noise can significantly affect the performance. Finally, it can be seen that expectedly, strategic sleeping is always better than random sleeping for the same fraction of sleeping MBSs. In Fig.6.4, we choose the strategic sleeping model to have a activity 1 with probability q, represented by the x-axis, and activity 0 otherwise. Likewise the sleeping strategy is 1 if the activity is 1, 0 otherwise. To obtain a fair comparison, we also plot the random sleeping with MBS staying awake with probability q so that both plots have the same fraction of active MBSs. From Fig 6.4, we observe that the energy efficiency for a strategic sleeping strategy is also higher than random sleeping and in fact, for these set of parameters, is about half of the interference-limited regime case for all values of q.

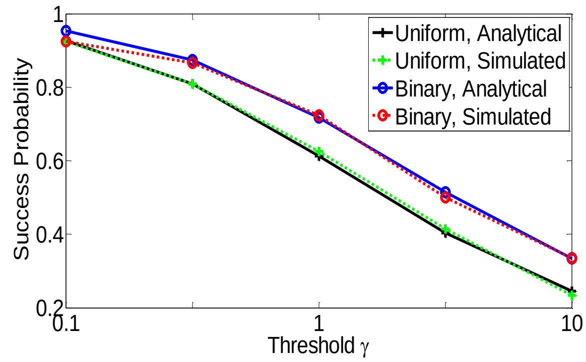

Fig.6.1. Comparison of analytical expressions vs. simulated results for strategic sleeping mode.

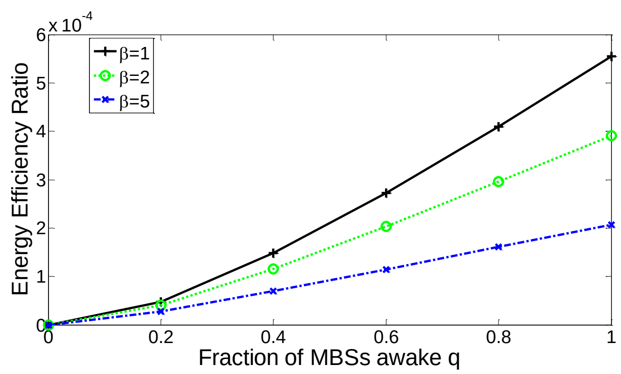

Fig. 6.2. Effect of power control on energy efficiency.

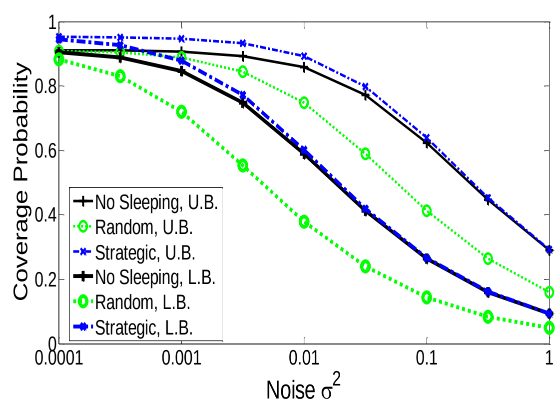

Fig. 6.3. Coverage probabilities for different sleeping strategies.

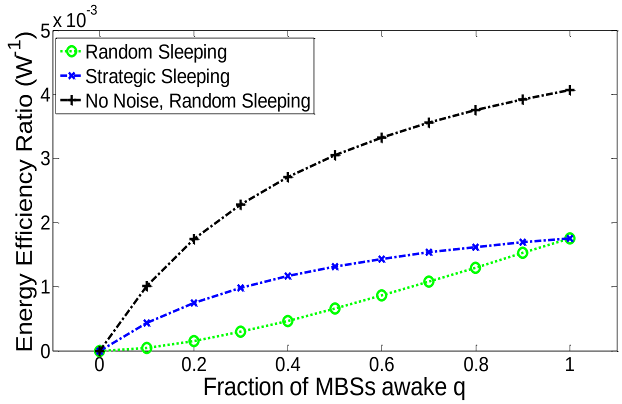

Fig.6.4. Energy efficiency ratio for different sleeping strategies.

CONCLUSION

In this thesis, we investigated the design of energy efficient cellular networks through the employment of base station sleep mode strategies as well as small cells, and investigated the trade off issues associated with these techniques. Using a stochastic geometry based model, we derived the success probability and energy efficiency under sleeping strategies in homogeneous macro cell and heterogeneous K-tier networks. In addition, we formulated optimization problems in the form of power consumption minimization and energy efficiency maximization and determined the optimal operating frequency of the macro cell base station. In particular, we investigated the impact of random sleeping and strategic sleeping on the power consumption and energy efficiency. Numerical results confirmed the effectiveness of sleeping strategy in homogeneous macro cell networks but the gain in energy efficiency depends on the type of sleeping strategy used. In addition, the deployment of small cells generally leads to higher energy efficiency but this gain saturates as the density of small cells increases. Future work may include the extension of the above model to the case where base stations have multiple antennas and may perform opportunistic user selection. It would also be of interest to explore how random spatial placements of base stations that model repulsion or inhibition affect the results in terms of throughput and energy efficiency. Finally, the energy efficiency metric investigated here is only dependent on the power consumption and the coverage within the network, and does not take into account the infrastructure cost and backhaul overhead associated with implementing small cell networks.

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ANNEXURE- 1

Performance Analysis of Energy Efficient Heterogeneous Cellular Networks

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Abstract- *With the exponential increase in mobile internet traffic driven by a new generation of wireless devices, future cellular networks face a great challenge to meet this overwhelming demand of network capacity. At the same time, the demand for higher data rates and the ever-increasing number of wireless users led to rapid increases in power consumption and operating cost of cellular networks. One potential solution to address these issues is to overlay small cell networks with macrocell networks as a means to provide higher network capacity and better coverage. Another technique to improve energy efficiency in cellular networks is to introduce active/sleep (on/off) modes in macrocell base stations. In this paperwe investigate the design and the associated tradeoffs of energy efficient cellular networks through the deployment of sleeping strategies and small cells. We derive the success probability and energy efficiency in heterogeneous K-tier wireless networks under different sleeping policies. In addition, we formulate the power consumption minimization and energy efficiency maximization problems, and determine the optimal operating regimes for macrocell base stations. In addition, the deployment of small cells generally leads to higher energy efficiency but this gain saturates as the density of small cells increases. In a nutshell, our proposed framework provides an essential understanding on the deployment of future green heterogeneous networks.*

Keywords- Cellular networks, Energy efficiency , heterogeneous K-tier wireless networks

