

# Efficient Energy Management in Ultra-Dense Wireless Networks

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Supervisor:

Ass/Prof. Olabisi Falowo



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University of Cape Town

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To; God, for providing me the ability to complete this work,

My parents, for their prayers and tremendous support,

My supervisor, for his guidance along the journey.

## Abstract

The increase in demand for more network capacity has led to the evolution of wireless networks from being largely Heterogeneous (Het-Nets) to the now existing Ultra-dense (UDNs). In UDNs, small cells are densely deployed with the goal of shortening the physical distance between the base stations (BSs) and the UEs, so as to support more user equipment (UEs) at peak times while ensuring high data rates. Compared to Het-Nets, Ultra-dense networks (UDNs) have many advantages. These include, more network capacity, higher flexibility to routine configurations, and more suitability to achieve load-balancing, hence, fewer blind spots as well as lower call blocking probability.

It should be noted that, in practice, due to the high density of deployed small cells in Ultra-Dense Networks, a number of issues, or rather concerns, come with this evolution from Het-Nets. Among these issues include problems with efficient radio resource management, user-cell association, inter- and intra-cell interference management and, last but not least, efficient energy consumption. Some of these issues which impact the overall network efficiency are largely due to the use of obsolete algorithms, especially those whose resource allocation is based solely on received signal power (RSSP). In this paper, the focus is solely on the efficient energy management dilemma and how to optimally reduce the overall network energy consumption.

Through an extensive literature review, a detailed report into the growing concern of efficient energy management in UDNs is provided in Chapter 2. The literature review report highlights the classification as well as the evolution of some of the Mobile Wireless Technologies and Mobile Wireless Networks in general. The literature review report provides reasons as to why the energy consumption issue has become a very serious concern in Ultra-Dense networks as well as the various techniques and measures taken to mitigate this. It is shown that, due to the increasing Mobile Wireless Systems' carbon footprint which carries serious negative environmental impact, and the general need to lower operating costs by the network operators, the management of energy consumption increases in priority.

By using the architecture of a Fourth Generation Long Term Evolution (4G-LTE) Ultra-Dense Network, the report further shows that more than 65% of the overall energy consumption is by the access network and base stations in particular. This phenomenon explains why most attention in energy efficiency management in UDNs is largely centred on reducing the energy consumption of the deployed base stations more than any other network components like the data servers or backhauling features used. Furthermore, the report also provides detailed information on the methods/techniques, their classification, implementation, as well as a critical analysis of the said implementations in literature.

This study proposes a sub-optimal algorithm and Distributed Cell Resource Allocation with a Base Station On/Off scheme that aims at reducing the overall base station power consumption in UDNs, while ensuring that the overall Quality of Service (QoS) for each User Equipment (UE) as specified in its service class is met. The modeling of the system model used and hence formulation of the Network Energy Efficiency (NEE) optimization problem is done

using stochastic geometry. The network model comprises both evolved Node B (eNB) type macro and small cells operating on different frequency bands as well as taking into account factors that impact NEE such as UE mobility, UE spatial distribution and small cells spatial distribution. The channel model takes into account signal interference from all base stations, path loss, fading, log normal shadowing, modulation and coding schemes used on each UE's communication channels when computing throughput. The power consumption model used takes into account both static (site cooling, circuit power) and active (transmission or load based) base station power consumption.

The formulation of the NEE optimization problem takes into consideration the user's Quality-of-service (QoS), inter-cell interference, as well as each user's spectral efficiency and coverage/success probability. The formulated NEE optimization problem is of type Nondeterministic Polynomial time (NP)-hard, due to the user-cell association. The proposed solution to the formulated optimization problem makes use of constraint relaxation to transform the NP-hard problem into a more solvable, convex and linear optimization one. This, combined with Lagrangian dual decomposition, is used to create a distributed solution. After cell-association and resource allocation phases, the proposed solution in order to further reduce power consumption performs Cell On/Off.

Then, by using the computer simulation tools/environments, the "Distributed Resource Allocation with Cell On/Off" scheme's performance, in comparison to four other resource allocation schemes, is analysed and evaluated given a number of different network scenarios. Finally, the statistical and mathematical results generated through the simulations indicate that the proposed scheme is the closest in NEE performance to the Exhaustive Search algorithm, and hence superior to the other sub-optimal algorithms it is compared to.

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## List of Abbreviations

2G	Second Generation
3G	Third Generation
3GPP	Third Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
EDGE	Enhanced Data Rates for GSM Evolution
eNB	Evolved Node B
GSM	Global System for Mobile Communication
Het-Net	Heterogeneous Wireless Network
LTE	Long Term Evolution
LTE-A	Long Term Evolution Advanced
MIMO	Multiple Input Multiple Output
MWN	Mobile Wireless network
MNO	Mobile Network Operator
OFDM	Orthogonal Frequency Division Multiplexing
PDSCH	Physical Downlink Shared Channel
QoS	Quality of Service
RAN	Radio Access Network
RAT	Radio Access Technology
RB	Resource Block
RSSP	Received Signal Power

UE

UDN

User Equipment

Ultra-Dense Network



# Chapter 1 Introduction

## 1.1 Background

The demand for higher data rates and more network capacity over the years has led to an evolution of Mobile Wireless Networks (MWNs) from being largely Heterogeneous Wireless Networks (Het-Nets) to being Ultra-Dense Networks (UDNs). In [1], it has been estimated that by 2020, there will be over 50 billion networked devices. This would imply more than 6 networked devices per person, counting not only human but machine communications as well. Buzzi *et al* in [1] envision that we will have a connected society in which sensors, vehicles, drones, medical and wearable devices are all networked through Mobile Wireless Networks (MWNs). Through the Mobile Wireless Networks (MWNs), these devices will be able to communicate with human end-users with the aim of rendering a series of inventive and novel services like smart homes, smart cities, smart cars, tele surgery, and advanced security [1].

It is further estimated by Buzzi *et al* in [1] that by 2020, the network traffic volume per month will be in tens of Exabytes ( $1000^6$  Bytes). Most Mobile Wireless Networks (MWNs) today are Het-Nets, and the above estimations would require the capacity provided by the Next Generation Mobile Wireless Networks (NGMWNs) to be at least 1000 times higher than it is in Het-Nets, in order to accommodate the large number of terminals.

Attempting to achieve the required network capacity while relying on the paradigms and architectures of Het-Nets, is not sustainable. The reason being, most Het-Nets were designed to maximize capacity by scaling up the transmission powers to increase the Signal to Noise Ratio (SINR). Using more and more energy to increase the SINR and hence network capacity would inevitably result into unacceptable operating costs, not to mention serious environmental concerns [3]. The environmental concerns mentioned are due to the fact that most of the power consuming systems in most countries are powered by traditional carbon-based energy sources, Mobile Wireless Communication Systems, of course, being one of them [3]. Carbon-based energy sources are a big factor in the world's crisis with CO<sub>2</sub> emissions. Therefore, an increase in demand and consumption of energy by communication and wireless systems would lead to an increase in the carbon emissions from the carbon-based power-generating plants and sources.

1[3]. Therefore, it is due to the above that Mobile Wireless Networks are evolving to the aforementioned Ultra-Dense Networks (UDNs). In Ultra Dense Networks, small cells are densely deployed to supplement the existing macro cells in order to meet demands such as, the thousand-fold traffic volume, multi-gigabit per second data rates, and the millions of communication terminals. These small cells use lower transmission power due to advantageous path loss conditions, and therefore, provide a better alternative in the effort to increase Mobile Wireless Network (MWN) capacity when deployed in large numbers across the macro cell coverage areas. However, due to the high density of deployed small cells, a number of issues arise, such as spectral inefficiency, energy inefficiency, control overhead, among others. This study focuses on the aforementioned energy efficiency issue in the Ultra-Dense Networks (UDNs).

## **1.2 Problem Statement**

Despite the fact that small cells have low transmission power, the total network energy consumption becomes more significant because these small cells are densely and randomly deployed in Ultra-Dense Networks. Furthermore, in Mobile Wireless Networks according to [4], the main energy consumers are data servers, base stations and backhaul routers. This, combined with the fact that approximately 80% of the network energy is consumed by base stations [4], explains why efficient energy management in Ultra-Dense Networks is critical, and also why most of the studies done on energy efficiency in mobile networks are focused on base stations.

Most User Equipment (UE)-Cell Association schemes being implemented in Ultra-Dense Networks, for example, those whose UE-Cell association and hence resource allocation is solely based on the Received Signal Power (RSSP) and Coverage/Success or Outage probability, are faced with challenges with respect to energy efficiency. These challenges are explained in detail below:

1. Inefficient UE-Cell association, leading to inefficient Resource Allocation with respect to the Network Energy Efficiency.
2. Inefficient base station power utilization throughout the day as UEs' change position.

These two challenges/problems are further examined below;

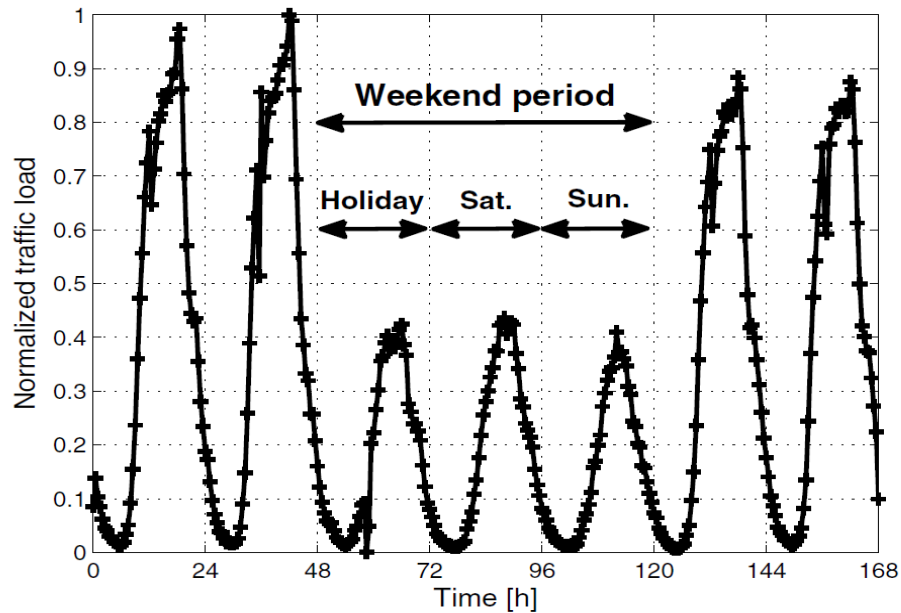
### **1.2.1 Inefficient Resource Allocation with respect to Energy Efficiency**

In any Mobile Wireless Network, a UE demanding bandwidth or resource elements that lie within the network coverage must be associated with a cell, regardless of whether it is stationary or moving from one cell to another. Most schemes implemented do not take into account the Energy Efficiency aspect during this UE-Cell association, which leads to inefficient resource allocation. Each resource block given to a UE has impact on the base station power consumption and hence overall network consumption. The more resource blocks (RBs) given out by the network, the more the network power is consumed. On the other hand, giving more resource blocks does not necessarily mean higher data rates. If more resource blocks are hence given without substantial increase in data rates, then a problem of inefficient energy utilization is created within the base station and network.

In summary, schemes that do not consider the impact of each additional or any Resource Block given to a UE demanding bandwidth will, as has been stated above, result into poor Network Energy Efficiency. Therefore, base stations and networks in general have to find/work out and operate as a close to an optimum value with regards to throughput and power consumption. This requires using schemes and algorithms that make the UE-Cell Association and Resource allocation processes more energy efficient.

### 1.2.2 Inefficient Base Station Power Utilization throughout the day

In relatively urban areas with largely residential and commercial areas, it is found that there is inefficient base station power consumption throughout the day. *Figure 1* below shows the normalized real traffic profile for a relatively commercial area in one week that was recorded by an anonymous Mobile Network Operator (MNO). The information that was recorded featured both voice and data type calls over a one-week period, has a resolution of one second and is averaged over a thirty-minute time-interval [30].



**Figure 1 :** A graph showing normalized real traffic load for one week versus time of day [30]

The traffic load during night hours, as shown in *Figure 1*, is much less than that during the day. The vast difference between the weekend/holiday and weekday traffic loads is also noticeably visible in *Figure 1*. This variance in traffic load throughout the week leads the Mobile Network Operator to deploy base stations strategically in order to support and cope with peak time traffic loads while ensuring high Quality of Service for each user (QoS).

However, the under-utilization of the deployed base stations and hence poor base station energy efficiency becomes inevitable due to the same variance in traffic loads throughout the day and the week. Son *et al* [30] makes note of the fact that it is during the periods of little to no

activity, i.e. a few to no users associated with a particular base station or cell, when most the peak power is consumed by the deployed base stations. It is, therefore, why the use of dynamic switching between idle and active base station modes can lead to potential saving in power consumption and improve overall network energy efficiency.

### **1.3 Research Objectives**

The objectives and aims of this research are detailed below:

1. Develop a scheme that handles UE-Cell association and Resource allocation while taking into account the base station energy efficiency, the User's Quality of Service (QoS) requirements, Signal to Noise Ratio (SINR), UE mobility and Coverage Success of each UE demanding network resources.
2. Formulate mathematical models for both the proposed schemes and the network environment in which they operate.
3. Evaluate the performance of the proposed schemes versus other Network Energy Efficiency schemes under different network scenarios.

### **1.4 Research Methodology**

In this study, both Qualitative and Quantitative Research are used. Qualitative Research, which is largely exploratory study, is used to gain an understanding of the underlying reasons and motivation for Efficiency Energy management in Ultra-Dense Networks. Through qualitative research, an extensive review of the existing studies in relation to this thesis is in Chapter 2. Chapter 2 shows some of the main concepts behind the 4G Long Term Evolution (LTE), as well as the power consumption distribution within the network using valid models for all the network branches. Furthermore, detailed descriptions and general classifications of the different techniques and methods used in reducing power consumption, as well as increasing energy efficiency in Ultra-Dense Networks (UDNs), are provided. Finally, a review of different studies, considering switching of base station modes, efficient resource allocation and cell zooming, while taking into account guaranteed quality of service, is done.

Secondly, a strategy to increase the overall network energy efficiency is proposed taking into account each user's quality of service (QoS), Inter-Cell Interference, Control over heads and coding rate in calculating the throughput of the LTE downlink in Chapter 3. An analytical model of the Ultra-Dense Network is designed, well described and used in Chapter 3 in developing the said strategy. The traffic is modelled using the Markov chain and system model using stochastic geometry based on the models evaluated in Chapter 2.

Through Quantitative Research, implementation and evaluation of the proposed strategy is done as described in Chapter 4. The multi-threaded JAVA simulation environment coupled with MATLAB for graphing purposes allowed for a more realistic scenario for the LTE Ultra-Dense Network functioning. The created multi-class JAVA model enables the formulation of the Network Energy Efficiency problem which is solved using linear programming optimization and Lagrangian dual de-composition methods. The solution created is tested and compared with other schemes under a number of different system or network model scenarios. The algorithm performance is tested with respect to execution times, power consumption as well as network energy efficiency and the results are studied and analysed after. Finally, the conclusion remarks of the study and recommendation briefs for future work are made and showcased in the last chapter.

## **1.5 Scope and Limitations**

This study considers a Fourth generation (4G) Long Term Evolution (LTE) Ultra-Dense Wireless Network (UDN) located in largely urban areas with a commercial district and residential suburbs. Following that this study focuses on a relatively urban geographical area, Non-Line of sight (NLOS) Communication is assumed, hence, the use of Multiple Input Multiple Output (MIMO) technology. In an NLOS environment, each signal from the various transmitters bounces off walls, buildings, trees and other obstacles in a slightly different way which enhances the effectiveness of the MIMO base stations and user equipment. All base stations and user equipment in this study are assumed to be all of 2x2 MIMO - capability.

The study is limited only to the Physical Downlink Shared Channel (PDSCH) of the 4G-LTE hence the Orthogonal Frequency Division Multiplexing Access (OFDMA)-based Mobile Wireless Network. This urban area is assumed to have a total number of seven macro base stations, each operating in a tri-sector cell and using Fractional Frequency Re-use to mitigate inter-cell interference. The coverage of these macro base stations is supplemented by a large number of normally and uniformly distributed small cells across both regions. These small cells are of both femto and pico types. The assumption is that for every one pico cell, there is about 10 or more femto-cells, hence, making the number of the pico cells very small and insignificant compared to the total number of femto-cells deployed.

The users, and hence user equipment, are assumed to have absolute freedom of mobility at a constant speed throughout the day. The arrival rates of the users are mathematically modelled to follow the Markovian process and are, therefore, independent of each other.

## ***1.6 Contribution to knowledge***

This work investigates the challenge of high base station power consumption and overall Network Energy Efficiency (NEE), which are largely ignored in the current Ultra-Dense Networks (UDNs) User-Cell Association and Resource Allocation schemes. The main contributions of this work are:

1. The proposed Distributed Resource Allocation with Cell On/Off algorithm, which takes into account the demanded User Equipment's Quality of Service (QoS), Inter-Cell Interference, Control overheads and coding rate in calculating the throughput of the LTE PDSCH downlink channel.
2. The proposed algorithm at each cell ranks the User Equipment's within its coverage area based on their service class, Signal to Noise Ratio (SINR) and demanded data rate before allocating Resource Blocks (RBs) based on a qualification index and computed multiplier. In so doing, the base station power consumption is minimised with an aim of attaining higher overall Network Energy Efficiency.

These contributions are contained in the author's publication stated below:

1. Paul James Wambi and O.E. Falowo, "Towards Optimum Energy Efficiency in Ultra-Dense Networks using Distributed Resource Allocation with Cell On/Off," proceedings of the Annual 12<sup>th</sup> IEEE International Conference on Signal Processing and Communication Systems (ICSPCS), 17-19 December 2018, Cairns (Barrier Reef), Australia.

## ***1.7 Outline of Thesis***

The rest of this work is structured as follows:

Chapter 2 presents a background into Mobile Wireless Technologies, their classification, as well as brief summary on the evolution of mobile cellular technologies. The evolution and motivation, as well as challenges that arise due to the said evolution of Mobile Wireless networks in general, are also well documented in this Chapter. This chapter also provides a detailed investigation report on related works in the field of Efficient Energy Management in LTE-Ultra-Dense Networks, especially as it pertains the Access Network. Last but not least,

Chapter 2 not only shows the different Energy Efficiency Management Techniques, their groupings, a few examples as implemented in literature under grouping, but also critical analysis of each implementation providing the benefits and shortcomings.

Chapter 3 covers the proposed scheme, which is Distributed Resource Allocation combined with Cell On/Off. Chapter 3 also presents the analytical system model and all assumptions made. A multidimensional Markov model based on Poisson Point Processes and M/G/1 queue is presented. A load Distributed Resource Allocation with Dynamic Cell On/Off algorithm adopted in this work is modelled. A mobility and traffic model to examine the response of the scheme to the mobility and traffic patterns of UEs is also presented. The motivation and reasons for this scheme are detailed in this chapter. This chapter also details the Algorithm flow as well as some of the mathematical models that support or justify the scheme. The integration of the proposed scheme into an LTE-UDN is also detailed.