I. INTRODUCTION

A new wireless technology generation is introduced every decade and the standardization is guided by the International Telecommunication Union (ITU), which provides the minimum performance requirements. For example, 4G was designed to satisfy the IMT-Advanced requirements [1] on spectral efficiency, bandwidth, latency, and mobility. Similarly, the new 5G standard [2] is supposed to satisfy the minimum requirements of being an IMT-2020 radio interface [3]. In addition to more stringent requirements in the aforementioned four categories, a new metric has been included in [3]: energy efficiency (EE). A basic definition of the EE is [4], [5].

$$\mathrm{EE[bit/Joule]} = \frac{\text{Data rate [bit/s]}}{\text{Energy consumption [Joule/s]}} \quad (1)$$

This is a benefit-cost ratio and the energy consumption term includes transmit power and dissipation in the transceiver hardware and baseband processing [5], [6]. A general concern is that higher data rates can only be achieved by consuming more energy; if the EE is constant, then 100× higher data rate in 5G is associated with a 100× higher energy consumption. This is an environmental concern since wireless networks are generally not powered from renewable green sources. It is desirable to vastly increase the EE in 5G, but IMT-2020 provides no measurable targets for it, but claims that higher spectral efficiency will be sufficient. There are two main ways to improve the spectral efficiency: smaller cells [6], [7] and massive multiple-input multiple-output (MIMO) [8], [9]. The former gives substantially higher signal-to-noise ratios (SNRs) by reducing the propagation distances and the latter allows for spatial multiplexing of many users and/or higher SNRs. Since these gains are achieved by deploying more transceiver hardware per km2, higher spectral efficiency will not necessarily improve the EE; the EE first grows with smaller cell sizes and more antennas, but there is an inflection point where it starts decaying instead [10]. The bandwidth is fixed in these prior works, but many other parameters are optimized for maximum EE. There are other non-trivial tradeoffs, such as the fact that transceiver hardware becomes more efficient with time [6], [11], so the energy consumption of a given network topology gradually reduces.

While the Shannon capacity [12] manifests the maximal spectral efficiency over a channel and the speed of light limits the latency, the corresponding upper limit on the EE is unknown. A comprehensive study of the EE of 4G base stations is found in [13]. It shows that a macro site delivering 28 Mbit/s has an energy consumption of 1.35kW, leading to an EE of 20 kbit/Joule. Recent papers report EE numbers in the order of 10 Mbit/Joule [5], [14], [15] when considering future 5G deployment scenarios and using estimates of current transceivers' energy consumption. There is also numerous papers that consider normalized setups (e.g., 1 Hz of bandwidth) that give no insights into the EE that can be achieved in practice. Finally, the channel capacity per unit cost was studied for additive white Gaussian noise (AWGN) channels in [16], which is a rigorous but normalized form of EE analysis.

The goal of this paper is to analyze the physical EE limits in a few different cases and, particularly, give practically relevant numbers on the maximum achievable EE. Existing cellular architectures are designed to cater to large coverage areas, which often fail to achieve the expected throughput to ensure seamless mobile broadband in the uplink as users move far away from the base station. This is mainly due to the increase in inter-cell interference, as well as constraints on the transmit power of the mobile devices. Another limitation of conventional macrocell approach is the poor indoor penetration and the presence of dead spots, which result in drastically reduced indoor coverage. In order to overcome these issues and provide a significant network performance leap, heterogeneous networks have been introduced in the LTE-Advanced standardization [1]–[3]. A heterogeneous network uses a mixture of macrocells and small cells such as microcells, picocells, and femtocells. These small cells can potentially improve spatial reuse and coverage by allowing future cellular systems to achieve higher data rates, while retaining seamless connectivity and mobility in cellular networks. Besides the issue of meeting overwhelming traffic demands, network operators around the world now realize the importance of managing their cellular networks in an energy efficient manner and reducing the amount of CO2 emission levels simultaneously [4]–[7]. Current studies show that the amount of CO2 emission levels due to information and communication technologies is already 2%. With the exponential increase in data traffic and mobile devices, this figure is projected to increase significantly. Improving energy efficiency also helps network operators reduce the operational cost as energy constitutes a significant part of their expenditure. As a result, the terminology of ”green cellular network” has become very popular recently, showing the current sentiment of the telecom industries to place more emphasis on energy efficiency as one of the key performance indicators for cellular network design [7]. Although the deployment of small cell networks is seen to be a promising way of catering to the ever increasing traffic demands, the dense and random deployment of small cells and their uncoordinated operation raise important questions about the implication of energy efficiency in such multitier networks [8]–[11]. Besides introducing small cells into existing macrocell networks, another effective technique is to introduce sleep mode in macrocell base stations (MBSs) [12]–[15]. The main motivation is that current cellular networks usually assume that the traffic demand is always high and so the MBSs are always powered on at all times. However, studies have shown that there are high fluctuations in traffic demand over space and time in cellular networks [6]. For example, the traffic demands in urban and rural areas or traffic demands in day and night time are entirely different. From this perspective, there is potential in energy savings by adapting the sleeping mode of MBSs to the demanded traffic. Nevertheless, when we switch some MBSs off, certain users may need to connect to MBSs located further away while experiencing a lower amount of intercell interference. For the case of dense deployment of MBSs, we know that these two effects cancel out equally and the coverage probability is independent of the sleeping mode [16]. However, for sparse deployment of MBSs, it is expected that we need to maintain the coverage of the cellular networks when we implement sleeping mode in MBSs either through power control or open access small cells. Since both techniques consume power, it is unclear which technique is more energy efficient and how the energy efficiency depends on the intensity of small cells and access policy. On the other hand, one of the major challenges in small cell deployment is the incursion of inter-tier interference due to aggressive frequency reuse, which can deteriorate the effectiveness of small cell architecture [1]–[3]. As a result, there has been a significant amount of research on managing inter-tier and intra-tier interference in a two-tier small cell network, which consists of a macrocell network overlaid with small cells [17], [18]. In [17], the authors proposed a spectrum partitioning approach to avoid the inter-tier interference between the macrocell and small cell tiers by using orthogonal spectrum allocation. However, under a sparse small cell deployment setting, this approach is clearly inefficient and much higher area spectrum efficiency can be attained if spectrum sharing is allowed [18]. On the other hand, for spectrum sharing in two-tier small cell networks, it becomes imperative to properly manage the inter-tier interference using techniques such as access control [18], [19], power control [20], [21], multiple antennas [22], or cognitive radio [23]–[25]. Besides interference management techniques, interference modeling in two-tier networks using stochastic geometry has also gathered considerable attention due to its accuracy and tractability [26]–[28]. The spatial distribution of MBSs in the network is usually modeled by lattices or hexagonal cells since their deployment is considered well-planned, centralized, and hence regular. Nevertheless, it has been recently shown that modeling MBSs by a homogeneous Poisson point process (PPP) and associating macrocell users to their closest MBSs is a tractable yet accurate macrocell network model [16]. On the other hand, femtocell access points (FAPs) are extensively modeled as PPP as well, mainly due to uncoordinated and random deployment and operation. In this work, we apply the tools from stochastic geometry to analyze the energy efficiency of cellular networks through the deployment of sleeping strategy as well as small cells. By assuming that the network operators have some information of the traffic usage patterns, they can employ a coordinated sleeping mode, where certain MBSs will be shut off while others increase their coverage areas to avoid coverage hole. In particular, we model the sleeping mode at each MBS as a Bernoulli random variable, where q denotes the probability that a MBS remains in operation and the underlying spatial distribution of MBSs is modeled as a PPP. In practice the network operators will have a predetermined policy of sending MBSs to sleep that ensures reasonable coverage over the entire network, i.e., such as spacing out sleeping MBSs regularly. We nevertheless adopt a marked PPP to model the dynamics of the sleeping mode (which is a random process) for its tractability in order to come up with reasonable design guidelines of green cellular network design. To maintain similar network coverage after some MBSs have been switched off, we need to perform some form of power control. Given no knowledge of the channel state information, we will employ fixed power control. One question we will explore is the effect that q has on the energy efficiency when we shut some MBSs off.

While we will reduce the interference from some MBSs, this will cause certain macrocell users to connect to MBSs which are even further away. Besides homogeneous macrocell networks with sleeping strategy, we will also investigate the energy efficiency in heterogeneous K-tier networks with open access small cells. In addition, we formulate optimization problems in the form of power consumption minimization and energy efficiency maximization and determine the optimal operating frequency of the macrocell base station. Numerical results confirm that the effectiveness of sleeping strategy in homogeneous macrocell networks but the gain in energy efficiency depends on the type of sleeping strategy used. In addition, the deployment of small cells generally lead to higher energy efficiency but this gain saturates as the density of small cells increases.

The mobile industry faces a critical energy consumption challenge. Anticipated by Gartner [1],by 2013 smartphones will exceed 1.82 billion units and surpass PCs as the most common web access devices. Consequently, more wireless infrastructures have to be deployed with large demands on energy. Meanwhile, data-intensive services are beginning to dominate mobile services. The network data volume is expected to increase by a factor of 10 every five years, associated with a 16–20 percent increase of energy consumption [2]. Applying this rate to mobile communications, which contribute 15–20 percent of the entire information and communications technologies (ICT) energy footprint and 0.3–0.4 percent of global CO_2 emissions [2], the mobile industry faces a great sustainable development problem in energy consumption. It is crucial to develop energy-efficient wireless technologies to meet this challenge. We study In this papere the energy efficiency (EE) of the wireless access network, which is broadly defined as any wireless system using radio base stations (RBSs) or access points (AP) to interface mobile devices with the core network or Internet. The reasons to focus on wireless access networks are following. First, since wireless access networks are the most widely deployed wireless networks in the world, energy-efficient solutions designed for wireless access networks are expected to significantly improve EE in the ICT sector. Second, as a long tradition, the standards of wireless access networks are mainly focused on throughput performance. Only recently has EE been receiving increasing attention. Significant studies are needed to balance performance and EE. Third, the demand from mobile users for EE is urgent in order to enjoy better mobile services. As shown in Fig.1.1, statistics indicate that the RBS is the main source of energy consumption in the network of a mobile operator [3]. Energy efficient solutions for wireless access networks are mainly concentrated on RBSs. Among all components in an RBS, power amplifiers (PAs) drain the most energy. Energy is also dissipated in alternating current/direct current (AC/DC) converting, cabling, and cooling. Various solutions have been proposed to improve EE of the RBS, such as increasing PA efficiency, using non-active cooling techniques, employing masthead PA to reduce feeder loss, exploiting energy efficient backhaul solutions, applying energy-efficient deployment strategies, and introducing energy-efficient protocols. This papere overviews soft methods to improve EE of RBSs, with an emphasis on Long Term Evolution (LTE) sys tems. Soft methods do not upgrade hardware, but tune parameters in protocols, and apply enhanced architecture and deployment strategies for EE improvement. They enable flexible and cost-efficient solutions with minimum impact on hardware implementation.

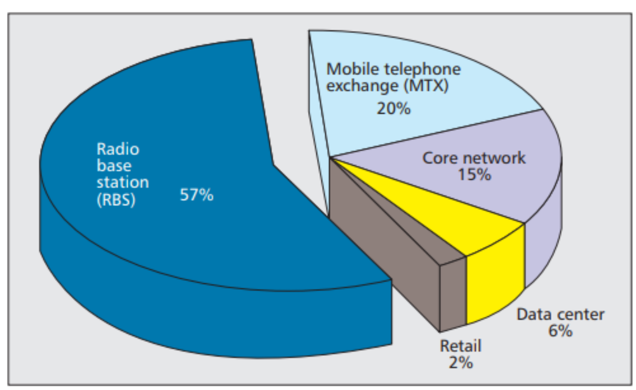

Figure 1.1 Energy consumption composition of a mobile operator [3].

II. SYSTEM MODEL

2.1 Network Model :

We consider a wireless cellular network consisting of MBSs located according to a homogeneous PPP ΘM of intensity λM in the Euclidean plane. Users are distributed according to a different independent stationary point process of intensity μ. Each macrocell user is associated with its geographically closest MBS and the analysis is performed for a randomly selected typical user. Since ΘM is a stationary process, the distribution of distance RM between a macrocell user and its designated MBS remains the same regardless of the exact locations, and its probability density function (pdf) is given by $f_{R_M}(r) = 2\pi\lambda_M r\exp(-\lambda_M \pi r^2)$. We assume universal frequency reuse among base stations and that each MBS serves only one user. If there are multiple users in a Poisson-Voronoi cell, some form of orthogonal resource sharing (e.g. frequency or time division multiple access) is performed.

2.2. Signal-to-Interference-plus-Noise Ratio:

For notational convenience, we denote a base station by its location while the user is at the origin 0. For downlink transmission of a MBS x to the typical user 0, the signal-to interference-plus-noise ratio (SINR) experienced by a macrocell user is given by

$$\mathrm{SINR}_M(x \to u) = \frac{P_{t,i} h_x g(x)}{\sum_{y \in \Theta_M} P_{t,y} h_y g(y) + \sigma^2} \quad (2)$$

where Θ(x) denotes the set of nodes interfering with x, Pt,i denotes the transmit power at tier i, and hx,hy are the channel power gain due to small-scale fading from x, y respectively. In the following, we assume that hx ~ exp(1) and hy ~ exp(1) (Rayleigh fading). The background noise is assumed to be additive white Gaussian with variance σ2 and the path loss function is denoted by $g(x) = \|x\|^{-\alpha}$, with α being the path loss exponent.