In Chapter 4, the simulation parameters, simulations and results of the simulations are presented, as well as the algorithms to which the performance of the proposed scheme is compared. The algorithms are described briefly, and their performance under the different network scenarios is documented and highlighted in this chapter. Finally, numerical examples and evaluation of the results for each of the algorithms/schemes are given.

Chapter 5 presents the conclusions drawn from the results formulated, as well as recommendations for future works in relation to this study.

## Chapter 2 Literature Review

### 2.1 Mobile Wireless Networks

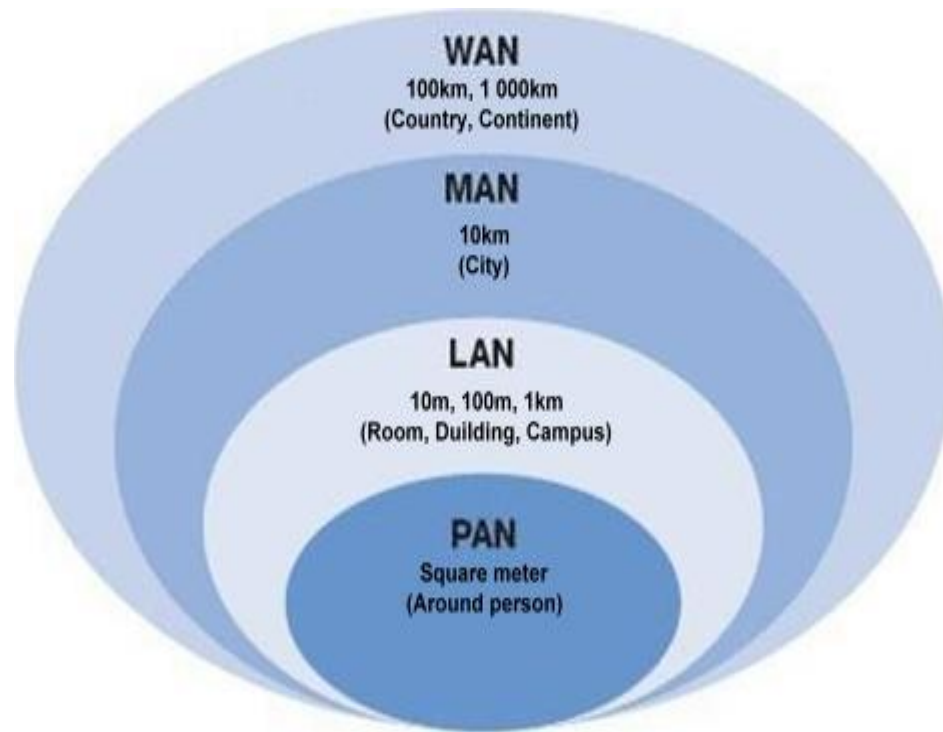
Mobile Wireless Networks transfer information and data between network nodes using radio signals through air as the medium of transfer. Mobile Wireless Networks (MWNs) not only revolutionized the way people communicate but also the way people carry out economic activities, receive healthcare, travel and generally live their lives. Sinha *et al* [5] state that MWNs have increasingly become an essential part of life in many parts of the world, reaching even some of the more remote areas around the world since 2010.

Proof that Mobile Wireless Networks (MWNs) have become an essential part of peoples' lives, especially with respect to remote areas in 3<sup>rd</sup> world countries, can be found in the crucial field of healthcare. Mobile wireless networks have greatly improved and facilitated the distribution of relevant and much needed treatment guidelines as well as medical information. According to a recent United Nations Report [40], UEs like smartphones and tablets are used in Uganda by health care administrators to help not only in dissipating relevant medical information and healthcare guidelines, but also in collecting medical data that is instrumental in preventing the spread of outbreaks, like typhoid [40].

Mobile Wireless Networks consist of one or several types of mobile wireless technologies. In as much as these mobile wireless technologies can be classified in a number of ways, the best and most accurate way is that which is based on each of the technology's coverage range or radius [6]. Consequently, 'Coverage based' classification is the most popularly applied classification in literature today. Based on Coverage Classification, Mobile Wireless Technologies can be grouped into four major categories [5].

#### 2.1.1 Mobile Wireless Networks Coverage Based Classification

The four different categories as shown in *Figure 2* are Wireless Personal Area Network (WPAN), Wireless Local Area Network (WLAN), Wireless Metropolitan Area Network (WMAN) and Wireless Wide Area (WWAN).



**Figure 2: Classification of Mobile Wireless Networks based on Coverage [5]**

### **2.1.1.1 Wireless Personal Area Network (WPAN)**

Wireless Personal Area Networks not only connect User Equipment to each other but also to access points in a short-range coverage of about ten metres [5]. WPANs are defined in the IEEE 802.15 standard and include IEEE 802.15.1 known as Bluetooth and IEEE 802.15.4 known as ZigBee. ZigBee, unlike Bluetooth, is less complex and cheaper. By accessing the 2.4GHz ISM band, User Equipment (UEs) can transmit and receive signals using WPANs, provided the transmission power of the said equipment is less than 100mW [5]. These networks are the best for connecting and signalling personal devices in small office spaces and around the home given their cost and accessibility. However, they are deemed inefficient when it comes to sending large chunks of data or information as they are basically designed to transfer very small files.

### **2.1.1.2 Wireless Local Area Network (WLAN)**

Wireless Local Area Networks have a coverage range of about 200m and have two basic modes of operation namely; the Ad hoc mode, whereby UEs communicate with each other without the use of centralized infrastructure hence peer to peer; and the Infrastructure mode, whereby UEs communicate via access points [5]. WLANs are defined under the IEEE 802.11

standard. A few examples of WLANs include IEEE 802.11a, which is accessed at the 5GHz band, IEEE 802.11b accessed at the 2.4GHz band and IEEE 802.11n [5].

WLANS allow for users in areas, like a university campus or library, to form a network or gain access to other networks and the internet. WLANs, if given the ability, enable peer-peer connection and allow for a temporary network to be formed by a few UEs without the need of an access point, in the event that they do not need access to network resources. It is also noted by Bondanese *et al* in [10] that, of the four categories, WLANS have the highest performance with respect to throughput. This is largely due to the fact that WLANs offer and support large data rates, for example, the IEEE 802.11a can support up to 54Mbps using Orthogonal Frequency Division Multiplexing (OFDM) [6].

### **2.1.1.3 Wireless Metropolitan Area Network (WMAN)**

Wireless Metropolitan Area Networks are defined under the IEEE 802.16 standard and have a coverage range of about 50km. One common example of a WMAN is the Worldwide Interoperability for Microwave Access (WiMAX) [5]. Wireless Wide Area Networks are used to cover areas like entire large buildings or malls in urban areas. Gotsis *et al* [12] make the observation that WMANs can also be used as an alternative or backup to laying copper or fiber cabling, given most of them deployed today use MIMO (Multiple Input and Multiple Output) and Beamforming technologies. It is also worth noting that WiMAX in particular makes use of OFDM which enables support of high data rates, thereby making it a relatively suitable alternative to cabling [9].

### **2.1.1.4 Wireless Wide Area Network (WWAN)**

Wide Area Networks, like Cellular networks, are used to cover large areas like countries or cities via a number of satellite systems and large antenna sites operated by an Internet Service Provider (ISP). A few examples of these radio access technologies include 4G-LTE, 2G-GSM, 2.5G-GPRS, and 3G-CDMA2000. These Cellular networks are classified into Generations based on their underlying architecture and services rendered as shown in **Figure 3**. These Generations represent evolution of communication systems, technologies and services rendered from the First Generation (1G) technologies in the 1970s to the now largely in use Fourth Generation (4G) technologies.

### **2.1.2 Evolution of Mobile Wireless Technologies**

The First Generation (1G) was comprised of analog transmission technologies for voice only, like Nippon Telephone and Telegraph in 1979 in Tokyo, Japan. A few years later, the Advanced Mobile Phone System (AMPS) was launched in 1982 in U.S.A. AMPS used a 7 cell reuse factor because 7 was the smallest reuse factor that could fulfil the 18dB Signal to Interference Ratio (SINR) using the 120° directional antennas [7]. Furthermore, the AMPS used the Frequency Modulation and Frequency Division Multiple Access (FDMA) scheme. Then, in 1991, mobile network technologies evolved from analog to digital in what was termed the Second Generation (2G) [7]. 2G not only saw the migration from analog to digital but also the introduction of the Short Message Service (SMS) and implementation of the Time Division Multiple Access scheme. One common example of 2G technology is Global System for Mobile Communication (GSM), which is a circuit switched network [7] [9]. 2.5G not only supported voice service, web browsing and SMS, but also saw the introduction of Multi-Media Messages (MMS) with the emergence of the General Packet Radio Service (GPRS) in 1999, which included packet switching.

The turn of the century then saw an evolution to Third Generation (3G) mobile technologies. 3G networks provided better voice service and much faster data rates. Common examples of 3G technologies include the Universal Mobile Telecommunication System (UMTS), Wide Code Division Multiple Access (WCDMA) and CDMA2000 [7] [9]. 3G technologies saw the introduction of video and music streaming as well as faster web service to mobile users. 2010 saw the migration to using only Internet Protocol (IP) or packet switched networks which were termed Fourth Generation technologies. 4G saw the emergence of Voice over Internet Protocol (VoIP). Examples of 4G technologies include WiMAX, LTE and LTE-A [9].

As of 2018, the development of Fifth Generation (5G) technologies by a few companies is well underway. 5G will make use of millimetre waves and Multiple Input Multiple Output (MIMO) technologies [8]. 5G technologies will help power the huge rise in the Internet of Things (IoT) technology by providing the infrastructure needed to carry huge amounts of traffic, allowing for a smarter and inter-connected society. With development well underway, 5G networks are expected to launch across the world by 2020, working alongside the existing 3G and 4G technology to provide higher data rates and the ability to maintain online status for UEs

regardless of location [8].

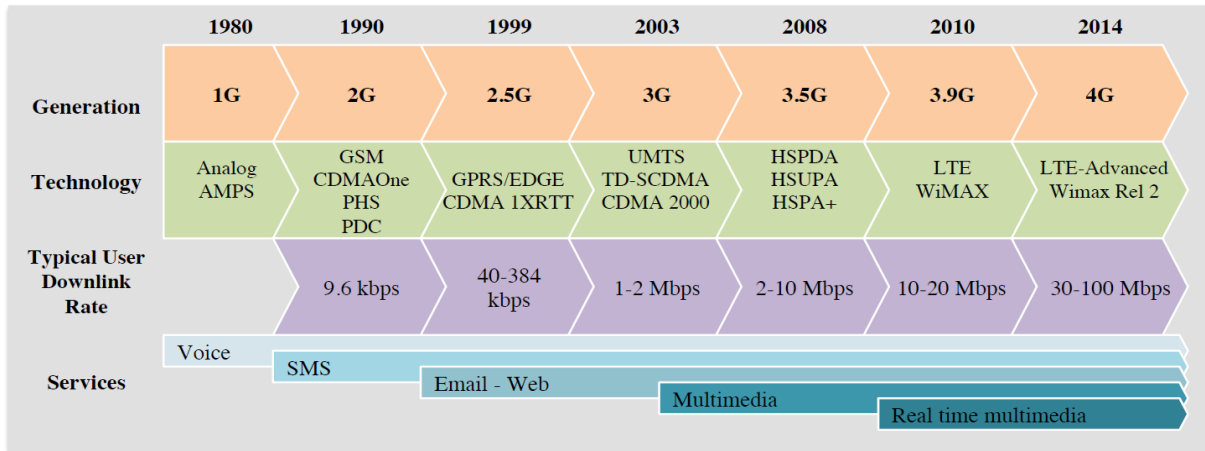


Figure 3: Evolution of Mobile Technologies [7]

## 2.2 Heterogeneous Wireless Networks (Het-Nets)

Heterogeneous Wireless networks in general combine a number of wireless/radio access technologies and access points as shown in *Figure 4*. A Radio Access Technology or (RAT) is the underlying physical medium for a Wireless based communication network. A given Het-Net can be comprised of a number of radio access technologies (RATS), such as 4G-LTE, 3G-UMTS and Wi-MAX, all co-existing in the same geographical area and operated by the same or different MNOs.

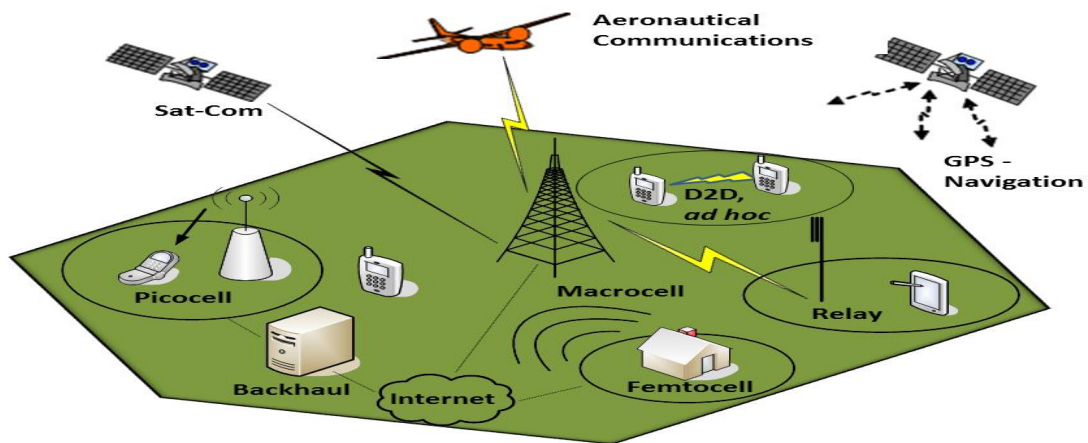


Figure 4 : A Het-Net showing different Access technologies

Furthermore, the deployment of heterogeneous wireless technologies allows UEs with multi-interfaces (or multimodal) to exploit this diversity of base stations/cells to benefit from higher data rates and improve the quality of service (QoS). Small cell access points, shown in *Figure 4*, can be residential, public (hot-spot) or organized in community networks. This then makes it possible to communicate through a 4G network and switch an entire session to say a Wi-Fi network when possible (if you go through a Wi-Fi covered area). It also becomes possible to use simultaneously the different interfaces of the UE for different flows or even share the same stream.

### **2.2.1 Motivation for Heterogeneous Wireless Networks (Het-Nets)**

Most mobile network operators, despite acquiring new technologies, retain the old Radio Access Technologies (RATs). Bondanese *et al* in [10] point out, that this ability to retain the old RATs after acquiring new ones to form a network containing multiple RATs is made possible by the complementary nature of some of the RATs.

On top of some RATs being complementary with old Generation RATs, there are two major motivation and justification for the keeping and operating of the old Generation RATs by some Mobile network operators, as pointed out in [41] by Coucheney *et al*. Users having legacy devices that cannot support new radio access technology capabilities creates the necessity to retain old RATs, while some of the modern user equipment, having multi-modality and multi-homing, creates the ability to retain some of the old generation RATs [41]. Multi-modality is the ability of a UE to support several RATs such as Bluetooth, Wi-Fi, 3G and 4G while Multi-homing is the ability of a UE supporting more than one RAT at a time.

Therefore, as stated above, some mobile network operators retain their older generation technologies to ensure satisfaction for all their customers, especially those with legacy devices. The coexistence of these different RATs within the same geographical areas leads to the existence of Heterogeneous Wireless Networks (Het-Nets).

Cao *et al* [9] point out another key motivation for Het-Nets, which is, that most mobile broadband data is highly localized, given that majority of the traffic is generated indoors and in hotspots, such as shopping malls and other popular meeting places. This, combined with the ever

increasing demand for network capacity, compelled Mobile Network Operators (MNOs) to look for innovative ways to expand their network capacity at sustainable operating costs [10]. Mobile Network Operators discovered that, by adopting the use of more than one radio access technology operating on both licensed and unlicensed spectra, hence the emergence of Het-Nets, more UEs were accommodated, and the goal of increased network capacity was attained.

Through deploying an overlay of small cells in those regions of the macro cell coverage that generate heavy traffic, MNOs not only achieved an increase in network capacity where it was needed, but also foresaw a reduction in expansion and operating costs [10]. Small cells, due to their lower costs compared to macro cells, can save mobile network operators (MNOs) 26% in Capital Expenditure (CAPEX) and 6% in Operating Expenditure (OPEX) depending on traffic profile, due to lower transmission power [10].

### **2.2.2 Challenges of Heterogeneous Wireless Networks**

The coexistence of different radio access technologies (RATS) within the same geographical area does not come without its number of challenges. Some of these challenges include common billing, interference management, radio resource and management, UE mobility management, among a few.

The small base stations deployed in Het-Nets to cover holes in macro cell coverage are at a disadvantage relative to the high transmission power macro cell base stations. In Het-Nets, most of the users will be attracted to the high transmission powered macro cells given their larger cell coverage and higher transmission power [10]. Most users, being admitted into macro cells than the small cells, will lead to load in-balancing and overall reduction in Quality of service (QoS) for most users within the network. In addition, the deployment of the small cell base stations within macro cell coverage leads to increase in signals transmitted, hence, increased spectral area interference and reduced achievable data rate for each user's communication channel.

Another major challenge faced by Mobile Network Companies operating Het-Nets is in coping with the ever increasing demand for more network capacity and higher data rates. Buzzi *et al* [1] predict that by 2020, there will be an even higher demand for network capacity, approximately 6 devices per person, and traffic volume in tens of Exabytes monthly. As

predicted, MNOs operating Het-Nets face yet another challenge with an even much higher priority to solve in order to maintain and sustain their customer bases.

### 2.2.3 Solution to increased demand for Capacity in Heterogeneous Wireless Networks (Het-Nets)

The need to increase network capacity and provide faster data rates led to an evolution of Het-Nets and emergence of Ultra-Dense Networks. Mobile Network Operators discovered that coping with the ever increasing demand for more network capacity and faster data rates while relying on the paradigms and architectures of Het-Nets is not sustainable [1]. Therefore, in order to cope with said demands, mobile network operators resorted to the densification of Het-Nets with loads of small cells. Large numbers of pico and femto cells are deployed within the macro cell coverage areas with the aim of coping with demands for more network capacity and faster data rates. This densification of Het-Nets with very large numbers of pico and femto-cells creates what are termed as Ultra-Dense Networks (UDNs) [1]. *Figure 5* below graphically shows the transformation or evolution of Mobile Wireless Networks.