2.3. Power Consumption Model: K

We also consider a general K-tier heterogeneous network model, where the base stations in each tier are modeled as independent homogeneous PPP Θi with intensity λi. We will always use Θ1 for the macro tier ΘM. In addition, we consider again that all base stations in the K tiers share the same bandwidth. Without employing any sleeping mode at each base station in the i-th tier, the average power consumption of the i-th tier heterogeneous networks is given by

$$P_{Het,i} = \lambda_i (P_{i0} + \Delta_i P_i) \quad (3)$$

where Pi0 is the static power expenditure of the base station in the i-th tier, Pi is the RF output power of the i-th tier base station, and Δi is the slope of the load-dependent power consumption the base station in the i-th tier.

2.4. Base Station Sleep Mode Strategies:

In this paper, we present the two main policies that we propose and analyze in order to optimize the power consumption at each MBS. We investigate policies of dynamically switching off MBS, where the power consumed by a switched off MBS in sleep mode is P_{sleep}. Note that we consider that $P_{sleep} < P_{M0}$ which is a valid assumption for future base stations with sleeping mode capabilities. To maintain similar network coverage after some MBSs having been switched off, we employ power control by selecting $P_{t,M}$ = $\beta^{P_{t_0,M}}$, where β denotes the uniform increase in transmission power for MBS. The attractiveness of fixed power control is that it compensates for the sleeping activity without the need for obtaining instantaneous channel state information for the macrocell users.

2.4.1 Random Sleeping:

In random sleeping, we model the sleeping strategy as a Bernoulli trial such that each station continues to operate with probability q and sleeps (is turned off) with probability 1−q, independently of all the other base stations. Therefore, after applying random sleeping at the macro tier, the average total power consumption of the macrocell network is given by

$$P_{RS} = \lambda_{Mq}(P_{M0} + \Delta_M \beta P_M) + \lambda_M(1 - q)P_{sleep} \quad (4)$$

2.4.2 Strategic Sleeping:

Instead of randomly switching MBSs off, we can also switch off MBSs when their activity levels are low, e.g. when load or traffic demands are low. Specifically, we model this strategic sleeping as a function s : [0, 1] → [0, 1] which says that if the activity level of the coverage area associated with the MBS has activity level x, then it operates with probability s(x) and sleeps with probability 1−s(x), independently. This sleep mode strategy can be seen as a load-aware policy and it can incorporate traffic profile in the optimization problem. As a result, the average power consumption of the macrocell network after employing strategic sleeping is given by

$$P_{SS} = \lambda_M E\{s\}(P_{M0} + \beta \Delta_M P_M) + \lambda_M (1 - E\{s\}) P_{sleep}, \quad (5)$$

where E{s} = $\int_0^1 s(x) f_A(x) dx$ and $f_A(x)$ is the pdf of A and A denotes the random activity within a cell and takes values in [0, 1]. The rationale behind the proposed strategic sleeping is the following: while random sleeping models a network that is adaptive to the fluctuating activity levels during the day, strategic sleeping goes one step further and models a network that is adaptive to the fluctuating activity levels within the location. Furthermore, the strategic sleeping model may be used as a method of measuring the impact of cooperation among MBSs. Let us illustrate this with an example. Suppose that we have a pair of cooperating MBSs. If the activity level in the combined coverage area is expected to be below half of the full capacity, then the pair may choose to keep only one of them awake. Then, the awake MBS may serve both coverage areas or the coverage areas can be reassigned among all remaining awake MBSs. The above cooperation model can be modeled by strategic sleeping by having, say, both MBS to stay awake with probability s = 0.5. While an explicit association between neighboring MBSs is technically absent, this model may nevertheless be seen as a way to measure the energy savings by introducing cooperation within the network.

III. HOMOGENEOUS MACROCELL NETWORK

In this paper, we study the effect of switching off MBSs based on the aforementioned sleeping policies, i.e. randomly and dynamically. The performance measure is the coverage probability and the effect of noise is taken into account, i.e. $\sigma^2 > 0$. In recent work analyzing coverage in macro cellular networks, it is shown that the coverage probability is independent of the intensity of the base stations in the interference-limited regime ($\sigma^2 \to 0$) [16]. This also holds true in heterogeneous *K*-tier networks [18], [29-31]. The main reason behind this is the fact that in dense networks, the improvement in received signal power by adding more MBSs and bringing the transmitters closer to the receivers is equally canceled out by the increased interference from more MBSs (interferers). Nevertheless, when MBS sleeping policies are applied, the effect of noise is noticeable and cannot be ignored as the number of interferers may be significantly decreased. Therefore, in this work we also consider the case where $\sigma^2 > 0$.

3 .1 Random Sleeping :

As explained in Paper 3, the random sleeping strategy is simply equivalent to modeling the active MBSs as a marked PPP with intensity $q\lambda_M$ and increasing the transmission power of the active MBSs to βP_M.

Theorem 1. In homogeneous macrocell networks with random sleeping, the coverage probability of a randomly located macrocell user is given by

$$\mathbb{P}_{RS}(\beta,\gamma) = 2\pi q\lambda_M \int_{r=0}^{\infty} r\exp\left(-\pi r^2 q\lambda_M\left(1+\rho(\gamma,\alpha)\right)\right) \times \exp\left(-r^\alpha \gamma\sigma^2/\beta P_{t,m}\right) dr \tag{6}$$

Where $\rho(\gamma,\alpha) = \gamma^{2/\alpha}\int_{\gamma^{-2/\alpha}}^{\infty} \frac{1}{1+u^{\alpha/2}} du$

Furthermore, for $\sigma^2 = 0$, $\mathbb{P}_{RS}(\beta, \gamma)$ can be simplified as

$$\mathbb{P}_{RS}(\beta,\gamma) = \frac{1}{1+\rho(\gamma,\alpha)}$$

Proof :

The coverage probability is defined as

$$\int_{r=0}^{\infty} \mathcal{L}_I(r)\mathcal{L}_N(r) f_{\lambda_M}(r) dr \tag{7}$$

where the probability density function of the MBS $f_{\lambda_M}(r)$ is $2\pi\lambda_M r \exp(-\pi\lambda_M r^2)$ (without sleeping) and $2\pi q\lambda_M r \exp(-\pi q\lambda_M r^2)$ (with sleeping).

We can see that the coverage probability is completely independent of the sleeping policy, the density of MBSs λ_M, as well as the power control β when $\sigma^2 = 0$.The only parameter that affects the coverage probability is the target SINR threshold γ. In the case of $\sigma^2 > 0$, numerical integration is required to calculate the coverage probability.

3.2 Strategic Sleeping:

Here we analyze the strategic MBS switching off that is based on the activity of macrocell users in each cell. We assign i.i.d. random variables $A_i \sim A$ to each MBS $i \in \Theta_M$, such that A takes values in [0, 1]. A_i represents user activity within the Poisson-Voronoi cell that the MBS covers. That is to say, for any user located in a Poisson-Voronoi cell of a MBS with activity level a, the user is active with probability a, i.e. it is actually connected to the MBS with probability a. Therefore, we can model the sleeping strategy as a function s :[0, 1] → [0, 1], which implies that if the activity level of the MBS has activity level x, then it operates with probability s(x) and sleeps with probability 1 − s(x). In addition, we impose that s(x) is increasing. Using this model, the active MBSs are distributed accordingly to a homogeneous PPP with intensity $\lambda_M E\{s\} = \lambda_M \int_0^1 s(x) f_A(x) dx$. Therefore, the coverage probability that captures the activity of the macrocell user is provided in the next theorem.

Theorem 2. The coverage probability of the active macrocell user2 is given by

$$\mathbb{P}_{SS}(\beta,\gamma) = \frac{1}{E\{a\}}\Big\{\int_0^1 xs(x)\, f_A(x)dx \int_{r=0}^{\infty} exp\big(-\pi r^2\lambda_M E\{s\}\big(\rho(\gamma,\alpha)\big) \times \exp\left(-r^{\alpha}\gamma\sigma^2/\beta P_{t,m}\right) g_1 r dr + \int_0^1 x(1 - s(x)) f_A(x)dx \sum_{i=2}^{\infty} \int_{r=0}^{\infty} exp\big(-\pi r^2\lambda_M E\{s\}\big(\rho(\gamma,\alpha)\big) \times \exp\left(-r^{\alpha}\gamma\sigma^2/\beta P_{t,M}\right) g_i r dr \tag{8}$$

where $g_i(r)$ is the pdf of the i-th nearest point from a PPP, such that $g_i(r) = \frac{2\pi^i r^{2i-1}\lambda_M^i}{(i-1)!} exp(-\pi r^2 \lambda_M)$. For $\sigma^2 = 0$, $\mathbb{P}_{SS}(\beta,\gamma)$ can be simplified as

$$\mathbb{P}_{SS}(\beta,\gamma) = \frac{1+\rho(\gamma,\alpha)E\{as(a)\}/E\{a\}}{1+E\{s\}\rho(\gamma,\alpha)\,(1+\rho(\gamma,\alpha))} \tag{9}$$

Proof: The first step is to condition on the activity of a typical cell a(x). Next, we enumerate all the MBSs in increasing order of distance from the user, starting from the distance of each MBS from the user is almost surely distinct. Nord denotes the order of the MBS the user connects to and $f_A(x)$ denotes the pdf of A. The success probability per link is thus given by

$$\mathbb{P}_{SS} \overset{(a)}{\triangleq} \frac{1}{E\{a\}}\int_0^1 x\mathbb{P}(SINR > \gamma|x)\, f_A(x)dx$$
$$\overset{(b)}{\triangleq} \frac{1}{E\{a\}}\int_0^1 \{x\mathbb{P}(N_{ord}=1)\mathbb{P}(SINR>\gamma|N_{ord}=1) + x\mathbb{P}(N_{ord}>1)\mathbb{P}(SINR>\gamma|N_{ord}>1)\} f_A(x)dx$$
$$\overset{(c)}{\triangleq} \frac{1}{E\{a\}}\Big\{\int_0^1 xs(x) \int_{r=0}^{\infty} \exp\left(-\pi r^2\lambda_M E\{s\}\rho\right) exp(-\pi r^2\lambda_M) \exp\left(-r^{\alpha}\gamma\sigma^2/\beta P_{t,M}\right)dr + x(1-s(x))\mathbb{P}(SINR>\gamma|N_{ord}>1)\Big\} f_A(x)dx \tag{10}$$

where (*a*) is by definition of a coverage probability weighted over the active user links, (*b*) partitions into the event of the nearest MBS being awake and the event of the nearest MBS being asleep, and (*c*) is from the Laplace transform of the remaining active interferers, distributed as a PPP with intensity $E\{s\}\lambda_M$, and the pdf of the nearest MBS. This leads us to $\mathbb{P}(SINR > \gamma|N_{ord} > 1)$, which is given by

$$\mathbb{P}_{SS}(\rightarrow|N_{ord}>1) \overset{(a)}{\triangleq} \sum_{i=2}^{\infty} \mathbb{P}(N_{ord}=i|N_{ord}>1)\mathbb{P}_{SS}(\rightarrow|N_{ord}=i)$$
$$\overset{(a)}{\triangleq} \sum_{i=2}^{\infty} E\{s\}(1 - E\{s\})^{i-2}\int_{r=0}^{\infty} exp\left(-\frac{r^{\alpha}\gamma\sigma^2}{\beta P_{t,M}}\right)\exp\big(-\pi r^2\lambda_M E\{s\}(1+\rho)\big)\, 2(\lambda_M\pi)^i r^{2i-1}dr \tag{11}$$

where (a) splits into the events "connect to the i-th MBS",(b) is the Laplace transform of the interference term and the pdf of the i-th MBS.

In the case where $\sigma^2 = 0$, the term $P(SINR > \gamma|N_{ord} > 1)$ simplifies to

$\sum_{i=2}^{\infty} \frac{E\{s\}(1-E\{s\})^{i-2}}{(1+E\{s\}\rho)^i} = \frac{1}{1+\rho}\frac{1}{1+E\{s\}\rho}$ which,combined with (10), leads to (9).

For the case of $\sigma^2 = 0$, we can see that the coverage probability is independent of the intensity of MBSs and the transmit power. Unlike the case of random sleeping, the strategic sleeping has an effect on the coverage probability even in the interference-limited regime (σ^2=0). Using (9),which corresponds to the interference-limited regime, we can show an interesting property of the strategic sleeping: the coverage probability of the active macrocell user is at least as good as in the case where no sleeping mode is employed.

3.3. Constrained Optimization Framework:

In the following, we use the results from the previous heading to solve several energy efficiency related optimization problems under different sleeping policies:

3.3.1 Power Consumption Minimization with Random Sleeping:

In the first problem, we minimize the power consumption subject to a coverage probability constraint, which can be interpreted as a QoS constraint. In the case of random sleeping, the problem is formulated as follows

$$P_{RS}: \begin{cases} \underbrace{min}_{q} \quad \lambda_M q(P_{M0} + \Delta_M \beta P_M) \\ \quad . \quad +\lambda_M(1-q)P_{sleep} \\ \quad s.t. \quad \mathbb{P}_{RS}(\beta,\gamma) \geq \epsilon \end{cases} \tag{12}$$

where q is the fraction of MBSs that are still operating. In order to solve the above problem, we first show that the coverage probability is an increasing function of a certain variable x. Then, we find the value x^* that satisfies the constraint tightly, and finally, we solve the minimization problem subject to the condition x^* .Therefore, rewriting $q\lambda_M = S$ in Theorem 1,we have

3.3.2. Power Consumption Minimization with Strategic Sleeping:

The minimization problem in the case of strategic sleeping is formulated similarly as

$$P_{SS}:\begin{cases}\underbrace{min}_{s} & \lambda_M(E\{s\})(P_{M0}+\Delta_M\beta P_M)\\ . & +\lambda_M(1-E\{s\})P_{sleep}\\ & s.t.\quad \mathbb{P}_{SS}(\beta,\gamma)\geq\epsilon\end{cases} \qquad (13)\ (16)$$

Solving the above optimization problem is more challenging in the case of strategic sleeping since before stating that the constraint is satisfied by equality, we first need to compute the optimal strategy as shown in the following lemma.