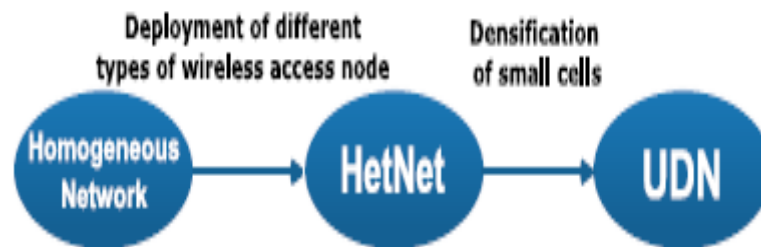
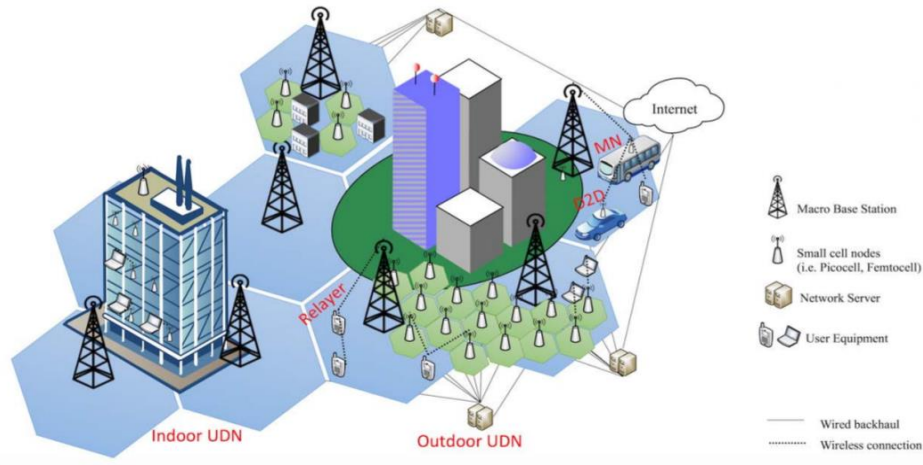


Figure 5 : The homogeneous network evolved to Het-Net, and Het-Net evolved to UDN [1]

## 2.3 Ultra-Dense Networks (UDNs)

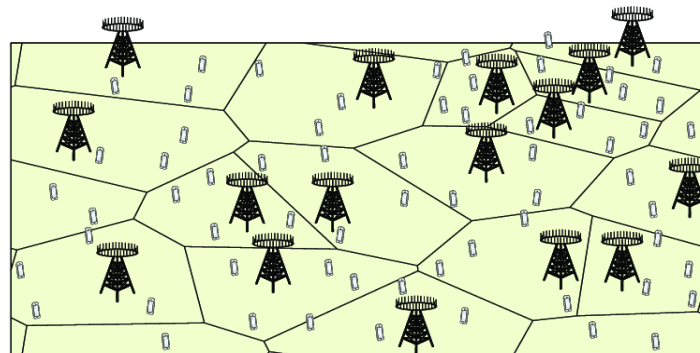
Ultra-Dense Networks, in simple terms, are Het-Nets densified with very large numbers of low power small cells namely; pico and femto-cells. This densification with pico and femto-cells occurs both vertically and horizontally with the aim of increasing network capacity within the macro cell geographical area [1]. The quantitative measure of the cell density at which a mobile wireless network can be considered ultra-dense is  $\geq 10^3 \text{ cells/km}^2$ . In Ultra-Dense Networks the pico-cells and femto-cells are deployed differently. The pico cells, with a range of 200m and transmission power of 30dBm, are deployed in hotspots (indoor or outdoor) by mobile network operators with an aim of serving active UEs by relocating their traffic from the macro

base station [1]. On the other hand, femto-cells with range 50m and transmission power 17dBm, are largely used and randomly deployed mostly indoors [1]. **Figure 6** below shows an example of an Ultra-Dense Network with both horizontal and vertical densifications.



**Figure 6 : Ultra-Dense Network with small cell horizontal and vertical densification [20]**

However, it has to be noted that Ultra-Dense Networks primarily differ from Het-Nets given that Ultra-Dense Networks are based on the idea of rationing a geographical area into what are known as Voronoi cells [19]. A Voronoi cell is a geographical area where a low power base station is utilized not only to increase network capacity but also spatial reuse [12]. **Figure 7** shows a Voronoi Tessellation of a densified small cell network within a macro-cell coverage area, rationed into a number of Voronoi cells, each having one of the 15 low power access point.



**Figure 7 : Voronoi tessellation of a small cell network**

### 2.3.1 Motivation for Ultra-Dense Networks (UDNs)

Ultra-Dense networks serve to satisfy not only the ever increasing demand for more network capacity and faster data rates at sustainable costs, but also the reduction of the overall carbon footprint of Mobile Wireless systems. The alternative of scaling up the transmission power of base stations in Het-Nets in order to increase the Signal to Noise ratio and hence

network capacity would not only increase operating costs, but also have serious environmental impact with regards to the overall mobile networks' carbon footprint [2].

According to a survey done by A. Capone *et al*, most of the power consuming systems, including Mobile wireless systems in most countries, are powered by traditional carbon based energy sources [11]. Carbon based energy sources are a big factor in the world's crisis with CO<sub>2</sub> emissions. Therefore, an increase in demand and consumption of energy by communication and wireless systems would inevitably lead to an increase in the carbon emissions from the carbon based power generating plants [3][3].

### **2.3.2 Challenges of Ultra-Dense Networks (UDNs)**

Despite the positive impact densification of Het-Nets with large numbers of small-cells forming (UDNs) has on overall network performance in terms of network coverage and capacity, it also introduces a number of challenges that need to be dealt with in order to realize said benefits. Given that, in UDNs, small-cells are densely deployed in order to meet demands such as the thousand-fold traffic volume and multi-gigabit per second data rates, a high a number of issues arises, some of which are discussed below;

#### **2.3.2.1 User-Cell Association Challenge**

The closeness in proximity of the densely deployed small-cells leads to line of sight component which causes severe interference, making User-Cell association a major challenge. In an ideal scheme, each UE will make a choice of access point to associate with from one nearby or closest and continue using the established channel for as long as the minimum Quality of Service (QoS) demanded is being guaranteed [15]. However, due to the severe interference, this scheme is rendered inefficient and ineffective, hence, requiring the use of novel UE-Cell association rules which exploit the base station idle modes [1].

#### **2.3.2.2 Interference Management**

The densification of Het-Nets with large numbers of small-cells to supplement macro-cell coverage and increase network capacity leads to unwanted signals, also known as signal interference, not only to the macro-cell User Equipment (UE) but also to the small-cell base stations. Interference management is of crucial importance [19] in the operation of Ultra-Dense Networks as it affects network capacity, resource allocation, energy efficiency and overall Quality of Service (QoS) experienced by each UE, therefore, making effective interference suppression the major challenge in regards to performance of Ultra-Dense Networks [14].

### **2.3.2.3 Backhauling Challenge**

Backhauling is regarded as the bottleneck for networks with large numbers of deployed small-cells, thus, making the provision of ideal backhaul solutions to all deployed small-cells non-trivial. Ideal backhaul solutions with 10GHz bandwidth, like optical fibre, are required to realize the full potential of Ultra-Dense Networks [16]. Despite their ability to guarantee high capacity, these ideal solutions, most of them being wired, are prohibited in practice due to deployment costs and geographical limitations in certain areas [16]. The deployment costs and geographical limitations in certain areas, therefore, leave wireless backhauling as the other viable alternative, using techniques such as, millimetre waves (mmW) links, massive Multiple Input Multiple Output (MIMO) and relay links. Wireless backhauling is flexible, scalable and cheaper to deploy. However, it not only introduces challenges with limited capacity but also challenges with access [16].

### **2.3.2.4 Mobility Management**

User Equipment (UE) has become more prevalent with advances in technology and network architecture. The densification of Het-Nets with large numbers of small cells not only increases network capacity, but also yields better spectral efficiency as a result of more efficient frequency reuse [17]. The benefits accrued by stationary UEs in UDNs are unambiguous. However, due to the small range coverage of small cells, and the fact that UEs normally change network access point as they transition from one cell to another in a process known as ‘call handover’, the support of mobile UEs requires effective collaborative-based management and solutions in order to prevent high call dropping probability, and hence, reduce the rendered Quality of Service (QoS) [17].

### **2.3.2.5 Energy Inefficiency**

The deployment of small cells to supplement macro-cell coverage and increase network capacity has tremendous potential to not only improve the area spectral efficiency but also enhance the transmit power efficiency, given that small cells use less transmit power compared to macro-cells [18]. However, despite the fact that small cells use low transmission power due to smaller coverage area compared to macro-cells and advantageous path loss conditions, the large numbers of deployed small cells within the macro-cell coverage areas make the total network energy consumption to become immense [19].

The maximization of the overall network energy efficiency while taking into account each UE’s Quality of Service (QoS) in UDN creates for an interesting model which is investigated in detail in this study. It also has to be noted, that the backhauling strategy deployed, be it wireless or wired, has great impact on the energy efficiency performance of UDN [20].

Given that the focus of this study is Efficient Energy management, the Ultra Dense network challenge that is investigated in the latter sections is the Energy Inefficiency problem. Efficient energy management, in simple terms, deals with how to reduce overall network energy consumption while taking into account the Quality of service (QoS) for each user.

## 2.4 Energy Consumption in Ultra-Dense Networks (UDNs)

All network entities user equipment (UEs), backhaul routers, servers, base stations, switches, among others, all consume or use energy. Energy consumption has always been an increasingly important issue not only in the Telecommunications sector but also in other industries, given that it directly affects not just the operating expenditure (OPEX) but both the climate and environment. For Mobile Network Operators (MNOs) in particular, it is of concern as it pertains to their ever dire need to expand network coverage in order to increase customer numbers, and also increase network capacity, in order to deliver ever increasing traffic levels, all the while maintaining sustainable OPEX.

### 2.4.1 Energy Consumption Distribution in Ultra-Dense Networks (UDNs)

Given that this study focuses on a 4G-LTE Ultra-Dense Network, the investigation into how energy consumption is distributed within a network will be based on *Figure 8* below, which shows the architecture of a 4G-LTE UDN.

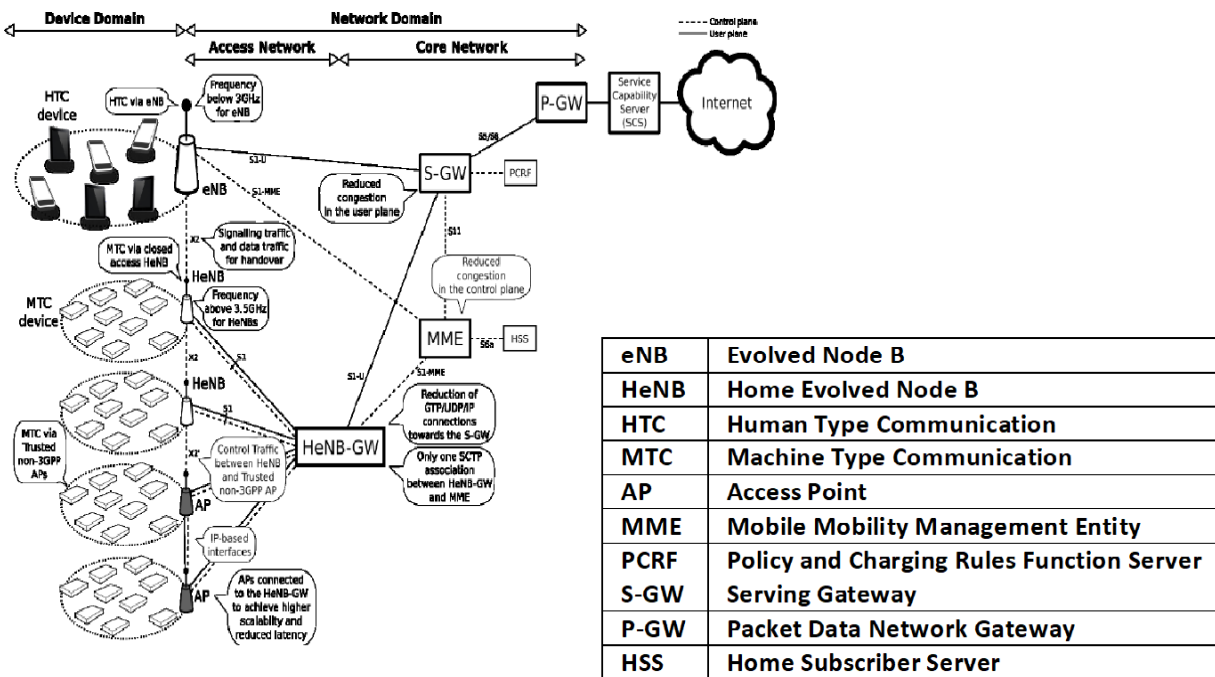


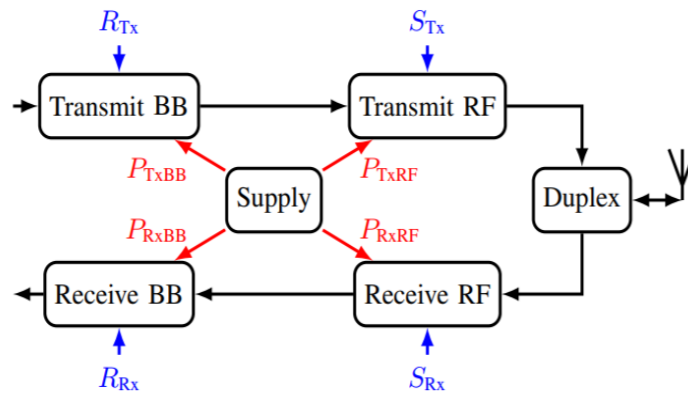
Figure 8: 4G Long Term Evolution (LTE) Architecture

The separation between Network and Device Domain is shown in **Figure 8**. The device domain is comprised of both User Equipment (UE) and Machine Type Communication Devices. The Network domain is comprised of the radio access network and core network. The radio access network (RAN) contains evolved node B (eNB) type access points, and the core network is made up of the backhaul routers and servers that guide traffic back to the Internal Protocol (IP) network.

### 2.4.1.1 Device Domain Power Consumption

The Device Domain is comprised of both Human and Machine to Machine communication type devices as shown in **Figure 8**. In relation to the device domain, this study focuses on the human hand-held devices also known as User Equipment (UE). All User Equipment are made up of the Mobile Terminal (MT) that has the functionality of handling all the communication, and the Universal Integrated Circuit Card (UICC), which is an integrated circuit designed to identify the subscriber [21]. The UICC runs the Universal Subscriber Identity Module (USIM) which stores the International Mobile Subscriber Identity (IMSI) number, home network identity and its related security keys [21].

In order to determine what impacts UE battery life and hence the device domain power consumption, the LTE UE model designed by Jensen *et al* shown in **Figure 9** is used. This Carrier Aggregation model used is derived from the existing LTE release 8 (R8) power model and is the best fit power model, given it takes into account both uplink and downlink power consumption. The LTE UE Physical layer has four components, and is based on the dependency of signal power and data rates on radio frequency as well as baseband power consumption [22].



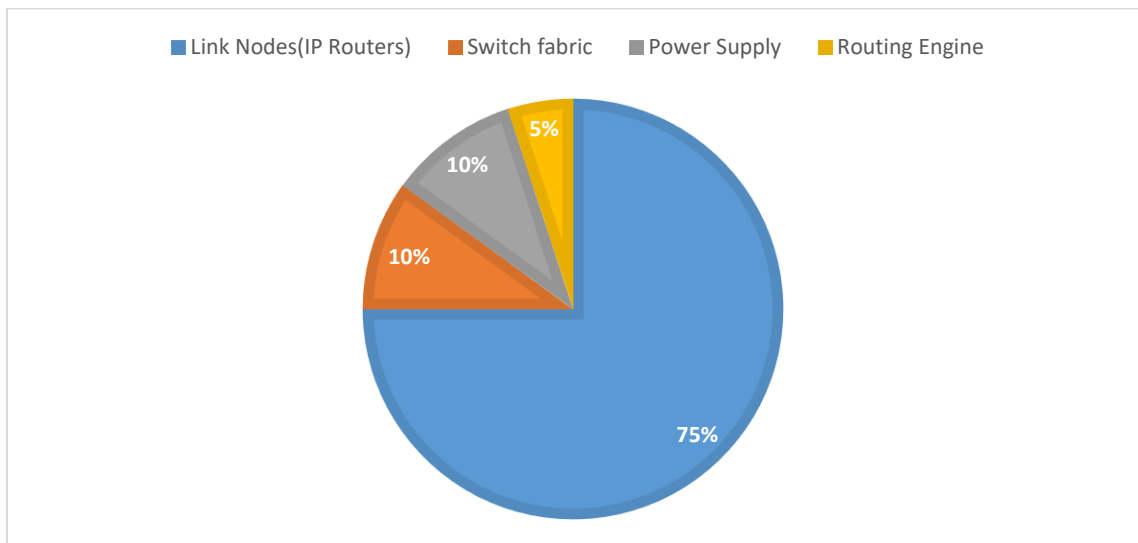
**Figure 9: LTE UE Physical Layer [21]**

Looking at the LTE uplink or data transmission, the Transmit baseband (BB) is tasked with the responsibility of turbo encoding information with Forward Error Correction codes. The turbo encoding complexity graphs linearly with the amount of information to encode despite being independent of the uplink transmit power [21].

Given that the radio frequency depends on the uplink data rate, the Transmit Radio Frequency power consumption will depend on the uplink transmit power. On the LTE downlink, the Receive baseband (BB) is tasked with channel estimation, channel equalization as well as turbo decoding the received data. The turbo decoding complexity and hence power consumption scale graphs linearly with the downlink data rate. On the other hand, the Receive Radio Frequency power consumption is independent of the downlink data rate despite dependency on the downlink receive power level [21].

#### 2.4.1.2 Core Network Power Consumption

The 4G LTE Core network is a packet switched only core network with five main components as shown in **Figure 8** namely; the Packet Data Network Gateway (PGW), the Serving Gateway (SGW), the Policy Charging and Rules Function Server (PCRF), the Home Subscriber Server (HSS) and the Mobile Mobility Management Entity (MME). The HSS is a database that contains UE-related information [18]. The HSS provides support functions in call and session setup, user authentication and access authorization. The SGW is the point of interconnect between the Core and Access networks and is responsible for routing the IP data traffic to and fro. The PGW is the interconnect between the Core and external Packet data networks. The MME is responsible for the control plane, indicated by the dotted line from eNB to MME in **Figure 8**, by handling the mobility and security related signals for the LTE radio access network [21].



**Figure 10; Generalized LTE Core Network Power Consumption Distribution**

As shown in **Figure 10** the major share, about 75% of core network power consumption is concentrated in the link nodes. The links, by way of optical amplifiers, use up to about 10%. Jahid *et al* [27] note that in order to determine the power consumption distribution among the core network components, Juniper T-Series core routers datasheets are used.

It is further indicated that the line cards which are responsible for packet forwarding are the major power consumers in the core routers. The line cards each have layer 1 and 2 media interface which are responsible for packet framing, line speed signalling, and physical connection to a specific network media type such as Ethernet [27].

### 2.4.1.3 Access Network Power Consumption

The Access network as shown in **Figure 8** is only composed of several types of logical element known as Evolved Node B (eNB), which is the equivalent of the Base Station (BS) in the 2G and 3G technologies. Given that in the 4G LTE architecture there is no Radio Network Controller (RNC) as in 2G and 3G technologies, control of the access network is distributed between the installed eNBs. The other functionalities of the eNB Network include connection setup and release, Radio Resource Management (RRM), encrypting of user data, IP header compressing, routing user plane data towards Serving Gateway (SGW) and vice versa, scheduling and transmission of paging messages originating from the Mobility Management Entity (MME) [23].

Generally, the overall energy consumption of an LTE base station can be broken down into fixed and variable consumption. Fixed power consumption does not depend on the level of charge nor transmissions in progress of the base station. Fixed consumption consists of the power consumed mainly by the rectifier and cooling fans [28]. The variable or rather active power consumption depends on the number of users and the volume of traffic generated in the cell. It mainly consists of power used by the power amplifier and the transceiver.

In literature, several models of energy consumption have been proposed for base stations. Unfortunately, most of these models are valid only for macro base stations but not for small stations (pico and femto). Deruyck *et al* in [23] show that for small and low transmission power stations, the network load only affects less than 30% of the overall power consumption.

Han *et al* in [24] make note of the fact that manufacturers have different Base Station (BS) designs which they rarely reveal. This, coupled with the fact that Base Station architecture and designs continually evolve, further makes creating a base station model that is valid and accurate for all base stations very challenging. However, it has to be noted that using an appropriate and valid model to quantify each Base Station's power consumption is not trivial, despite the challenges in base station modelling. Therefore, the Project Earth model, which is known to be valid for eNB type BSs by Gunther *et al* [26] shown below in **Figure 11**, is used in order to analyse base station power consumption within the LTE access network.

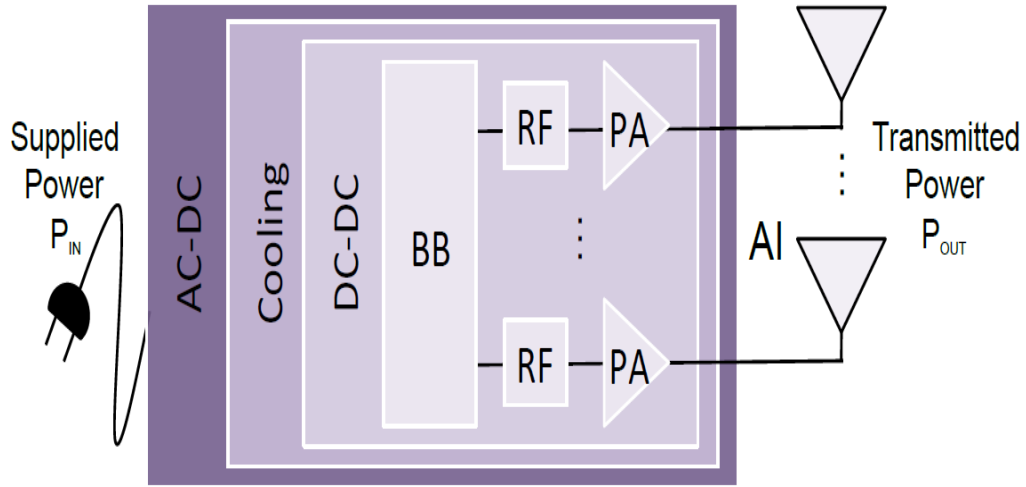


Figure 11: LTE eNB Generic Architecture [26]

The Project Power earth model is formulated as shown below:

$$P_{in} = \begin{cases} N_{trx} * (P_o + \Delta_p P_{out}), & 0 < P_{out} \leq P_{max} \\ N_{trx} P_s, & P_{out} = 0 \end{cases} \quad (1)$$

where:

$N_{trx}$  is the number of transmission –reception chains.

$P_{max}$  is the is the maximum transmission power reached when the base station load is at its maximum.

$P_s$  is the power consumption in idle mode.

$P_o$  is the power consumption of the base station in the active mode.

$\Delta_p$  is the is a factor that reflects the increase in the power consumed by the amplifier as a function of the load (factor related to the load of the base station).

$P_{out}$  is the transmission power.

For these different parameters of the Project earth power model, the values for the different base stations are listed below in **Table 2**:

**Table 2: Energy model parameter values for different types of base stations [26]**

BS Type	$N_{trx}$	$P_{max}$ (W)	$P_o$ (W)	$\Delta_p$	$P_s$ (W)
Macro	6	20	118.7	5.32	93
Micro	2	6.3	53.0	3.1	39
Pico	2	0.13	6.8	4.0	4.3
Femto	2	0.05	4.8	7.5	2.9

The general architecture of an eNB type Base station in **Figure 11** shows that each eNB BS site contains at least one or more antennas in one or more sectors for communication with the UEs. The architecture also shows that for each antenna, the eNB has one Transceiver (TRX). Therefore, in the case of multiple antennas (MIMO), the eNB will have as many Transceivers in what is known as a Transceiver chain. The architecture also shows that each eNB site has the following elements; Power Amplifier (PA), Antenna Interface (AI), Radio Frequency (RF) transceiver module, Transmit Baseband (BB), Receive Baseband (BB), DC-DC power supply, Active Cooling system, AC-DC unit (Main supply) for connection to the electrical power grid.

The different eNB type base stations, their coverage specifications and power consumption breakdown are shown in **Table 3** below. The coverage range is determined by the radiated power at the antenna or antennas of each BS type [25].

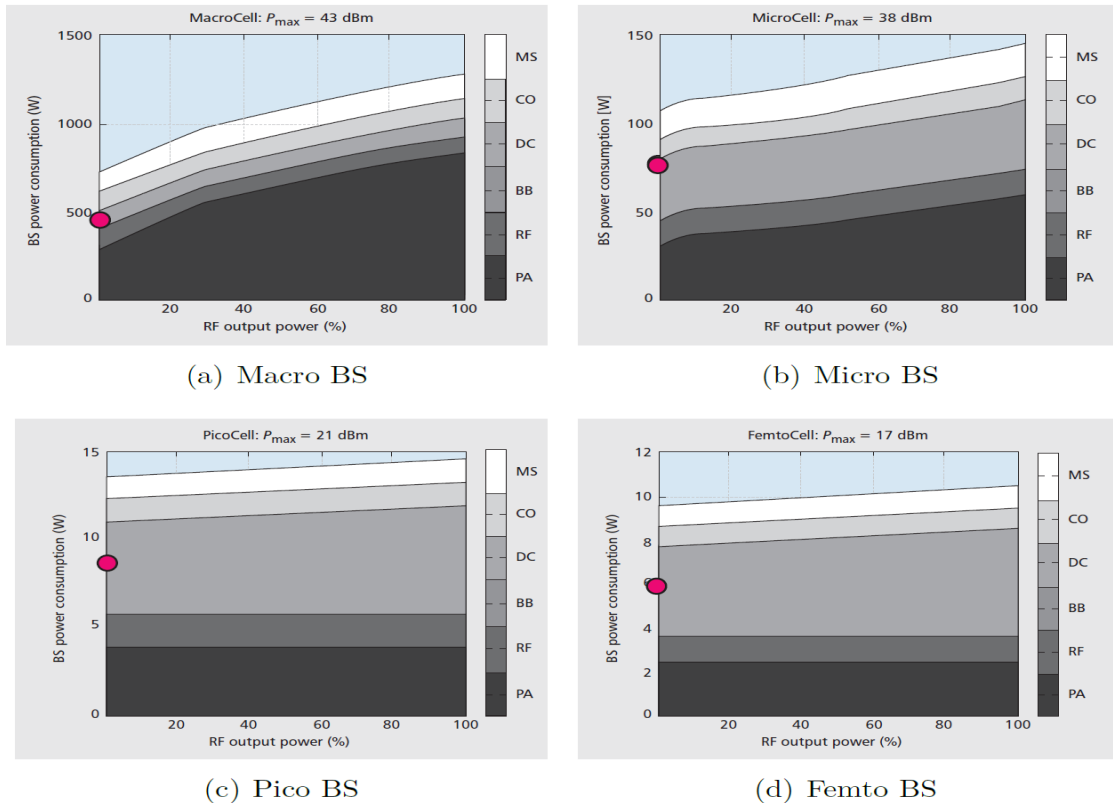
**Table 3: LTE BS Power Consumption Breakdown for the different BS types [25]**

BS Type	BS Coverage area and Range	Main Supply	DC-DC	Power Amplifier	Baseband(BB)	Radio Frequency(RF)	Cooling
Macro	Wide area coverage i.e. > 500m	8%	6%	57%	13%	6%	10%
Micro	Medium range i.e. $\leq 250$ m	8%	7%	38%	38%	9%	0%
Pico	Local area coverage i.e. $\leq 100$ m	11%	8%	26%	41%	14%	0%
Femto	Indoor Coverage i.e. <50m	11%	8%	22%	47%	12%	0%

It has to be noted that, given the different coverage specification for the different BS types, the component selection for each BS within the generic architecture shown **Figure 11** will differ [25]. Therefore, this implies that the overall total energy consumption will obviously vary for the different BS types. Small cell base stations (pico-cells and femto), due to their small ranges, may use less power consuming and dedicated components, while the macro and micro

type base stations for re-configuration purposes may require the use of more programmable and more energy consuming integrated circuits like Field Programmable Gate Arrays (FPGAs) [25].

The overall total power consumption for each BS type depending on the available signal load is shown below in **Figure 12**. Gunther *et al* [26] make note of the fact that the values shown in **Figure 12** of what is known as dynamic power consumption in many studies about eNB power management were calculated when each BS type was operating at full load.



**Figure 12: Overall BS Power Consumption depending on the signal load for the different eNB BS types [26]**

It is worth noting that the access network, and in particular the base stations, are the highest power consuming network elements [2] [28] [29]. The power consumption distribution across the architecture of a 4G LTE Ultra-Dense Network is depicted in **Figure 13** below. The fact that, in Ultra-Dense networks, large numbers of small cells are deployed by users and mobile network operators to supplement macro cell coverage makes the access network the highest power consuming part of the UDN. This explains why most studies related to power consumption reduction and increasing energy efficiency in UDNs are focused on the access network and base stations in particular. Furthermore, it has to be noted that the power per subscriber is heavily dependent on the subscriber density in the area covered by each individual base station [27].

Despite the pico-cells and femto-cells having low transmission power, the overall base station power consumption is much higher than in any other network entity due the high density of these deployed eNBs in Ultra-Dense Networks. However, Wu *et al* [29] make note of the fact that the same dense pico-cell and femto base station deployments in Ultra-Dense Networks, which create small cell coverage areas and more random traffic profiles for each eNB, make the dynamic switching of base station modes feasible and desirable in attempting to reduce the overall network power consumption while taking into account impact to each user's Quality of Service (QoS).

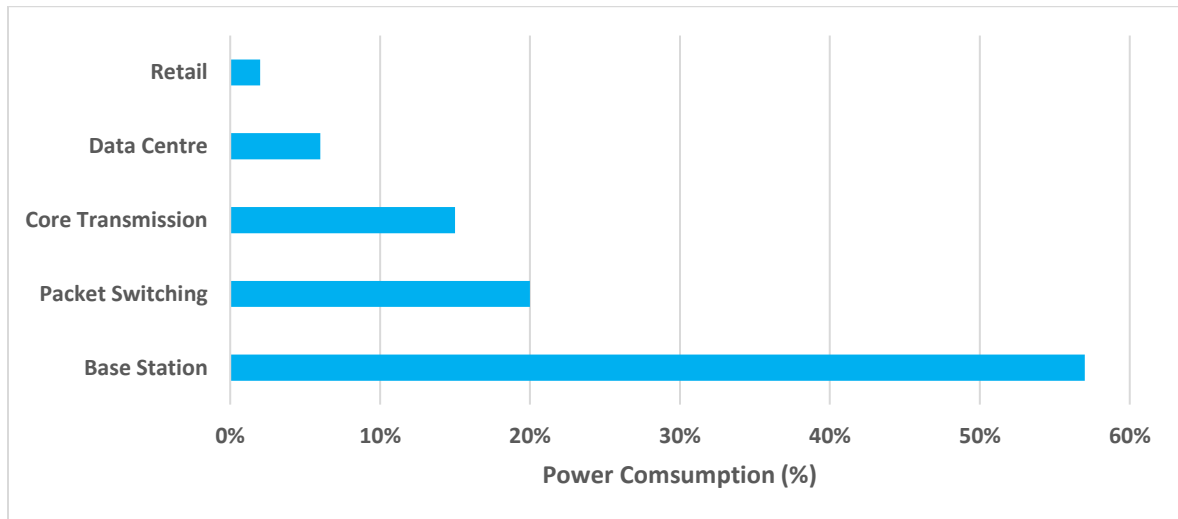


Figure 13: Overall Power Consumption in 4G-LTE Ultra-Dense Network

### 2.4.2 Energy Consumption Reduction in Ultra-Dense Networks (UDNs)

As stated earlier, reducing the overall network power consumption is of utmost importance, not just to the Mobile Network Operator with regards to operating expenditure (OPEX), but also to the environment in regard to CO<sub>2</sub> emissions released into the atmosphere. The network power consumption/usage has a direct impact on the overall network energy consumption. It is now currently acknowledged by researchers and Mobile Network Operators at large that, even though fairly recent surveys [29][30][31] show that Communication Systems contribute about 2% to the earth's CO<sub>2</sub> emissions, this contribution is increasing at a worryingly 10% annual rate.

Given the increasing knowledge and information regarding the probable adverse impact to the environment brought about by CO<sub>2</sub> emissions, coupled with the dangers that the depletion of non-renewable energy sources, like coal reserves, threaten to impose on industrialisation and the growth of many countries' economies, it has become more critical than ever before to reduce the overall energy consumption not only in ICT but other industry sectors as well. Therefore, this has led to an upheaval in the amount of research studies in the area of power consumption reduction and achieving energy efficiency in mobile wireless networks.

It must be noted, however, that energy consumption reduction and energy efficiency increase may not necessarily mean the same thing. Reducing the overall consumption of a system does not necessarily lead to an increase in that system's energy efficiency, and vice versa. This is best explained in a scenario where a given base station during its active mode has very high-power consumption. This same base station could still be termed to have high energy efficiency given it had a very large throughput in a small high consuming time period. Therefore, energy consumption reduction by itself only takes into account total power consumed and the overall network carbon footprint, without factoring in the Quality of Service experienced by the network users.

Some of the strategies that serve to reduce the overall energy power consumption and wireless networks' carbon footprint include; scheduled switching between active and idle modes of network components especially the base stations, proper network planning and deployment of base stations and adopting the use of renewable energy resources like solar , wind and hydro-electricity compared to non-renewable energy sources like coal which not only increase the CO<sub>2</sub> emissions but are threatened by depletion [29]. These strategies, like scheduled switching of base station modes during peak and off-peak hours, serve to reduce the overall power consumed, but may not necessarily increase the overall network energy efficiency. For instance, this strategy runs a risk of reducing throughput, hence, lowering Quality of Service (QoS) for users in certain areas where a number of base stations are scheduled to be switched off in what are expected to be off peak hours.

#### **2.4.2.1 Energy Harvesting and Green Power Solutions**

Using renewable energy sources to power Ultra-Dense Networks via energy harvesting has recently been proposed as a promising solution to achieve green networking. In 2012, a program called "Green Power for Mobile" intended to supply power to base stations using renewable energy sources was started by some of the leading Mobile network Operators, such as MTN Uganda and Zain, under the Global Systems for Mobile communications Association (GSMA) [59]. The goal of the program is to power over 100,000 new and off-grid base stations in developing countries by utilizing energy sources such as wind, solar and biofuels. This would not only inevitably lead to a 0.35% savings in the annual consumption of diesel by the diesel-powered generators at substations at dams, but also reduce the yearly carbon emissions by up to 7 tonnes.

In order to benefit from the greenness advantages energy harvesting accrues while overcoming the instability issues brought about by the renewable energy sources, Ultra-Dense Networks supplied by hybrid energy have emerged. Hybrid supplied Ultra-Dense networks, a new paradigm for green networks, are those that are powered by both energy harvesting and the traditional electric grid.

Mao *et al* [58] propose a design methodology for a hybrid energy source green network with the assistance of Lyapunov optimization techniques. Mao et al utilise base station assignment and power control to optimise the network service cost, a performance metric which

factors in both the achievable Quality of Service (QoS) and the traditional grid energy consumption. The proposed Lyapunov optimization-based BAPC (LBAPC) algorithm, which is an online and not complex algorithm, basically reduces the long-term average network service cost. The major advantage of LBAPC is that there is no need for the information of distribution of links and energy harvesting processes during the decision-making process. Furthermore, network operation is determined deterministically on a per-time slot basis, which allows for the smooth working of an efficient inner-outer optimization algorithm.

However, as stated in the previous section, green power solutions and energy harvesting serve to reduce the carbon foot print of wireless networks, reduce the overall consumption and dependency of wireless networks on the traditional energy sources and not necessarily increase energy efficiency. Furthermore, given the intermittence of renewable energy generation, due to factors like sunlight intensity, as well as cloud cover for solar panels, natural and artificial obstructions to wind flow as well as air temperature for wind energy, making these Hybrid Networks reliable can become challenging. Even with the use of back up methods like batteries to store the excess energy generated, the costs to purchase high quality ones, not to mention the energy efficient ones, as well as the maintenance costs of these batteries, might prove too high for most mobile network operators.

#### **2.4.2.2 Cognitive Radio**

Another solution aimed towards green communication and reducing overall energy consumption is Cognitive Radio. The main goal of the Cognitive Radio is to utilize the unused spectrum bands while collecting overall frequency usage information. However, it is worth noting that the original definition of Cognitive Radio according to Maguire *et al* in [61] was not purely about efficient spectrum management, but rather the detailed cognition of all network parameters, and using these to enable network reconfiguration in order to deliver a certain functionality or desired level of Quality of Service. This, combined with the fact that this dynamic under Shannon's capacity law exists where the capacity increases linearly with bandwidth while it only logarithmically increases with power, makes it feasible to reduce the power consumption by attaining more bandwidth or efficiently and dynamically managing the available spectrum, which falls under cognitive radio.

It has, in fact, been shown through simulations in [60] by Greshma *et al* that energy savings of up to 50% can be achieved using Cognitive Radio. Greshma *et al* propose an energy harvesting cognitive radio network model with the goal of reducing the energy consumed during the spectrum sensing phase of primary user localization, which is very crucial to network reliability despite consuming a significant amount of energy. This proposed model serves to increase the network lifetime as well as the transmission window for secondary users by employing energy harvesting during this sensing phase. The use of energy harvesting in this phase would serve to reduce the total amount of energy consumed off the traditional grid while also ensuring localization accuracy to support efficient spectrum usage.

Despite the advantages of Cognitive radio towards efficient spectrum management and in some cases reduction in energy consumption, it is worth noting that the spectrum sensing phase requires a significant amount of energy and a trade-off has to be made, which may affect the overall efficacy of Cognitive radio as a solution towards green communication.

### 2.4.3 Energy Efficiency in Ultra-Dense Networks (UDNs)

Energy Efficiency, or the efficacy with which energy is consumed by a system, is the ratio between the gain accrued and the total overall energy consumed [32]. In Mobile Wireless Systems and base stations in particular, the total energy consumed is comprised of radiated energy, energy lost as result of using non-ideal power amplifiers and static energy consumed in the rest of the base station hardware components [1].