For a fixed E{s}, the strategy that optimizes the success probability per active user is to have $s(a) = 1_{\{a\geq a0\}}(a)$ for some a_0. That is to say, the strategy takes a form of a threshold function where the MBS is switched on if the activity exceeds a_0.

Theorem 3. The optimal s*(a), denoted as a*, satisfies

$$\epsilon=\frac{1}{E\{a\}}\mathbb{P}(SINR>\gamma|N_{ord}=1)\int_{a^*}^{1}xf_A(x)\ dx+$$
$$\mathbb{P}(SINR>\gamma|N_{ord}>1)\int_{0}^{a^*}xf_A(x)dx\} \qquad (14)$$

Where

$$\mathbb{P}(SINR>\gamma|N_{ord}=1)=\int_{r=0}^{\infty}e^{\left(-\pi r^2\lambda_M E\{s\}\rho(\gamma,\alpha)\right)}e^{-\frac{r^\alpha\gamma\sigma^2}{\beta P_{t,M}}}g_1rdr,$$

and

$$\mathbb{P}(SINR>\gamma|N_{ord}>1)=\sum_{i=2}^{\infty}\int_{r=0}^{\infty}e^{\left(-\pi r^2\lambda_M E\{s\}\rho(\gamma,\alpha)\right)}e^{-\frac{r^\alpha\gamma\sigma^2}{\beta P_{t,M}}}g_irdr,$$

N_{ord} = i denotes the event the user is connected to the i-th nearest MBS.

Despite the simple form of the optimal strategy, which is to switch on MBSs when the activity level exceeds a threshold, it may be realistic to assume a probabilistic decision making function taking probabilities that are not in {0, 1}.This is because operators may choose to shut down MBSs in a coordinated fashion according to the activity in a certain location. While this does not model coordination between neighboring cells, we can use intermediate probabilities to model the effect of coordination with a neighboring MBS which the current MBS hands traffic over to.

IV. HETEROGENEOUS K-TIER NETWORKS

In this paper, we consider that all base stations in the heterogeneous networks operate in open access, i.e. any user is allowed to connect to access points (called below as BSs) from any tier [29]. We consider three different user association schemes, namely location based scheme, average signal based scheme, and instantaneous SINR based scheme.

Theorem 1: The coverage probability for the general mobile user operating under the location based scheme is given by

$$\mathbb{P}_{LOC}=\sum_{i=1}^{K}\int_{r=0}^{\infty}2\lambda_i\pi r\exp(-r^2c_i)\exp(-r^\alpha\alpha_i)\,dr$$

where ai = $\gamma\sigma^2/P_{t,i}$

and $c_i=\pi\lambda_i(1+\rho(\gamma,\alpha))+\frac{\pi}{\kappa_i^2}\sum_{j\neq i}\lambda_j\ (1+\rho\left(\gamma\frac{P_{t,j}\kappa_i^\alpha}{P_{t,i}\kappa_j^\alpha},\alpha\right))$ when $\sigma^2=0$

we have

$$\mathbb{P}_{LOC,\sigma^2=0}=\sum_{i=1}^{K}\frac{\lambda_i\kappa_i^2}{\sum_j\lambda_j\kappa_j^2\left(1+\rho\left(\gamma\frac{P_{t,j}\kappa_i^\alpha}{P_{t,i}\kappa_j^\alpha},\alpha\right)\right)}dr \qquad (15)$$

Proof: Let fi(r) = 2πλirexp(−πλir2) denotes the pdf of the distance to the nearest BS in tier i. First, we compute the probability of connecting to tier i, i.e. ℙ(κiri<κjrj∀j $\neq i$) as follows:

$$\mathbb{P}(\kappa iri<\kappa jrj\forall j\neq i)=\int_{r=0}^{\infty}f_i(r)\mathbb{P}(\kappa_i r<\kappa_j r_j\forall_j\neq i)dr$$

$$=\int_{r=0}^{\infty}f_i(r)\left(\prod_{j\neq i}\int_{r_j=r^{\kappa_i}/_{\kappa_j}}^{\infty}f_j(r_j)\,dr_j\right)dr$$

$$=\int_{r=0}^{\infty}f_i(r)\left(\prod_{j\neq i}\exp\left(-\pi\lambda_j\left(r^{\kappa_i}/_{\kappa_j}\right)^2\right)\right)dr$$

$$\frac{\lambda_i\kappa_i^2}{\sum_j\lambda_j\kappa_j^2} \qquad (16)$$

Now, conditioned on the event that the user is connected to the i-th tier, we derive the probability of a successful transmission. This requires us to determine the Laplace Transform of the interference and noise terms. For the Laplace Transform of the noise term, it is given in (25). As such, we need to derive the generic Laplace transform due to interference I from transmitters from a general tier j (including i) [16], [18]:

$$\mathscr{L}(j)(s)=\mathbb{E}_{\theta_j}[\exp_H(sh_yP_{t,i}x_y^{-\alpha})]]$$
$$=\mathbb{E}_{\theta_j}{}^{1}/(1+sP_{t,i}x_y^{-\alpha})]$$
$$=\exp\left(-2\pi\lambda_j\int_{r^{\kappa_i}/_{\kappa_j}}^{\infty}\left(1-\frac{1}{1+sv^{-\alpha}}\right)vdv\right) \qquad (17)$$

where the last step follows from known results about the probability generating functional (PGFL) of PPPs.

Following the definition of the success probability as $\mathbb{P}$(SINR > γ), we compute $\mathbb{E}_h$[Pt,ihr−α >γI(j)] and after some algebraic manipulations, we get $\mathcal{L}_{I(j)}(\gamma r^{\alpha}/P_{t,i}) = \exp\left(-2\pi\lambda_j \int_{r^{\kappa_i}/\kappa_j}^{\infty}\left(1-\frac{1}{1+sv^{-\alpha}}\right)v\,dv\right) = \exp\left(-\pi\left(r^{\kappa_i}/\kappa_j\right)^2\lambda_j\rho\left(\frac{\gamma P_{t,i}\kappa_j^{\alpha}}{P_{t,j}\kappa_i^{\alpha}},\alpha\right)\right)$.