These components, whose energy consumption makes up the static energy, include the up-down signal converter, frequency synthesizer, filters, cooling fans, AC-DC and DC-AC converters. Buzzi *et al* [1] make note of the fact that there are two general assumptions regarding the static energy and power amplifiers adopted, not only in their study, but also in many studies about base station energy consumption. The first assumption follows that the base station transmit amplifiers are linear in operation as opposed to operating in the non-linear region. The second assumption is that the static energy consumed in time period,  $T$ , is independent of the radiated energy. This therefore, leads the total energy,  $E$ , consumed to be computed using the formula below;

$$E = T(\mu R + P_c) \quad [Joules] \quad (2)$$

where  $R$  is the radiated power and  $P_c$  is the static power dissipated in all other hardware and circuit blocks.  $\mu = 1/\eta$ , with  $\eta$  being the efficiency of the linear operating transmit power amplifier. [32]

The gain accrued in a Mobile Wireless System in any given time period,  $T$ , is akin to the amount of reliable data/information transmitted within period,  $T$  [34]. In many studies, depending on the Mobile Wireless Network under analysis, quite a number of functions taking into account the amount of reliable data transmitted, have been used to get a measure of the performance in respect to energy consumed. Some of these wireless network performance metrics related to the amount of reliable information transmitted include the Shannon capacity/achievable rate, throughput, outage capacity to name a few.

- **Shannon capacity / Achievable rate.** The network capacity is the maximum mutual information or maximum rate of information. In scenarios where the capacity is unknown beforehand, the Shannon capacity is used as the best energy efficiency performance metric and is mostly referred to as the achievable rate [32]. However, the achievable rate does not take into account the modulation scheme, type of channel division, transmission time interval (TTI) and coding rate used, hence, giving a rough channel capacity estimate at best [35]. The achievable rate for each UE-Base station channel is expressed using the formula below;

$$Rate = B * \log_2(1 + SINR) \quad (3)$$

where the *Rate* is measured in bits/s, *B* the bandwidth in *Hz* and *SINR* the signal to noise ratio in *dB*

- **Throughput.** Unlike the Shannon capacity or achievable rate, the throughput as a performance metric factors in the actual rate at which data is transmitted [34]. Throughput is the most common and was the first energy efficiency performance metric used [1]. However, it has to be noted that defining the bit error rate, and hence modulation scheme, are a must when using the throughput as energy efficiency performance metric.
- **Outage capacity.** Outage capacity is defined as the likelihood that the uplink or downlink data rates are below the required and specified threshold data rates within a given time period [36]. An example where outage capacity is used and serves as the best energy efficiency performance metric is a scenario with slow fading, where outage is the greatest challenge to information transfer [1]. However, it is worth noting that using the outage capacity is very unpopular in literature, and in fact, only used in situations where perfect CSI (Channel State Information) is readily available at the base stations.

Despite being used differently, all the performance metrics above have two common features or similarities, which are that they can all be expressed in bits/second, and are dependent on the *SINR* of the communication channel. Therefore, the gain for any mobile wireless system can be expressed by a function of *SINR*,  $f(SINR)$ , where  $f$  is dependent on the system requiring energy efficiency optimization [34]. This leads to the generic energy efficiency, *EE*, formula below;

$$EE = \frac{T * f(SINR)}{T(\mu R + P_c)} = \frac{f(SINR)}{(\mu R + P_c)} \text{ bits/joule} \quad (4)$$

## 2.5 Solutions to Energy Efficiency Management in UDNs.

In this section, a number of the many techniques and methods used in literature to improve energy efficiency in Ultra-Dense networks are detailed. There are quite a number of techniques and methods in place today and in literature, used and defined to increase or optimize energy efficiency in Mobile Wireless Networks, let alone Ultra-Dense networks. These methods and techniques can be grouped and classified into mainly three major categories [34][27][3][1].

These three categories are Radio Resource Management techniques, Network Deployment as well as planning strategies, and finally, Hardware Upgrade Solutions. These techniques can further be characterized by the duration of how long it takes to achieve energy efficiency, or time scale of how long the energy efficiency impact lasts. They can be characterized into Short time scale solutions i.e. milliseconds, Medium scale i.e. hours, and Long time scale i.e. months and years, as shown in *Figure 14* below.

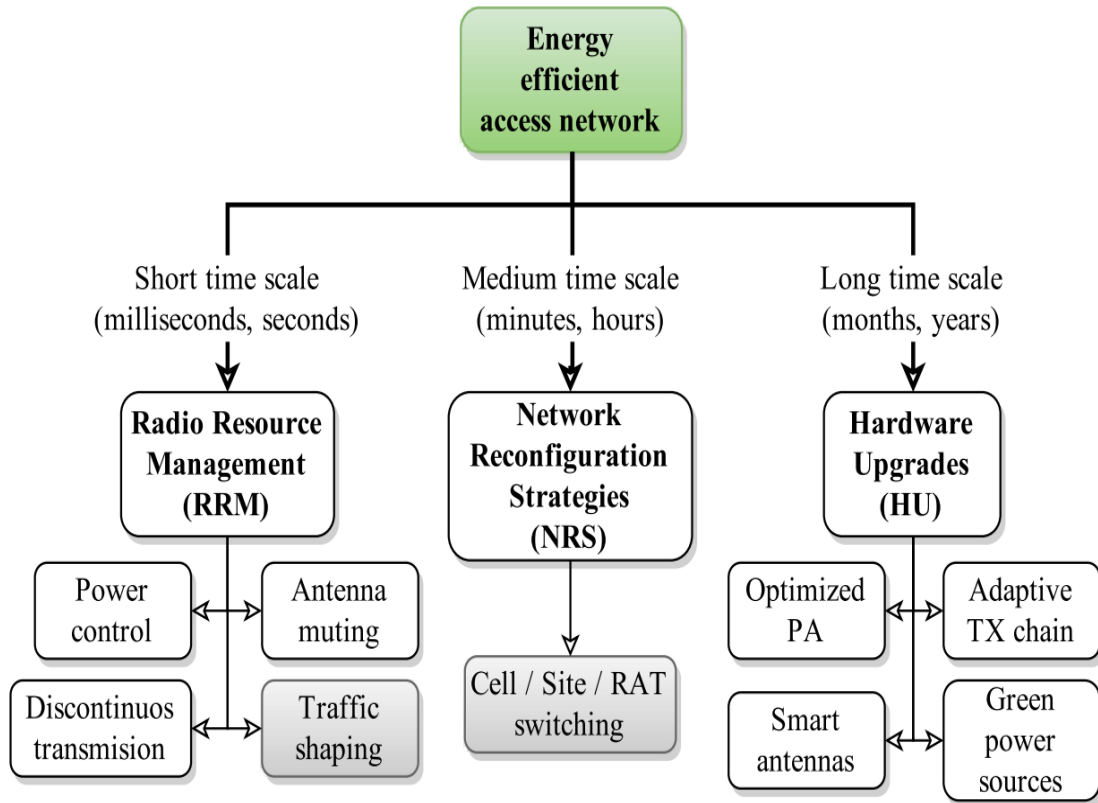


Figure 14: Energy Efficiency Techniques Classification

## 2.5.1 Hardware Upgrade Solutions

Base stations were traditionally designed to be operational at all times. However, having the base stations active at all times would result into very high operating costs and heavy power consumption, given that more base stations are deployed to cope with the ever-increasing demand for network capacity. Therefore, it becomes crucial to make base station components, like antenna or circuitry, to be more energy efficient and able to support functionalities like de-activation, when not being used to reduce the energy consumption levels, or more capacity without using more transmission power.

### 2.5.1.1 Base station Architecture Modification

In the case of macro and micro base stations, the power amplifier is the most energy consuming component. The energy efficiency of the power amplifiers can be optimized for full signal load and maximum output power, with the use of signal conditioning techniques, such as Digital Pre-Distortion (DPD), which serves to increase the linearity of the power amplifier, and Crest Factor Reduction (CFR), which reduces the Peak-to-Average Power Ratio (PAPR) [56]. However, when the signal load decreases, different levels of output power are possible, and the power amplifier does not always require the high levels of input power needed in the full load period.

Gonzalez *et al* proposed an adaptive transceiver chain for LTE macro base stations in [57]. The architecture, which includes the power amplifier, RF and the DC-DC power supply, is designed to allow for load flexibility of signals as well as very quick component deactivation. This transceiver chain requires one crucial component known as the Digital Signal Processor and Controller (DSPC), which is responsible for analysing the signals coming from the baseband unit, and controlling the other elements of this transceiver chain with the goal of adapting their functionality to the fast occurring signal load. With the use of adaptive clipping, the power amplifier's operation is adjusted to the signal load using adaptive clipping [57]. This adjustment in the power amplifier's operation results into the generation of variant levels/values of Peak-to-Average Power Ratio, which further allows for the minimisation of the demanded main supply voltage, in order to arrive at an optimum point of operation for the instantaneous signal load. Furthermore, the power amplifier is enabled to quick activate while the RF to fast deactivate a few of the transmit blocks in periods of empty symbols. On the other hand, the DC-DC supply is optimized to give only a range of voltages that the adaptive power amplifier requires, and is able to quickly transition through efficiently. This proposed adaptive transceiver chain through simulations showed significant reductions in power usage for the different load types [57].

However, it is worth noting that, despite the significance that the modification of base-station architecture has towards energy efficiency in networks, the capital costs involved in acquiring these new base stations is always quite high, and so is the cost to deploy them and replace the ones with energy inefficient components or architecture.

### **2.5.1.2 Multiple Input Multiple Output Antennas**

Another possible upgrade for eNB type base stations or base stations employing OFDM is the use of Multiple Input Multiple Output (MIMO) Antennas. The use of MIMO enables the ability to improve the signal quality through spatial diversity, as well as provide higher data rates when all antennas are active by taking advantage of spatial multiplexing and multipath environments in locations such as urban areas. Spatial diversity is the transmission of a data stream via multiple active antennas, with each antenna having a different code, or using a different frequency for the same data stream with the goal of guaranteeing high Quality of service (QoS). On the other hand, Spatial multiplexing is the sending of different streams via the multiple antennas especially in good channel conditions with the goal of accommodating more users and providing higher data rates [63].

Besides spatial multiplexing and spatial diversity, the other major characteristic of Multiple Input Multiple Output (MIMO) is beamforming. Beam forming is the adaptation of the transmitted signal's radiation pattern resulting into variation of the cell size or cell coverage with a goal of increasing the area spectral efficiency. Beamforming works by focusing the transmitted signals towards each user and concentrating the data transmission to increase throughput and range, so that more information reaches each user instead of radiating out into the atmosphere. Beamforming serves to improve spectrum utilization, increase throughput as well as network range. These advantages, in turn, lead to improvement in video streaming, voice quality, and other bandwidth- and latency-sensitive transmissions hence overall quality of service (QoS) [64].

## 2.5.2 Network Reconfiguration Strategies

The goal of Network reconfiguration strategies (NRS) is to change the radio access network configuration to the different load variations with the goal of minimising the amount of energy consumed. It is worth noting that, unlike the Radio resource management solutions that react to traffic load variations within an LTE OFDM sub-frame, Network Reconfiguration Strategies do not react to instantaneous traffic load variations but rather take minutes or hours to react to these changes, given that these solutions in most cases require overall coordination from all cells in the network [62]. These strategies that change the configuration of the radio access network are known in literature by different terms such as, Cell Zooming, and Dynamic switching of cell/base-station modes between idle and active.

The goal of all Network reconfiguration strategies (NRS) is to achieve energy efficiency by either partially or fully de-activating the unused or unrequired network resources depending on the traffic profile in that given geographical location. The traffic profile in any given location is dependent on the human activity in that location [54]. Therefore, human mobility as well as the routines of network subscribers, are the factors that create variance between any given two or more traffic profiles. For instance, social places such as malls and business parks, experience peak traffic during the afternoon hours, while residential areas experience peak traffic during evening hours.

It is also worth noting that the design of these Network Reconfiguration Strategies encompasses three factors namely; minimize overall network energy consumption, guarantee the demanded Quality of Service (QoS) to all users in any given area, and last but not least, ensure that each user's network experience is not compromised, while aiming to attain efficient energy usage of network resources [62]. The overall execution of Network Reconfiguration Strategies follows that, first, the traffic load information is acquired by estimation, measurement or historical data. Then, based on that information, the access network is reconfigured with an aim of reducing energy consumption.

### 2.5.2.1 Dynamic switching of base station modes

Switching the base stations to idle mode during periods of inactivity is one of the most studied and used techniques for overall energy conservation on radio access networks in literature to date. Given that the traffic load fluctuates throughout the day, the underutilized and unused eNBs can be dynamically switched to idle state to save energy. The power consumption of an eNB in idle state does not include transmission power and cooling operations. Therefore, Dynamic switching of base station modes is an efficient approach for both reducing network power consumption and improving network energy efficiency performance.

Feng *et al* in [49] showcase an example of a Mobile network Operator, China Mobile, that realised significant energy consumption savings by adopting the Dynamic Switching of base station modes. China mobile, which is one of China's biggest Mobile Network Operators, in

2009 adopted the dynamic switching of base station modes, and has since realised an estimated reduction of energy consumption of 36 million kWh/year. This high potential to reduce overall network power consumption is why there has been a lot of research and development put into the advancement and design of the Base Station ON-OFF switching algorithms in a number of varying network scenarios.

In [50], Nuo *et al* tackle the energy cost minimization problem by employing dynamic switching of BS modes. Nuo *et al* formulated the base station energy cost minimization problem as a minimum energy cost problem (MECP) while considering a 24-hour period. The formulated MECP involves determining the active base stations as well the adjustments in the transmission powers of the respective active BSs, while taking into account the transitions between base station states so as to minimize the energy cost. The authors' proposed scheme, which through simulations showed that significant energy savings can be achieved, solves the MECP in two steps. First Nuo *et al* proposed scheme minimizes the energy cost of all base stations and then using a network flow graph shows the BSs' state transitions.

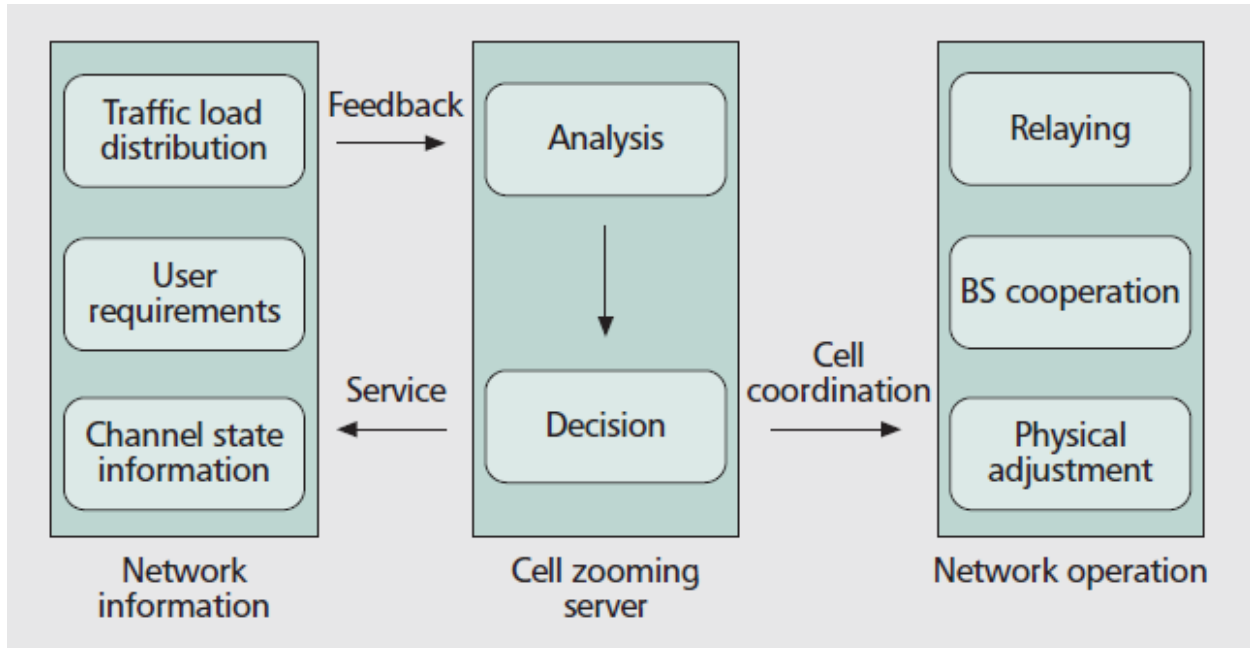
The authors in [51] proposed a dynamic cell-state switching scheme for small cells that bases its selection of active cells based on the estimated network traffic and each user's network preferences. The scheme proposed in [51] works by first clustering the small cells, followed by executing an algorithm aware of users' network preferences, and lastly, iteratively determining which small cells in each cluster will be active or idle using a sub-optimal greedy small-cells' state switching algorithm. The users' network preference scheme bases its association of users with cells on the SINR, delay requirement, estimated network load and traffic type. The simulation results obtained by Wu *et al* showed that significant energy reduction of up to 72% can be achieved in comparison to networks using optimal search and traditional algorithms.

However, the design and implementation of dynamic switching of base station modes faces special challenges, given that next generation network technologies like 5G are generally speaking a coordination of different techniques with a highly Ultra-Dense Network architecture [2]. Furthermore, it is worth noting that the energy savings accrued by employing dynamic switching of base station modes come at a cost. The reasons being that some implementations of dynamic base station switching do not factor in QoS requirements hence most users experience a degraded Quality of Service (QoS) when handed over to other cells, while others experience delays in service due to the untimely manner in which some cells are activated from sleep mode.

### **2.5.2.2 Dynamic Cell Zooming**

With increase in the number of devices per person as well as more people using networked devices, cell zooming, when implemented efficiently and dynamically as a power consumption reduction technique, achieves significant power savings. Cell zooming involves the adaptive reconfiguring of cell sizes or the base stations' coverage radii. The reconfiguration of the coverage radius for any given base station, and hence transmission power, is based on the current given traffic load or profile i.e. UE locations and demanded data rates as shown in

**Figure 15.** According to simulations, using cell zooming serves not only to reduce power consumption by 40% of a given base station during off-peak hours but also solve the problem of traffic imbalance. Therefore, the base station transmits at the minimum desired level given low traffic profile rather than transmit at maximum power all the time.



**Figure 15: Implementation of Cell Zooming**

Park *et al* in [54] proposed a base station centric cell zooming scheme aimed at transmission power control based on traffic load. The scheme uses average distance between UEs and base stations, based on a Voronoi Tessellation to determine UE-Cell association. Instead of the UEs selecting which base station is suitable based on received signal power (RSSP), the control server determines which UEs should be associated with each base station and hence resource allocation. After determining the UE-Cell association matrix, sorting is done based on which UE would use the least resources per base station. Following the sorting process, each UE is associated with a particular base station and the maximum transmit power and cell radius for that station is based on the furthest associated UE.

In [55] Xu *et al* propose an adaptive cell zooming scheme that combines cell sleeping to optimize UE-Cell association by adjusting cell sizes and increases energy efficiency by turning off cells with low traffic loads using the cell sleeping algorithm. The probability of a UE associating with a given cell is computed and is proportional to the cell zooming factor (CZF) and transmission power of given base station. The cell zooming factor (CZF) is defined as a closed form expression relating the macro-cell and small-cell densities. Xu *et al* basing on reduction of area of power consumption make use of game theory to optimize the cell zooming factor (CZF). Furthermore, using the cell sleeping scheme the UEs that are associated with low loaded small cells are offloaded to macro cells given that UEs are encouraged to associate with

small cells. It is worth noting that Xu et al compute the sleeping probabilities of the small cells using different thresholds.