The success probability is given by

$$\sum_i \frac{\lambda_i\kappa_i^2}{\sum_j \lambda_j\kappa_j^2}\int_{r_i=0}^{\infty}\left(\prod_j \mathcal{L}_{I(j)}\left(\frac{\gamma r^{\alpha}}{P_{t,i}}\right)\right)\mathcal{L}_N f_i(r)\,dr \qquad (18)$$

and so the final step is to combine the previously obtained expressions and integrate w.r.t. r.

Instead of deriving the coverage probability for the average signal based scheme, we show that the location based and the average signal based schemes are equal with an appropriate choice of biasing factor. This is because the average signal is averaged over the fading effect so the remaining factors are the transmission power and path loss, being identical to the location based scheme. We formally state this in the following lemma.

Theorem 2: The coverage probabilities for the instantaneous SINR based scheme are

$$\mathbb{P}_{INS} = \sum_{i=1}^{k}\lambda_i\int_{r=0}^{\infty}2\pi r\exp\left(-\left(\sum_k\lambda_k P_{t,k}^{2/\alpha}\right)C(\alpha)\left(\gamma_i/P_{t,i}\right)^{2/\alpha}r^2\right)\exp\left(-\left(\frac{\gamma_i}{P_{t,i}}\right)\sigma^2 r^{\alpha}\right)dr \qquad (11)$$

$$\mathbb{P}_{INS,\sigma^2=0} = \frac{\pi}{C(\alpha)}\frac{\sum_{i=1}^{k}\lambda_i P_i^{2/\alpha}\gamma_i^{-2/\alpha}}{\sum_{i=1}^{k}\lambda_i P_i^{2/\alpha}}dr \qquad (19)$$

Where $C(\alpha) = \frac{2\pi^2}{\alpha}\csc(2\pi/\alpha)$

4.1. Constrained Optimization Framework:

Similar to the previous paper, we investigate the problem of minimizing energy consumption subject to a QoS constraint in terms of coverage probability.

4.1.1 Power Consumption Minimization with Average Signal based Scheme:

In the following, we formulate an optimization problem that minimizes energy consumption across different tiers. Using Theorem 4, we obtain the following corollary.

Corollary 1. If we connect to the highest average SINR signal, the coverage probabilities are given by

$$\mathbb{P}_{SIG} = \sum_i \lambda_i P_i^{2/\alpha}\int_{r=0}^{\infty}2\pi r\exp\left(-r^{\alpha}\gamma\sigma^2\right)\exp\left(-\pi r^2\left(\sum_i\lambda_i P_i^{\frac{2}{\alpha}}\right)(1+\rho(\gamma,\alpha))\right)dr \qquad (20)$$

$$\mathbb{P}_{INS,\sigma^2=0} = \frac{1}{1+\rho(\gamma,\alpha)} \qquad (21)$$

Proof: Let $\kappa_i = P_{t,i}^{1/\alpha}$ in Theorem 4. The result is obtained after some algebraic manipulations.

We investigate now the following optimization problem:

$$P_{SIG}:\left\{\begin{matrix}\underbrace{\min}_{\lambda_i\forall i} & \sum_i\lambda_i(P_{i0}+P_i)\\ s.t. & \mathbb{P}_{OAP}\geq\epsilon\end{matrix}\right\} \qquad (22)$$

For our analysis, it is necessary to consider the cases σ2 = 0 and σ2 > 0 separately. When σ2 = 0, the solution is to choose λi as small as possible, for all i. Hence, when the network is dense, it is beneficial to shut down as many access points as possible. However, this observation is no longer valid when the network is sparse as the assumption σ2 = 0 is no longer valid. Now, suppose σ2 > 0, we denote $S = \sum_i\lambda_i P_{t,i}^{2/\alpha}$ for notational convenience. As a consequence of Lemma 3, the optimal $S^* = \sum_i\lambda_i^* P_{t,i}^{2/\alpha}$, satisfies

$$\epsilon = S^*\int_{r=0}^{\infty}2\pi r\exp\left(-r^2\pi S^*(1+\rho(\gamma,\alpha))\right)\exp\left(-r^{\alpha}\gamma\sigma^2\right)dr \qquad (23)$$

This reduces the original minimization problem in (5.12) to

$$P_{SIG}^{0}:\left\{\begin{matrix}\underbrace{\min}_{\lambda_i\forall i} & \sum_i\lambda_i(P_{i0}+P_i)\\ s.t. & \sum_i\lambda_i P_{t,i}^{2/\alpha}=S^*\end{matrix}\right\} \qquad (24)$$

which is a linear program having as solution the tier that minimizes $(P_{i0}+P_i)P_{t,i}^{2/\alpha}$. This minimization problem can be further adapted to include certain constraints on λi and it still gives a linear program (for example, the macro tier structure is an existing infrastructure and this could be reflected by fixing λM). In a more general setting, one could include βi representing power control as a decision variable (replace Pt,i with βiPt,i) though the resulting minimization problem would require numerical computation.

4.1.2 Energy Efficiency Optimization with Instantaneous SINR based Scheme: In the following, we shall consider that the network has two tiers, a macro tier where random sleeping is implemented and a femto tier that does not implement any sleeping strategy. Given the density of the femtocell access points λF , we want to determine the value of q^*_{INS} that optimizes the energy efficiency. Since the equations are intractable in general, we assume that σ2 = 0 as a means to obtain some insight. The problem formulation is given by

$$P_{INS}: \left\{ \underset{q}{\max} \quad \frac{\pi}{C(\alpha)} \frac{q\lambda_M P_{t,M}^{2/\alpha}\gamma_i^{-2/\alpha} + \lambda_F P_{t,F}^{2/\alpha}\gamma_i^{-2/\alpha}}{q\lambda_M P_{t,M}^{2/\alpha} + \lambda_F P_{t,F}^{2/\alpha}} \times \right.$$
$$\frac{\log_2(1+\gamma)(\lambda_M q+\lambda_F)}{\lambda_M(qP_{M0}+q\Delta_M P_M+(1-q)P_{sleep})+\lambda_F(P_{F0}+\Delta_F P_F)} \quad (25)$$

which is monotone decreasing in q and hence has optimal $q^*_{INS} = 0$.

V. SIMULATION RESULTS

In this paper, we use the default values in Table-1 unless otherwise stated. The parameters concerning the power consumption are obtained from [6].

TABLE-1
PARAMETER VALUES USED RESULT

Parameter	Value
α	4
λ, μ	10−4 m−2,10−3 m−2
Pt,M, Pt,F	43 dBm, 10 dBm
σ2	1
Γ	-10dB
Psleep	75.0 W (Macro only)
PM0, PF0	130.0 W, 4.8 W
ΔM,ΔF	4.7, 8.0
PM, PF	20.0 W, 0.05 W

We shall consider two models of activity levels: binary where the activity level associated with each coverage area, which in turn is associated with a particular MBS is either 0 or 1 with probability 0.5 each, and uniform where the activity level is drawn from a uniform [0, 1] random variable. The sleeping strategy for both cases is identical: if the activity level in the coverage area associated with the MBS is a, then the MBS stays awake with probability a. We also calculate the coverage probability through Monte Carlo simulation. The locations of the MBSs are distributed according to a PPP in a 5000m×5000m grid, with 5000 trials. Fig. 1 compares the analytical results versus the simulated results, verifying the validity of the expression (9) concerning the strategic sleeping strategy for σ2 = 0. From henceforth, all figures are numerical plots of the expressions obtained previously. Fig. 2 shows the energy efficiency with random sleeping with respect to q for various values of β (expression (6) divided by expression (4)). From this figure, we observe that the energy efficiency increases with q. This is because the network throughput decreases at a faster rate than the savings in power consumption when we decrease q. The figure also shows that the energy efficiency decreases with increasing β, which implies that the cost incurred from raising the power uniformly is not compensated by an increase in the data rate. Note that this result has not yet taken into account traffic demands and different operating power consumption parameters at the MBS. Therefore, it is likely that taking into account these additional parameters will give us new tradeoffs, which will be studied in future work. Nevertheless, our framework does give a simple tractable approach to study the effect of random sleeping in macrocell networks. Fig. 3 plots the coverage probability versus noise σ2 for different sleeping strategies (eq. (8)) while Fig. 4 plots the energy efficiency with respect to q for various sleeping strategies (eq. (8) divided by eq. (5)). For Fig. 3, the activity model for strategic sleeping is assumed to be 0 and 1 with equal probability 0.5. The sleeping strategy is modeled as 0 and 1, respectively. For random sleeping, MBSs are in sleep mode with probability 0.5. From the plots, we can see that the coverage probability per active user in strategic sleeping is only marginally better than no sleeping. We also see that strategic sleeping has a bigger margin of improvement over no sleeping when σ2 → 0. In this figure, we see that even for a contrived example, there is little improvement when noise is significant. On the other hand, our analytical results demonstrate that when σ2 = 0, any increasing strategy S(a) would suffice. This implies that the presence of noise can significantly affect the performance. Finally, it can be seen that expectedly, strategic sleeping is always better than random sleeping for the same fraction of sleeping MBSs. In Fig. 4, we choose the strategic sleeping model to have a activity 1 with probability q, represented by the x-axis, and activity 0 otherwise. Likewise the sleeping strategy is 1 if the activity is 1, 0 otherwise. To obtain a fair comparison, we also plot the random sleeping with MBS staying awake with probability q so that both plots have the same fraction of active MBSs. From Fig 4, we observe that the energy efficiency for a strategic sleeping strategy is also higher than random sleeping and in fact, for these set of parameters, is about half of the interference-limited regime case for all values of q.

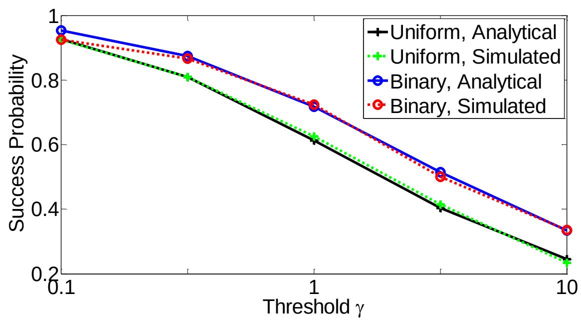

Fig. 1. Comparison of analytical expressions vs. simulated results for strategic sleeping mode.

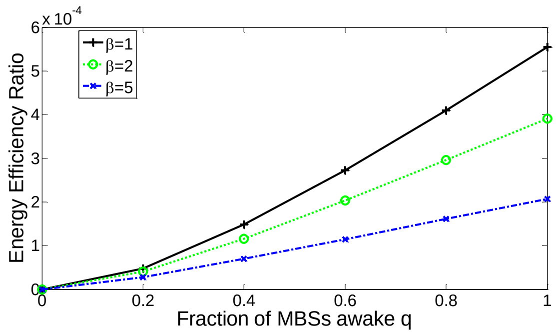

Fig. 2. Effect of power control on energy efficiency.

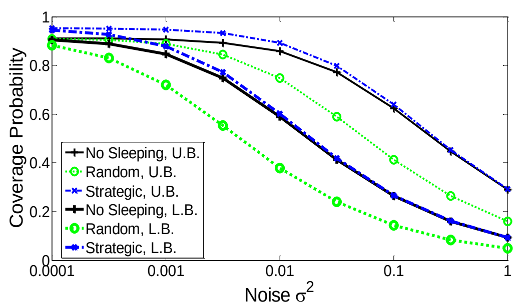

Fig.3. Coverage probabilities for different sleeping strategies.

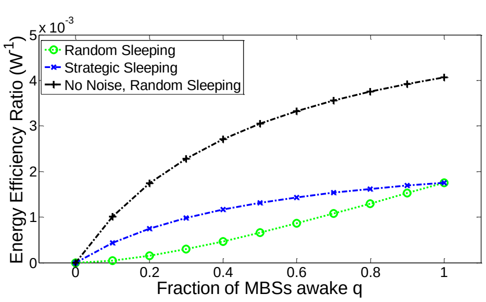

Fig.4. Energy efficiency ratio for different sleeping strategies.

V. CONCLUSION

In this papere, we investigated the design of energy efficient cellular networks through the employment of base station sleep mode strategies as well as small cells, and investigated the tradeoff issues associated with these techniques. Using a stochastic geometry based model, we derived the success probability and energy efficiency under sleeping strategies in homogeneous macrocell and heterogeneous K-tier networks. In addition, we formulated optimization problems in the form of power consumption minimization and energy efficiency maximization and determined the optimal operating frequency of the macrocell base station. In particular, we investigated the impact of random sleeping and strategic sleeping on the power consumption and energy efficiency. Numerical results confirmed the effectiveness of sleeping strategy in homogeneous macrocell networks but the gain in energy efficiency depends on the type of sleeping strategy used. In addition, the deployment of small cells generally leads to higher energy efficiency but this gain saturates as the density of small cells increases. Future work may include the extension of the above model to the case where base stations have multiple antennas and may perform opportunistic user selection. It would also be of interest to explore how random spatial placements of base stations that model repulsion or inhibition affect the results in terms of throughput and energy efficiency. Finally, the energy efficiency metric investigated here is only dependent on the power consumption and the coverage within the network, and does not take into account the infrastructure cost and backhaul overhead associated with implementing small cell networks.

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