Despite realising significant energy savings and ensuring traffic balance within the network, cell zooming's flexibility and efficiency heavily relies on traffic load fluctuations being closely monitored and relayed back to the cell zooming control server which creates an overhead. Secondly, some of the techniques of cell zooming such as adding extra equipment to adjust antenna height and tilt, cell cooperation and traffic information relay are not easily supported by the architecture of some of the Ultra-Dense Networks. Last but not least, cell zooming runs the risk of increasing inter-cell interference due to cell zooming and also creating holes in network coverage affecting the user network experience.

### **2.5.3 Radio Resource Management based Solutions**

The aim of Radio Resource management techniques is to efficiently maximize the radio spectrum and utilize the base station physical resources by employing genius methods, all the while taking into account each UE's Quality of Service (QoS). One common example of a radio resource management solution is Power Control [38]. Radio resource management solutions play a huge role in specifying which of the hardware resources (antennas, transceiver chains among others) are used by the base station to relay the traffic over the radio channel.

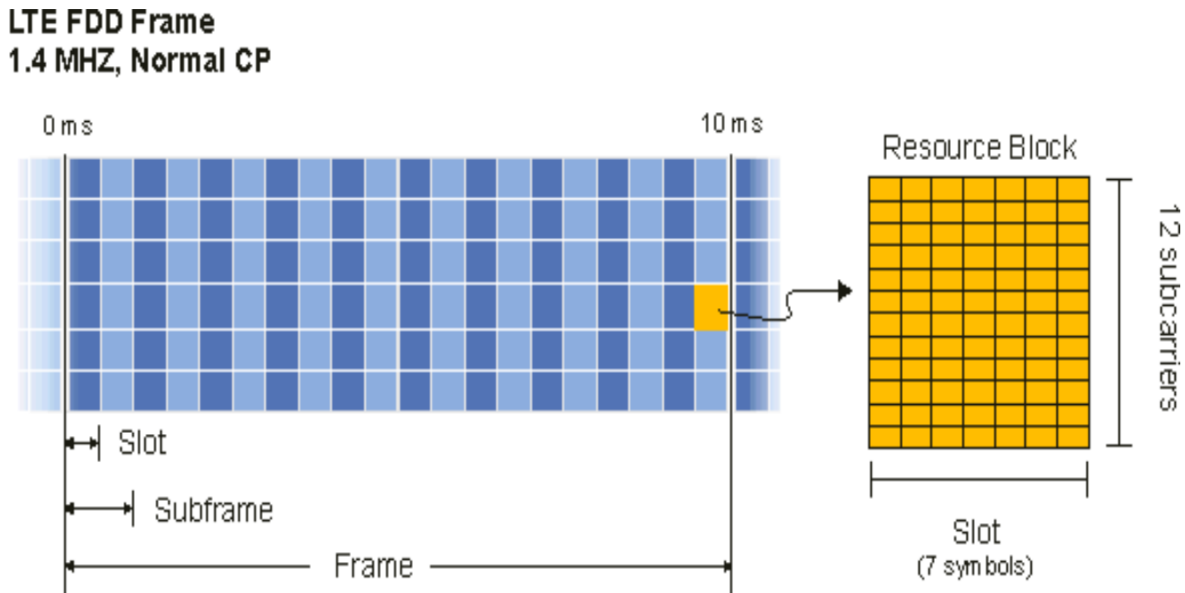
The solutions involving Power Control adapt the power transmission of the base stations depending on the network and traffic conditions. Most Power Control solutions not only involve reducing power consumption hence energy efficiency improvement, but interference management as well [39]. Examples of such techniques in literature include Efficient Subcarrier allocation techniques, Efficient User-Cell association, Efficient scheduling approaches. It is worth noting as indicated that the major power consumption of an operational Base Station is independent of the transmission power. This is why recently developed Energy Efficient Radio Resource Management schemes take into account the new flexible and adaptable base station hardware resources [43].

#### **2.5.3.1 Efficient Resource/Subcarrier Allocation Techniques**

One of the key elements of 4G-LTE is the use of OFDM, Orthogonal Frequency Division Multiplexing as the information carrier and the associated multiple access schemes, OFDMA (Orthogonal Frequency Division Multiplexing) for the downlink and SC-FDMA (Single Frequency Division Multiple Access) for the uplink. OFDM is a form of data transmission that uses a large number of closely spaced carriers that are modulated with low rate data [45]. OFDM is not only used in 4G-LTE but in other wireless systems such as Digital Audio Broadcasting (DAB), WLAN and WiMAX. OFDM despite its complexity, has a number of advantages, the major one being robustness to multipath fading and interference [47].

In the LTE OFDM downlink in particular, the frequency spectrum is split into several smaller bands of frequency called subcarriers of 15kHz each. These 15kHz subcarriers utilize specific values of frequency so as to be completely orthogonal to each other. Frequency units can

be expressed in number of subcarriers or resource blocks [48]. A resource block (RB), which is 180 kHz wide in frequency and 1 slot or 0.5ms long in time, is the smallest unit of resources that can be allocated to any user. In the frequency domain each resource block is either 12 x 15 kHz subcarriers or 24 x 7.5 kHz subcarriers wide. 12 is the number of subcarriers used per resource block for most channels using normal cyclic prefix as shown in **Figure 16** below. It is worth noting though that DC subcarrier is not included in a resource block.



**Figure 16: An Illustration of a Frequency Division Duplex (FDD) Frame [48]**

Dynamic subcarrier allocation, which is essentially a combinatorial resource allocation problem, makes use of channel condition information to significantly improve energy efficiency performance. The evidence for how it is implemented to achieve this is provided in the later paragraphs.

Frenger *et al* [44] in their attempt to increase energy efficiency in an LTE network applied the concept of applying discontinuous transmission (DTX) on the LTE downlink Orthogonal Frequency Division Multiplexing subframes (OFDM). It is further pointed out by Fregner *et al* in [44] that LTE networks in metropolitan areas, where DTX is applied to the downlink, can achieve up to 90% energy reductions theoretically. This theoretical prediction is explained by highlighting the impact of cell DTX from a life cycle assessment perspective on the overall energy efficiency performance of an eNB base station. It is shown in [44] through simulations and results that, by allowing for a brief or short component deactivation of the radio transceiver chain, energy savings of up to 61% can be realized in a realistic traffic scenario.

It is shown in [44] that during low traffic load periods, the reconfiguration of a cell uses 6 multi-cast and broadcast single frequency network sub-frames, which is the minimum amount allowed for signals that need to be transmitted in any eNB even with zero traffic. This reconfiguration leads to significant reduction in power consumption of the power amplifier due

to reducing the amplifier's total wake up time to 74% of the time in low power DTX mode in 74% of the time when there is no traffic in the cell.

In most of the implementations of dynamic subcarrier allocation in OFDM networks, time or power splitters are required at the transceiver chain to separate signal received for data decoding and energy harvesting. In [46], a subcarrier allocation based scheme is proposed which has no splitter required at the receiver. Given no splitter is required at the receiver to separate the received signals into 2, this allows for focusing on optimal and dynamic subcarrier allocation such that the harvested energy is maximized.

Despite the capability to realize significant energy savings, using efficient subcarrier allocation as an energy efficiency maximizing solution has a few limitations, given the number of the LTE standards that the base stations must comply, especially some minimum amount of transmissions, and such mandatory idle-mode transmissions can significantly limit the feasibility of cell DTX. Furthermore, given that Cell DTX is most efficient when the traffic load is low in a cell, this reduces its effectiveness and overall usage in reducing base station power consumption.

### **2.5.3.2 Efficient User-Cell Association**

Due to the densification of wireless networks with large numbers of small cells in order to increase network coverage and network capacity, two of the major challenges faced as a result are interference and efficient energy management. Some of the user-association schemes and solutions in use today do not consider the power consumed by eNB as a decision criterion for user association, while others take into account the energy aspects but do not deal with the case of Ultra-Dense LTE networks, where cells of different types coexist and overlap. However, through a number of studies on efficient energy and interference management in LTE Ultra-Dense Networks (UDNs), it has been shown that significant energy savings can be realized by cooperatively optimizing base station activation and user cell association based on the user-cell link conditions and the average network traffic.

Kuang *et al* propose a new two-step energy-efficient resource management framework in [52] that takes into account the inter-cell interference coupling effect resulting from the base station activation. The first step involves pre-calculating the achievable data rate for each user, also known as Shannon channel capacity, for all possible active/idle combinations of cells within the network, also known as interference patterns or scenarios. The second step involves performing resource allocation among the different cell active/idle combinations.

In the framework proposed by Kuang *et al*, the interference fluctuation resulting from cell activation and de-activation is considered, given that the scheme concurrently computes both the actual interference and user Shannon channel capacity for any all interference patterns [52]. Furthermore, the simulation results showed that the scheme was able to realize a more than significant improvement in energy saving.

The strategy proposed by Quan *et Al* in [52] is to have the user rate calculated beforehand under every probable network interference scenario, and thereafter do the allocation of RBs in

each interference scenario. This type of RBs allocation yields the realistic interference scenario and the respective link Shannon capacity that matches the interference at that time.

Lastly but not least, Chen *et al* in [53] propose a user association optimization algorithm with a goal of reducing the total power consumed by all base stations for any given time slot while ensuring that each user is given the demanded QoS specifications. This scheme determines user-cell association by computing the optimum traffic load value for each time slot.

However, it is worth noting that efficient resource management which takes into account the factors above is mathematically complex to solve, given the inherent non-convexity of the formulated optimization equations caused by inter-cell interference coupling. Hence, in order to make the problems tractable, previous studies involving efficient user cell association assumed worst case interference [53], average interference assumption [52] or altogether neglected inter-cell interference.

## 2.6 Chapter Summary

Section 2.1 showcases the classification of the different Mobile Wireless Technologies as well as giving examples, advantages and operating specifications of the technologies under each classification. This section also provides a brief coverage or report on the evolution of mobile cellular technologies and services rendered from the circuit switched and voice only First Generation (1G) technologies, like Advanced Mobile Phone System (AMPS) in the late 1970s to the now widely used packet switched 4G and 4.5G technologies like WiMAX, LTE, HSDPA+ and LTE-Advanced capable of providing Voice over Internet Protocol (VoIP), high data rates for streaming, browsing and video conferencing.

This section is followed by Section 2.2 which briefly covers Heterogeneous networks (Het-Nets). In this section, the motivation for Het-Nets as well as the benefits Mobile Network Operators (MNOs) and Customers accrued from the emergence of Het-nets are well laid out. The short-comings of the Het-Nets as well as the reasons that are leading to the shifting away from Het-nets are also documented. They evolved to Ultra-Dense Networks (UDNs).

Section 2.3 provides a brief overview into the evolution to Ultra-Dense Networks as well as the challenges that this evolution brings. The motivation for Ultra-Dense networks and benefits for UDNs to both MNOs and User are given.

In Section 2.4, focus is drawn to the challenge of increasing power consumption within the Ultra-Dense Networks. A detailed report is given on why the power consumption in a UDN is increasing based on an LTE-UDN architecture. It is also highlighted that the increasing energy consumption concern is growing in priority given its impact on the environment, as well as its effect on the CAPEX and OPEX of Mobile Network Operators. Section 2.4 also details the breakdown of power consumption in an LTE Ultra-Dense Network. A detailed report is given as to why most of the power consumed by a 4G-LTE Ultra-Dense Network architecture is within the access network and why the base stations in particular consume the most. This fact that base stations consume upwards of 60% of the total network power basically explains why most of the

research in this field dwells on the management of power of the base stations. Furthermore, section 2.4 highlights a few of the solutions implemented with the goal of reducing the overall power consumption, carbon foot print and dependency on the traditional electric grids.

Finally, Section 2.5 gives a detailed report on the three classifications of the different energy efficiency strategies/solutions as well as implementation of these strategies within literature. Details of each implementation as well as critical analysis of some of the short comings of each strategy are provided in section 2.5. This critical analysis provided in this section sets the stage and gives the motivation for the proposed Distribute Cell Association and Resource Allocation with Cell On/Off scheme that is proposed in this study.

## **Chapter 3      Distributed Cell Association and Resource Allocation with Cell On/Off scheme**

### **3.1 Introduction**

The evolution and emergence of Ultra-Dense Networks provides the user with a rich environment that if used wisely, can ensure better QoS for the different services. The deployment of several small cells that overlap and supplement macro cell coverage has been accompanied by an evolution of mobile devices that today support several standards. This has, hence, led to an increase in mobility within networks as well as increase in overall network capacity provided.

However, this deployment of several small cells to supplement the macro cell coverage, as discussed in Chapter 2, creates several different problems as well as the need to review a number of network procedures in order to improve the overall network efficiency. These network procedures in need of review include the packets' scheduling on the various channels/links and the routing of these packets on multiple paths, which can cross networks and domains, while taking into consideration the disparate QoS requirements for the various users. One major concern that arises in dealing with the review of how services are provided in new generation technologies like 4G LTE is the control of energy consumption, especially on the base station side. The activation or use of several small cells will induce a significant increase in energy consumption which would result into very high network operating as well as environmental concerns, hence the proposed scheme.

#### **3.1.1 Motivation for the Distributed Resource Allocation Algorithm**

Following the analytical and qualitative study done in Chapter 2 on the various techniques employed in achieving efficient energy usage in Ultra-Dense networks, the Distributed Resource Allocation Algorithm aims at achieving the same objective while attempting to tackle a few of the issues not considered and out of scope for the other strategies. In this study the System model and Problem Formulation take into account both macro and femto-cells, impact of both Non-Uniform and Uniform UE distribution on NEE, energy efficiency of BS Power Amplifier (PA), impact of user mobility on energy efficiency, impact of inter-cell interference experienced by UEs at the macro-cell edge as well as the impact of control signal overheads on each UE's achievable rate. These were all issues that were not considered by many of the strategies proposed in the related works covered in the previous section.

### **3.2 Analytical System Model**

#### **3.2.1 Network Model**

The focus of this paper is on the Physical Downlink Shared Channel (PDSCH). A relatively urban area, with size approximately  $(d \times d) \text{ km}^2$ , having 7 macro base stations supplemented by multiple small cell base stations, is considered. Each macro BS operates in a

tri-sector cell using Soft Fractional Frequency Re-Use. The frequency partition is only applicable to the cell edge UEs, while the effective frequency reuse factor remains close to one. Given an urban area is considered, Non-Line of sight (NLOS) Communication is assumed. In an NLOS environment, each signal from the transmitters bounces off walls, buildings, trees and other obstacles in a slightly different way which enhances the effectiveness of using MIMO to increase the network throughput [9].

The macro and small cells are all eNB but operate on different frequency bands. The set of base stations (BSs) is denoted by  $B = \{b_1, b_2, \dots, b_\tau\}$ , where  $\tau$  is sum of all the femto BSs plus the 7 macro BSs. All base stations have an active or idle status denoted binary variable,  $s_b$ , represented as follows;

$$s_b = \begin{cases} 1 & \text{if BS is on or active} \\ 0 & \text{idle} \end{cases}, \forall b \in B \quad (1)$$

The small cells are distributed following a Non-Uniform Spatial Point Process, which is model of stochastic geometry, within the area by the Mobile Network Operator (MNO) as shown in **Figure 15**. This Non-Uniform femto cell distribution is assumed because in practice, it is not probable to find uniform femto cells distribution especially in largely urban areas. It is furthermore important to note that this non-uniform femto cells distribution leads to forming of clusters in areas assumed to have high level activity, hence likely to have a higher number of UEs like large malls, large business centres and large residential areas. All femto cells share the same frequency band, have the same specifications and use either Digital Subscriber Line (DSL) or high data speed fibre to backhaul traffic back to the core network.

The small cell eNBs deployed in this area are mostly indoor user deployed (femto cells) compared to outdoor network operator deployed (pico-cells). Furthermore, the assumption is that for every pico-cell, there is about 10 or more femto cells, hence making the number of the pico-cells very small and negligible compared to the total number of femto cells,  $F$ , as the number of cells reaches the thousands. The number of these femto cells per region,  $F_R$ ; where  $R$  stands for region, follows a Poisson distribution with a mean,  $\lambda_R$ . Therefore, the probability of  $n$  cells in an area is given by;

$$P(n) = \frac{(\lambda_R)^n e^{-\lambda_R}}{n!} \quad n = 0,1,2 \dots \quad (1)$$

All the small femto cells share the same frequency band, have the same power specifications and bandwidth. Furthermore, these femto cells are assumed to use either DSL or high data speed fibre to backhaul traffic back to the core network.

The small femto cells can be distributed randomly following either a uniform or non-uniform distribution. The vector coordinates  $x$  and  $y$  of each femto eNB, are independent of each other and have no correlation. In a uniform femto cell distribution,  $x$  and  $y$  take on any integer,  $i$ , from set  $I$  with equal but independent probabilities. Set  $I$  has  $n$  integers and is denoted as;

$$I \in \left\{ -\frac{d}{2}, \dots, \frac{d}{2} \right\}; \text{ where } n = d$$

These probabilities that x or y take on any integer, i, in the set I are given by;

$$P(x = i) = P(y = i) = \frac{1}{n} = \frac{1}{d} \quad (2)$$

In a non-uniform femto cell distribution, x and y take on any integer, i, in the set I with a mean vector, mv, and a covariance matrix, cv. The mean vector, mv, is given by;

$$mv = \{\bar{x}, \bar{y}\} \quad (3)$$

where  $\bar{x}$  and  $\bar{y}$  are the means for x and y respectively

The covariance matrix, cv, is given by;

$$cv = \begin{Bmatrix} var_x & cov_{x,y} \\ cov_{y,x} & var_y \end{Bmatrix} \quad (4)$$

where  $var_x$  is the variance of x,  $var_y$  is the variance of y,  $cov_{x,y} = cov_{y,x} = 0$  are the covariance of x and y which are both equal to 0; as x and y are not correlated.

Therefore, x and y for each small eNB are computed as follows;

$$x = (j\sqrt{var_x} + \bar{x}) \text{ and } y = (j\sqrt{var_y} + \bar{y}) \quad (5)$$

where j is a random variable that follows a normal distribution with a mean of 0 and standard deviation of 1, hence a standard deviation.

The probability density function of the non-uniform distribution of random variable j with mean 0 and standard deviation 1 is as follows;

$$P(j|\mu = 0, \sigma = 1) = \frac{e^{-\frac{j^2}{2}}}{\sqrt{2\pi}} \quad (6)$$

The average number of UEs per region,  $UE_R$ , is computed using a simple queuing model.

All the UEs are assumed to support voice, video and browsing services and each UE has a service class denoted by  $\beta_k$  represented as follows;

$$\beta_k = \begin{cases} 1 & \text{if service is guaranteed} \\ 0 & \text{otherwise} \end{cases}, \forall k \in K \quad (2)$$

The UEs in the network follow can either a normal or uniform distribution depending on the activities in that particular area. The set of UEs is denoted by  $K = \{k_1, k_2, \dots, k_{N(t)}\}$ , where N(t) is average number of UEs and varies throughout the day. N(t) is computed using a simple

M/G/1 queuing model where the arrivals and departures follow a Poisson distribution with a single server, infinite queue length, infinite calling population and the queue discipline is First Come First Serve. M/G/1 is used, given the fact that each UE's service rate is a function of the communication link. The average number of arrivals of UEs into any of the area at any period in the day or arrival rate,  $\lambda(t)$ , depends on the period of the day and activities in that given area. Furthermore,  $\lambda(t)$  follows a poisson distribution and is referred to as a 'Markovian process,' because the arrivals of users into any of the four regions are independent of each other and system state. Following the principles of a poisson distribution, the probability of say  $n$  arrivals within a given interval  $t$  is given by;

$$P(n) = \frac{(\lambda(t))^n e^{-\lambda(t)}}{n!} \quad n = 0,1,2 \dots \quad (7)$$

where  $t$  is the time and  $n$  is the number of UE arrivals within a given interval  $t$ .

The arrival rate,  $\lambda(t)$ , of UEs into the considered urban area as stated depends on the period of the day and follows a poisson distribution. The service time of UEs at any given time of day,  $\mu(t)$ , has a general distribution and  $1/\mu(t)$  is referred to as the mean service time. The average time,  $W(t)$ , any UE spends in the considered area is given by;

$$W(t) = \frac{1}{\mu(t) - \lambda(t)} \quad (3)$$

This therefore means  $\mu(t)$  is given by;

$$\mu(t) = \lambda(t) + \frac{1}{W(t)} \quad (4)$$

The percentage of time the server in the M/G/1 queuing model is busy, known as the utilization factor,  $\rho(t)$ , and is given by;

$$\rho(t) = \frac{\lambda(t)}{\mu(t)} \quad (5)$$

Therefore, the average number of UEs at any given time,  $N(t)$ , is given by;

$$N(t) = \lambda(t) * W(t) = \frac{\lambda(t)}{\mu(t) - \lambda(t)} = \frac{\rho(t)}{1 - \rho(t)} \quad (6)$$

The figure below shows a MATLAB representation of the above network model.

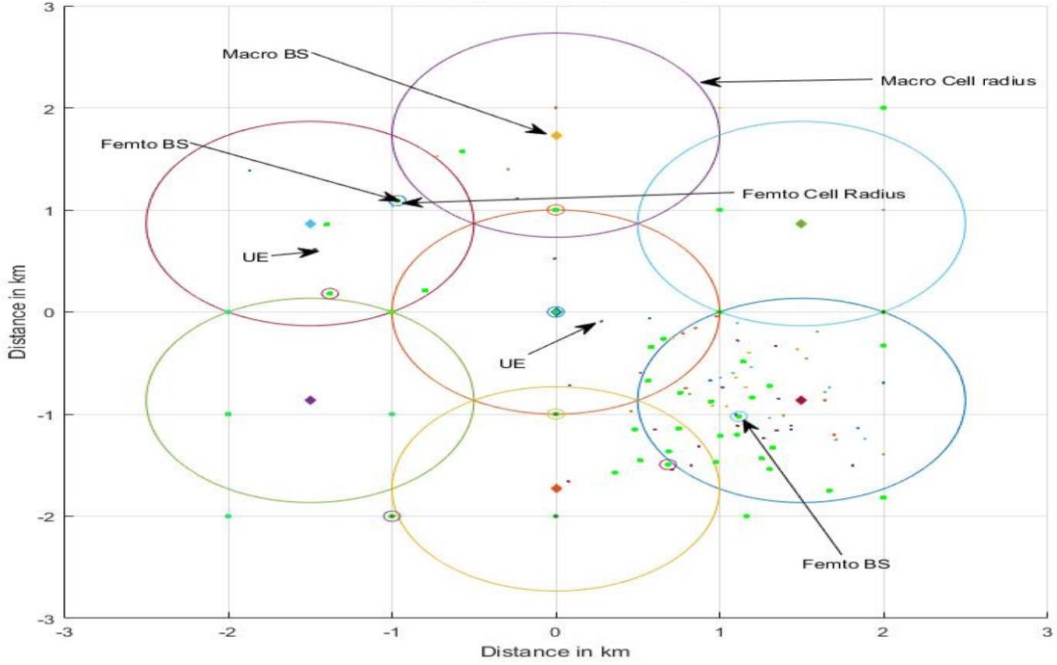


Figure 17: Network Model of Considered Ultra-Dense Network

### 3.2.2 Channel and Communication Link Model

The channel model used accounts for path-loss, log normal shadowing and Rayleigh fading. Therefore, the channel gain,  $G_{k,b}$ , between cell,  $b$ , and UE,  $k$ , is computed as follows;

$$G_{k,b} = L_{k,b}(d) * \alpha^2 * 10^{\frac{z}{10}}, \forall (k,b) \in B \times K \quad (7)$$

where  $\alpha^2$  is Rayleigh fading,  $10^{\frac{z}{10}}$  is the log normal shadowing and  $z$  is a random variable with a stipulated standard deviation.  $L_{k,b}(d)$  is the path-loss in dB, and  $d$  is distance in km between cell,  $b$ , and UE,  $k$ .

The UE-Cell association is based on the Signal to Interference plus Noise Ratio (SINR). Universal frequency reuse is considered and therefore, all signals from the other BSs in the area not associated with the UE are considered interference. The SINR of any UE,  $k$ , associated with a cell,  $b$ , is given as follows;

$$SINR_{k,b} = \frac{s_b P_{k,b} G_{k,b}}{\sigma + \sum_{b \neq B} s_b P_{k,b} G_{k,b}}, \forall (k,b) \in B \times K \quad (8)$$

where  $\sigma$  is the WGN power,  $G_{k,b}$  the UE-Cell channel gain and  $P_{k,b}$  is the transmit power of cell  $b$  for UE,  $k$ .

Each UE,  $k$ , can only be associated to only one active station,  $b$ , either macro or femto at a time not both, from which it registers the highest SINR. The binary variable,  $a_{k,b}$ , represents the association between UEs and BSs, as in the following;

$$a_{k,b} = \begin{cases} 1 & \text{if UE } k \text{ is served by BS } b \\ 0 & \text{otherwise} \end{cases}, \forall k \in K \quad (9)$$

### 3.2.3 UE Traffic and Mobility Model

All UEs are assumed to be fully mobile and able to move in all directions. Therefore, all UEs can change their uncorrelated  $x$  and  $y$  coordinates within the area independent of other UEs at a set or given constant speed,  $V$ , in km/hr.

### 3.2.4 Power Consumption Model

The power consumption model adopted is the earth power model, which follows that each cell,  $b$ , has static and transmit power consumption. The static power is responsible for site cooling, signalling, battery backup and circuit power. Therefore, total power consumption,  $P_b$ , of a BS,  $b$ , is given as;

$$P_b = \begin{cases} P_s^a + \eta_A \partial_b P_{tx} & \partial_b > 0 \\ P_s^i & \partial_b = 0 \end{cases}, \forall b \in B \quad (10)$$

where  $P_{tx}$  is transmission power,  $\eta_A$  amplifier efficiency,  $P_s^a$  is static power in active mode,  $\partial_b$  is the cell load and  $P_s^i$  is static power in idle mode.

## 3.3 Problem Formulation

The objective of the work in this section is to formulate an equation that represents the aim of trying to maximize the throughput of the network while minimizing the overall power consumption, as well as satisfying the QoS requirements of different UEs. Going by the Energy Efficiency model in [1], the energy efficiency of any system is defined as the ratio between the gain accrued and the total overall energy consumed. In this study, the gain accrued will be the throughput and the energy consumed consists of BS circuit and transmission power. Therefore, the NEE is modelled as follows;

$$NEE = \frac{T * R}{T * P} = \frac{R}{P} \text{ bits/joule} \quad (11)$$

where  $T$  is the time interval,  $R$  is the throughput and  $P$  is the total off all power dissipated in all circuit blocks and transmission power.

According to the Shannon Capacity theorem, the maximum throughput or achievable rate,  $R_{k,b}^{max}$ , of a UE-Cell radio channel is computed as shown;

$$R_{k,b}^{max} = C \theta_{k,b} \log_2(1 + SINR_{k,b}), \forall k \in K \quad (12)$$

where  $C$  is 180kHz, the bandwidth of a Resource Block (RB) in LTE, and  $\theta_{k,b}$  is the total number of RBs assigned to  $k$ .

Given that each UE,  $k$ , requests a data rate,  $R_k(t)$ , that is independent of other UEs,  $\theta_{k,b}$  is formulated as follows;

$$\theta_{k,b} = \frac{R_k(t) * \beta_k}{C \log_2(1 + SINR_{k,b})} \quad (13)$$

where  $\theta_{k,b}$  only takes on integer values in the range  $MaxRBs_b \geq \theta_{k,b} \geq 0$ .  $MaxRBs_b$  is the maximum number of RBs in  $b$ .

In order to compute the peak data rate of one RB,  $r_{k,b}$ , and hence UE throughput, the control signal overhead, coding rate and modulation scheme used have to be taken into account. There are 3 steps taken in computing the bandwidth of  $r_{k,b}$  in bps. The 1<sup>st</sup> step involves determining the modulation scheme and coding rate, which are determined using the Modulation and Coding scheme index (MCS) [10]. It is important to note that in order to determine the MCS, the channel quality information with respect to SINR must be known [12].

Therefore, the computed SINR is used to determine the Channel Quality Indicator (CQI) and then the CQI used to determine MCS. It is important to note that the mapping between MCS and CQI may vary from one MNO to another [13]. In this study, the LTE MCS to CQI mapping used is from [14]. The last step is determining the coding rate and modulation scheme, is to determine how many bits can be transmitted per Transmission Time Interval (TTI = 1ms).

Following all the steps detailed above gives the formula for  $r_{k,b}$  in bps as follows;

$$r_{k,b} = \frac{N_{TTI}^{RB} N_{RB}^{sym} N_{sym}^{bits} N_{RB}^{SC} Y_C}{TTI} \quad (14)$$

where:

- $N_{sym}^{bits}$  is the number of bits/symbol and  $Y_C$  is the coding rate. Both values are determined by MCS index and table.
- Given that this study focuses on an urban area, the LTE cyclic prefix (CP) used is the short CP of 4.7μsec. Therefore, the number symbols/RB,  $N_{RB}^{sym} = 7$ , and the number of subcarriers/RB,  $N_{RB}^{SC} = 12$ .

Therefore, the average throughput,  $R_{k,b}$ , for each UE is;

$$R_{k,b} = \sum_{b \in B} s_b a_{k,b} r_{k,b} \theta_{k,b}, \forall k \in K \quad (15)$$

Then, the total throughput of the UDN is given by;

$$\sum_{k \in UE} \sum_{b \in B} s_b a_{k,b} r_{k,b} \theta_{k,b}, \forall b \in B \quad (16)$$

Following the power earth model for BS power consumption showed in *Equation (10)*, the total power consumed within the network,  $P_{UDN}$ , is computed as below;

$$P_{UDN} = \sum_{b \in B_{active}} P_s^a + \eta_A \partial_b P_{tx} + \sum_{b \in B_{idle}} P_s^i \quad (17)$$

where  $B_{active}$  and  $B_{idle}$  are the sets of active and idle BSs respectively.  $B = B_{active} \cup B_{idle}$ .

The network energy efficiency,  $\eta_{EE}$ , is then computed as;

$$\eta_{EE} = \frac{\sum_{k \in UE} \sum_{b \in B_{active}} a_{k,b} r_{k,b} \theta_{k,b}}{\sum_{b \in B_{active}} (P_s^a + \eta_A \partial_b P_{tx}) + \sum_{b \in B_{idle}} P_s^i} \quad (18)$$

Finally, the  $\eta_{EE}$  maximization problem is as follows;

$$\max \left\{ \frac{\sum_{k \in UE} \sum_{b \in B_{active}} a_{k,b} r_{k,b} \theta_{k,b}}{\sum_{b \in B_{active}} (P_s^a + \eta_A \partial_b P_{tx}) + \sum_{b \in B_{idle}} P_s^i} \right\} \quad (19)$$

Despite *Equation (19)* being a mixed integer and complex combinatorial NP-Hard problem, the optimum solution is not trivial.

### 3.4 Algorithm Flow and Design

This proposed algorithm aims at finding a solution to *Equation (19)*, hence working towards optimum network energy usage. The algorithm aims at finding the minimum total network energy that can provide each UE with at least the minimum demanded data rate or QoS. This is represented as follows;

$$\min \left\{ \sum_{b \in B_{active}} P_s^a + \eta_A \partial_b P_{tx} + \sum_{b \in B_{idle}} P_s^i \right\} \quad (20)$$

subject to;

$$(AC); \quad \sum_{b \in B_{active}} a_{k,b} = 1, \forall k \in K \quad (21)$$

$$(RC); \quad \sum_{k \in UE} a_{k,b} \theta_{k,b} \leq RB_b, \forall b \in B_{active}, \quad (22)$$

$$(QoSC); \quad \sum_{b \in B_{active}} a_{k,b} r_{k,b} \theta_{k,b} \geq Q_k(t), \forall k \in K, \quad (23)$$

$$a_{k,b} \in \{0,1\}, \forall (k,b) \in UE \times B, \quad (24)$$

$$\theta_{k,b} \in \{0,1, \dots, RB_b\}, \forall (k,b) \in K \times B, \quad (25)$$

Equation (20), is subject to a number of constraints. The association constraint, (AC), ensures that each UE is always associated to at most one cell. The resource constraint, (RC), ensures that the total RBs allocated by a cell doesn't exceed its' maximum,  $MaxRB_b$ . The QoS constraint, (QoSC), ensures that each UE receives at least the minimum Guaranteed Bit Rate (GBR) as defined in each UE's service class,  $\beta_k$ . In order to make the problem tractable, the problem is solved in two steps; Cell association and resource allocation first then Cell On/Off second.

The first step involves determining,  $a_{k,b}$ , for each UE. Then  $\theta_{k,b}$  is fixed, however, not at arbitrary values since the QoSC needs to be satisfied during resource allocation. Therefore,  $\theta_{k,b}$  in the QoS Constraint is fixed by replacing it with  $\overline{\theta_{k,b}}$ , which is the minimum number of RBs required to satisfy the GBR as defined in each UE's service class,  $\beta_k$ .  $\overline{\theta_{k,b}}$  is given as;

$$\overline{\theta_{k,b}} = \min \left\{ \frac{R_k(t) * \beta_k}{\text{Clog}_2(1 + SINR_{k,b})}, RB_b \right\} \quad (26)$$

Given that  $\partial_b$  is a function of  $\theta_{k,b}$ , which is now fixed at  $\overline{\theta_{k,b}}$ , the active base station load in Equation (20) becomes  $\overline{\partial_b}$ .  $\overline{\partial_b}$  is the minimum load required to satisfy GBR for all UEs associated with cell  $b$

In order to change the combinatorial nature of Equation (20) to a continuous and a convex problem, constraint (24) is relaxed and replaced by  $0 \leq a_{k,b} \leq 1, \forall (k,b) \in B \times K$ . After relaxing constraint (24), the minimisation problem is then inspected and the constants are moved out. This leads to the below minimization problem;

$$G_a: \min \left\{ \sum_{b \in B_{active}} \frac{\sum_{k \in UE} a_{k,b} \overline{\theta_{k,b}}}{RB_b} \right\} \quad (27)$$

subject to;

$$(AC); \sum_{b \in B_{active}} a_{k,b} = 1, \forall k \in K$$

$$(RC); \sum_{k \in UE} a_{k,b} \overline{\theta_{k,b}} \leq RB_b, \forall b \in B_{active},$$

$$0 \leq a_{k,b} \leq 1, \forall (k,b) \in B \times K \quad (28)$$

Given that  $\overline{\theta_{k,b}}$  is treated as a constant, Equation (27) is a linear function in  $a_{k,b}$  with linear constraints linear and affine in  $a_{k,b}$ . Equation (20) is defined as a convex and linear optimization problem with respect to  $a_{k,b}$ .

### 3.4.1 Distributed Resource Allocation Phase

In order to create a distributed solution to Equation (27), Lagrange dual decomposition is used as done in. The Lagrangian dual function,  $G_{LD}(\mu)$ , is defined by dualizing the RC constraint. The function,  $G_{LD}(\mu)$ , is given as shown below;

$$G_{LD}(\mu) = \inf_{a_{k,b}} \sum_{k \in UE} \sum_{b \in B\_active} \frac{a_{k,b} \theta_{k,b}}{RB_b} + \sum_{b \in B\_active} \mu_b RB_b - \sum_{k \in UE} \sum_{b \in B\_active} \mu_b a_{k,b} \overline{\theta_{k,b}} \quad (29)$$

subject to;

$$(AC); \sum_{b \in B\_active} a_{k,b} = 1, \forall k \in K$$

$$0 \leq a_{k,b} \leq 1, \forall (k, b) \in B \times K$$

where  $\mu_b$  is a Lagrangian multiplier for the RC constraint at each base station and all  $\mu_b \geq 0$ .

The strong duality property, which follows that the optimum value of  $G_a$  is equal to the optimum value of its Lagrange dual function, holds for the linear program  $G_a$ . Given this strong duality, minimization over  $a_{k,b}$  is done first followed by maximization over  $\mu$ . Equation (29), given fixed  $\mu_b$  becomes separable with respect to each UE. Therefore, from Equation (29) for each UE the following problem has to be solved;

$$\forall k \in K : \inf_{a_{k,b}, b \in B\_active} \sum_{b \in B\_active} \left( \frac{1}{RB_b} - \mu_b \right) a_{k,b} \overline{\theta_{k,b}} \quad (30)$$

subject to;

$$(AC); \sum_{b \in B\_active} a_{k,b} = 1, \forall k \in K$$

$$0 \leq a_{k,b} \leq 1, \forall (k, b) \in B \times K$$

From Equation (30), it can be observed that the objective function for each UE is a weighted average of  $\left( \frac{1}{RB_b} - \mu_b \right) \overline{\theta_{k,b}}$ , where the weights take on values 0 or 1 and the sum of all weights for each UE is equal to one. Therefore, this means the solution for Equation (30) is got by attaining the minimum value of the objective function for all base stations.

The term  $\left( \frac{1}{RB_b} - \mu_b \right) \overline{\theta_{k,b}}$ , is referred to as the qualification index,  $QI_{k,b}$ , of b with respect to k.

Accordingly, the solution for Equation (30) for each UE, k, is;

$$a_{k,b} = \begin{cases} 1 & \text{if } QI_{k,b} = \text{argmin } QI_{k,b} \\ 0 & \text{if } QI_{k,b} \neq \text{argmin } QI_{k,b} \end{cases} \quad (31)$$

After finding  $a_{k,b}$ s for the fixed  $\mu_b$ s, the multipliers vector is then updated using the gradient descent method;

$$\mu_b(t+1) = \max \left\{ 0, \mu_b(t) - \beta(t) \left( RB_b - \sum_{k \in UE} a_{k,b} \overline{\theta_{k,b}} \right) \right\}, \forall b \in B \quad (32)$$

where  $t$  is iteration and  $\beta(t)$  is a step size function that satisfies the conditions below;

$$\lim_{t \rightarrow \infty} \beta(t) = 0, \text{ and } \sum_{t=1}^{\infty} \beta(t) = \infty \quad (33)$$

If the association indices are continuous variables in the form  $0 \leq a_{k,b} \leq 1$  and the step size satisfies the conditions above, the convergence of the gradient descent method is guaranteed.

### 3.4.2 Cell On/Off Phase

Using the Exhaustive Search Cell Switching algorithm to achieve optimum Energy Efficiency given our set  $B$ , with  $\tau$  number of base stations, would not be practical in real time and for delay tolerant services like VoIP. This is because, it would require  $2^\tau$  searching iterations to find the most optimal solution of active base stations needed to provide the required minimum QoS or minimum number of RBs to guarantee GBR for all UEs. For real time RB Allocation, this is algorithm given its exponential complexity would render the exhaustive search inefficient overall hence the use of a sub-optimal cell on/off algorithm.

The sub-optimal cell on/off algorithm bases its performance off the results of the resource allocation phase to further minimize the power consumption within the network by switching all BSs with  $\partial_b = 0$  to idle mode.

## 3.5 Chapter Summary

This chapter has presented the system model which takes into account a number of different scenarios as well as factors. The network model takes into account both macro and femto cells operating on different frequency bands. The seven macro-cell network uses frequency reuse at the cell edges to minimize cell interference, while the femto-cells' network on the other hand has a variable number of cells depending on the scenario. The users as well as the femto cells are modelled using a spatial point process, a tool of stochastic geometry, and are both assumed to follow either a Uniform or Non-Uniform distribution. All UEs are assumed to support voice, browsing and video streaming. The average number of users in an area at any given time of day is computed using a simple M/G/1 queuing model where the arrivals and departures follow a Markovian process. The channel model used accounts for path-loss, log normal shadowing and Rayleigh fading. The base station architecture assumed in this Chapter allows for the use of the earth power consumption model.

The problem formulation is also presented in this chapter. The problem formulation shows how the final equation for minimising the network energy consumption while ensuring guaranteed demanded bit rate to each UE was formulated. The final formulated equation is that which is then solved by the Distributed Resource Allocation Algorithm.

Finally, the algorithm flow and design show how the “Distributed Resource Allocation Algorithm” goes about to find a solution to the formulated equation by using tools such as constraint relaxation, Lagrangian dualization, gradient descent method and the sub-optimal cell activation/de-activation.

## Chapter 4 Simulations and Numerical Results

### 4.1 Introduction

This Chapter presents the results and analysis of simulations conducted. The performance of the proposed algorithm, under a number of different scenarios, is evaluated and compared to four other Resource Allocation strategies/algorithms namely; default/base-line, Exhaustive/Greedy Search, Minimum QoS SINR Resource allocation with Cell On/Off and Minimum QoS using Minimum RBs as Resource Allocation with Cell On/Off.

### 4.2 Simulations

This section presents the results of numerical simulations conducted and the performance of the Distributed Resource Allocation Algorithm in comparison to four other algorithms namely; default/base-line, Exhaustive/Greedy Search, Minimum QoS SINR Resource allocation with Cell On/Off and Minimum QoS using Minimum RB as Resource Allocation with Cell On/Off.

#### 4.2.1 Comparison Algorithms

The Default/base line algorithm is a very simple, linear and hence  $O(N)$  algorithm with no power control measures at all in place. The default algorithm is  $O(N)$  given its execution time is directly proportional to  $\tau$ , the total number of BSs. The base line aims at giving UEs maximum possible throughput at all times while basing its RBs' allocation solely on maximum SINR.

Exhaustive Search is a highly complex greedy algorithm that associates a UE and allocates the UE RBs, only if the NEE for that cell does not decrease, all the while ensuring that each UE receives at least the minimum number of RBs required to meet GBR as specified by service class. This algorithm is  $O(2^N)$  hence exponential given its high complexity, and that the execution time doubles with each additional BS to the input data set.

Minimum QoS using maximum SINR as RBs allocation combined with Cell On/off is a sub-optimal algorithm and so is the Minimum QoS using minimum RBs as Resource allocation with Cell On/Off. Both these two minimum QoS and sub-optimal algorithms Heuristic Cell On/Off and give just enough throughput to guarantee QoS as specified in each UE's service class. Both these algorithms contain at least four nested loops making both at least  $O(N^4)$ , hence polynomial in nature.

## 4.2.2 Simulation Parameters

Table 4: Simulation Parameters

<u>Network parameter</u>	<u>Setting</u>
Macro/Femto cell RBs	100/50
Macro/Femto cell transmission power	46dBm/17dBm
Active/Sleep circuit power of Macro cell	118.7/93kW
Active/Sleep circuit power of Femto cell	4.8W/2.9W
Path Loss macro cell	$128.1+37.6\log_{10} d$ , $d$ km
Path Loss femto cell	$131.1+42.8\log_{10} d$ , $d$ km
Log normal shadowing standard deviation	8
Thermal Noise PSD ( $\sigma$ )	$-174+\log_{10}(\Delta f)$ dBm
Macro/femto cell power amplifier efficiency	4.7/2.6
Macro/femto cell radius	1000m/50m
Channel model	Rayleigh fading model
Mobility model	Random direction at constant speed in km/hr.
Radio link failure SINR at	$< -9.478$ dB
Traffic model	Full buffer mode
LTE Scheduler	Time domain: Round Robbin
Transmission Time Interval (TTI)	1ms

## 4.3 Results and Analysis of Simulations

### 4.3.1 Power Consumption given similar Distributions of UEs and Femto-Cells

In the scenario where both UEs and cells are non-uniformly distributed resulting into formation of UE-Cell clusters, the “Distributed Resource Allocation Algorithm” is seen to have the least power consumption in certain parts of the day. Given that this scenario is more likely to occur in urban areas compared to the ideal uniform distribution scenario, the “Distributed Resource Allocation” strategy outperforms “Minimum QoS using Minimum RBs”. The reason for the observed outperformance is due to the fact that the resource allocation for the “Distributed Resource Allocation” on top of being distributed is not only based on minimum RBs but also uses multipliers that change on each iteration to take into account other factors like load and energy efficiency of other base stations.

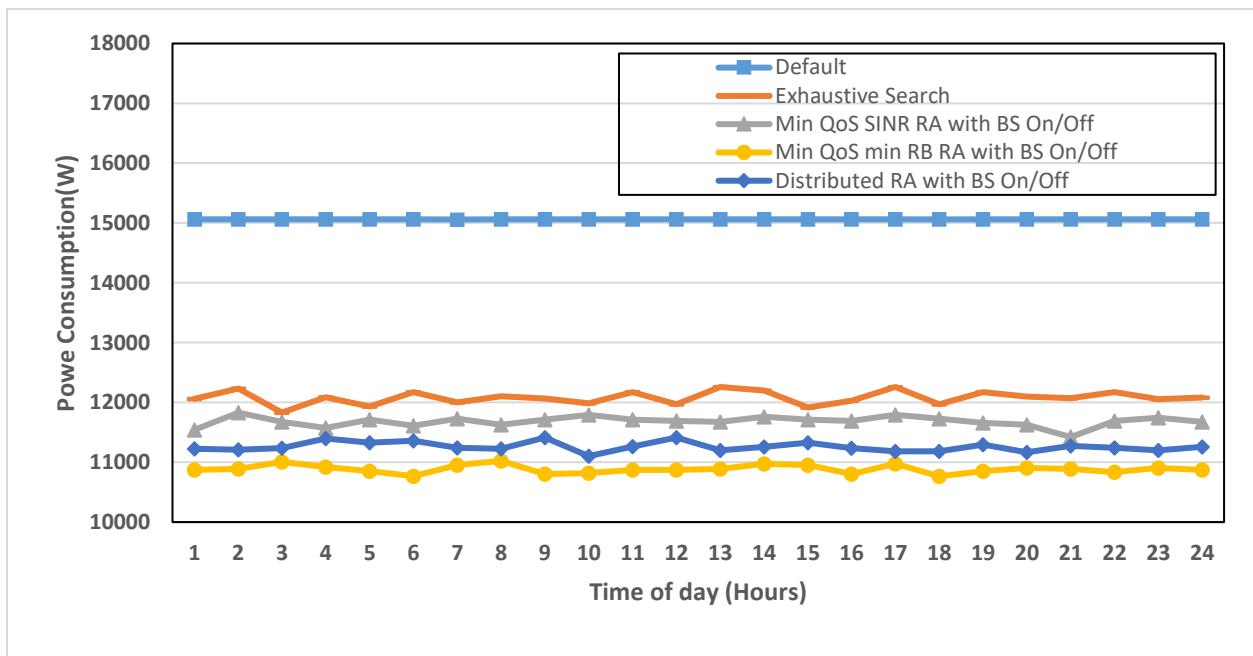


Figure 18: Comparison of Power Consumption versus time of day given Uniform Distributions of UEs and Femto-Cells

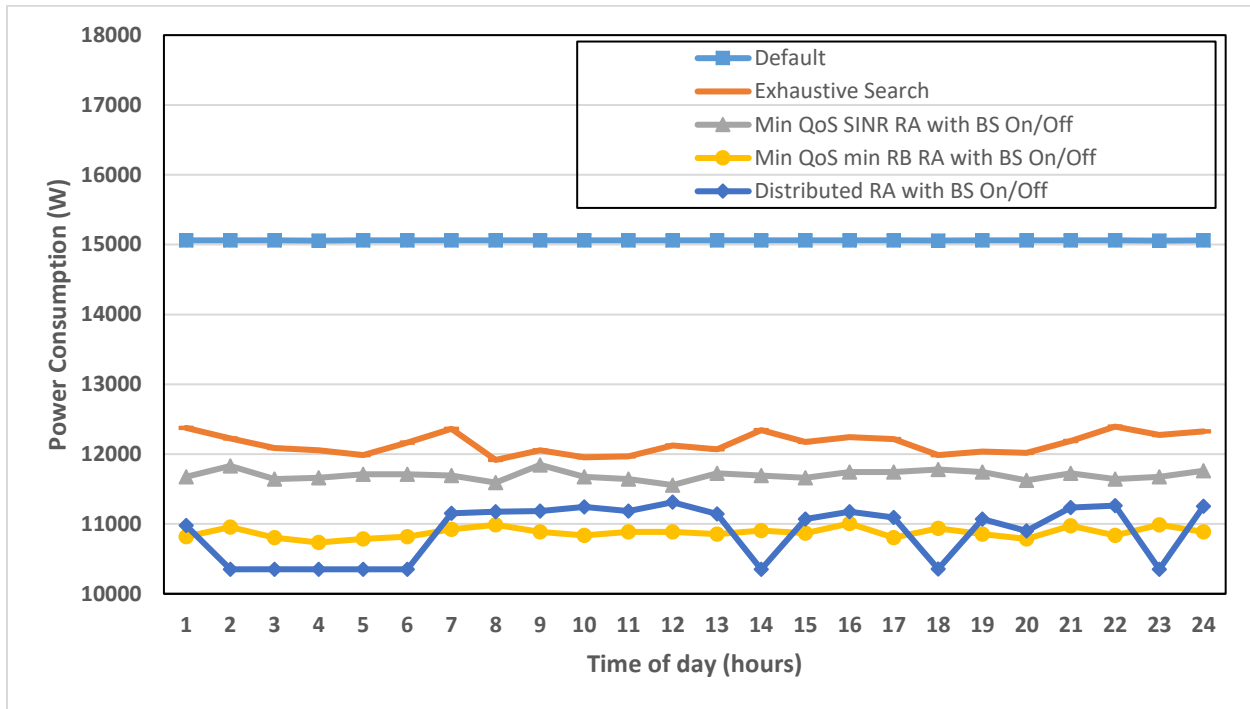


Figure 19: Comparison of Power Consumption versus time of day given Non-Uniform Distributions of UEs and Femto-Cells

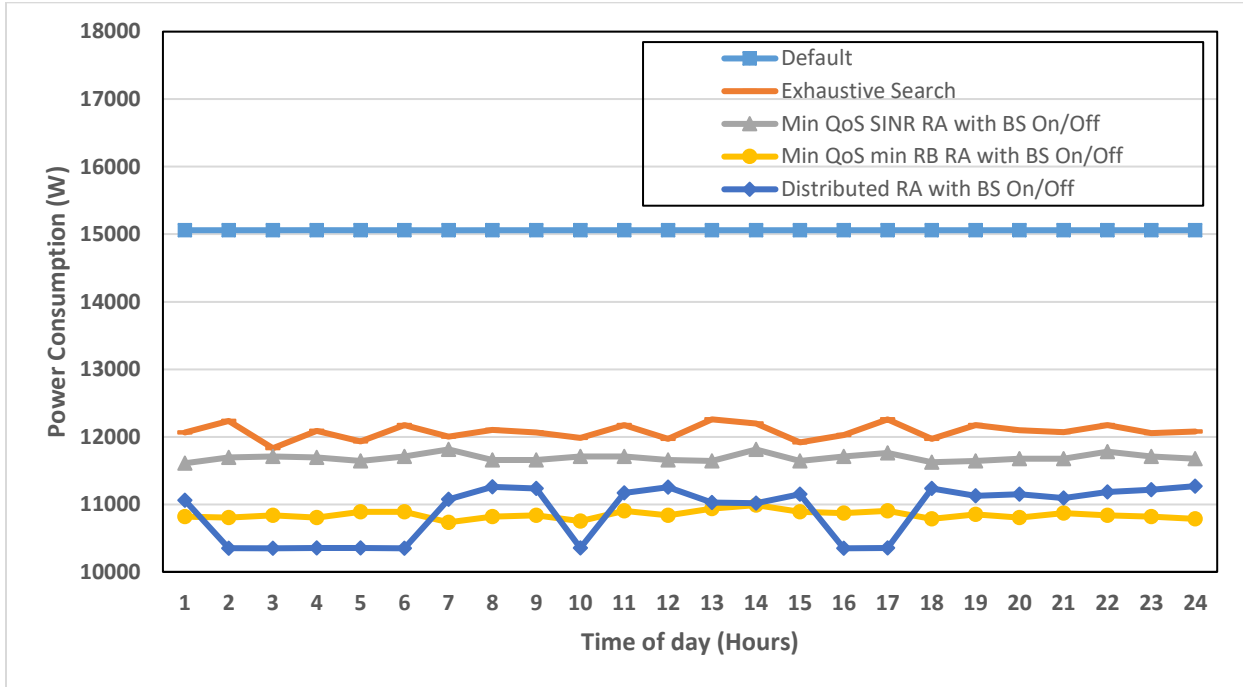
### 4.3.2 Power Consumption given different Distributions of UEs and Femto-Cells

In *Figure 20*, where we have the scenario of Non-Uniformly distributed femto-cells, we have a somewhat similar power consumption performance for all algorithms as shown in *Figure 19*. In both scenarios, the femto-cells are uniformly distributed and the algorithms power consumption performance is similar despite the distribution of the UEs. The somewhat similar power consumption performance for all algorithms can also be seen in *Figure 21* and *Figure 18* where the femto-cells are uniformly distributed in both scenarios.

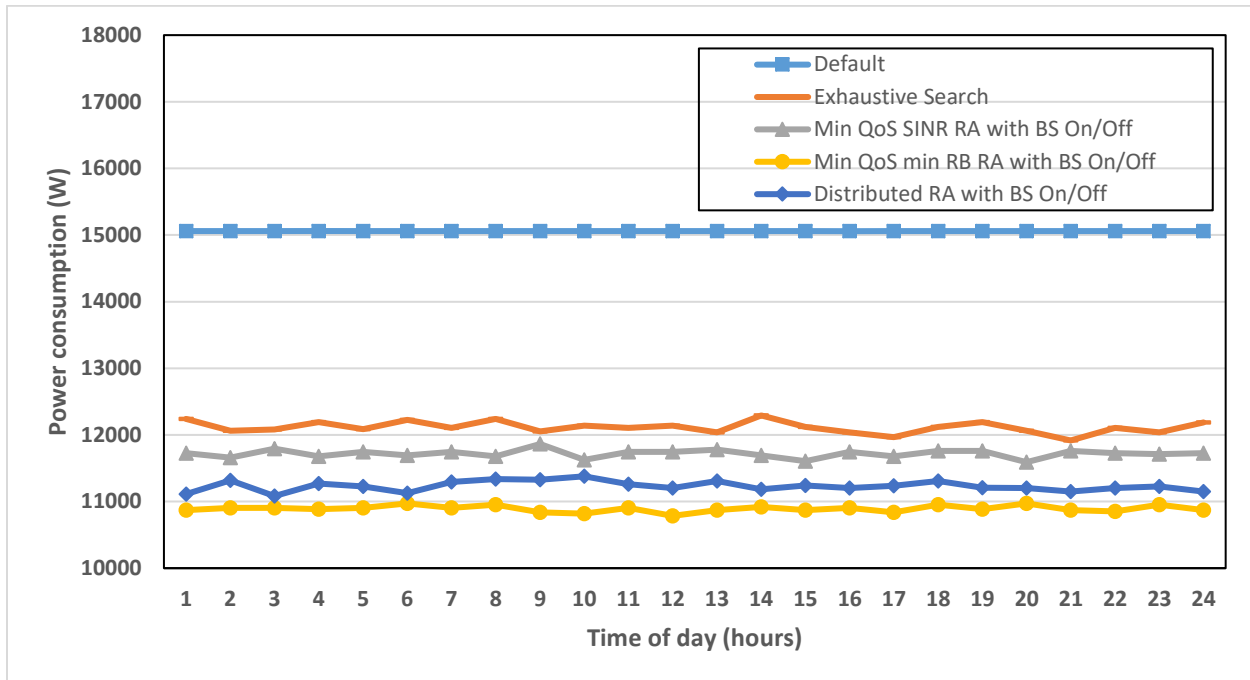
Even though it is more likely to have non-uniform distribution of UEs especially in urban areas, the results in the four figures *Figure 18*, *Figure 19*, *Figure 20*, and *Figure 21* above show that the distribution of UEs does not have a big bearing on the power consumption performance of the algorithms compared to the distribution of the femto-cells. Despite the UEs distribution having an obvious bearing on the UE per cell ratio, it is the distribution of the femto-cells, which are the majority within an Ultra-Dense Network, that clearly impacts the overall network power consumption. The distribution of the UEs will have a bigger bearing on whether a UE can associate and establish a link with a given cell, i.e. the outage probability as compared to the power consumption of the base station.

It is also worth noting that in all four figures *Figure 18*, *Figure 19*, *Figure 20*, and *Figure 21*, the exhaustive search has the second highest power consumption followed by the Minimum QoS using maximum SINR as RBs allocation combined with Cell On/off. The exhaustive search's resource allocation, despite using cell on/off will use a lot of power, given

that it gives more RBs to the UEs than demanded, hence the very high throughput. The Minimum QoS using maximum SINR as a resource allocation strategy results into having more cells active than the other sub-optimal algorithms, hence the higher power consumption.



**Figure 20: Comparison of Power Consumption versus time of day given Uniform Distribution of UEs and Non-Uniform Distribution of Femto-Cells**



**Figure 21: Comparison of Power Consumption versus time of day given Non-Uniform Distribution of UEs and Uniform Distribution of Femto-Cells**

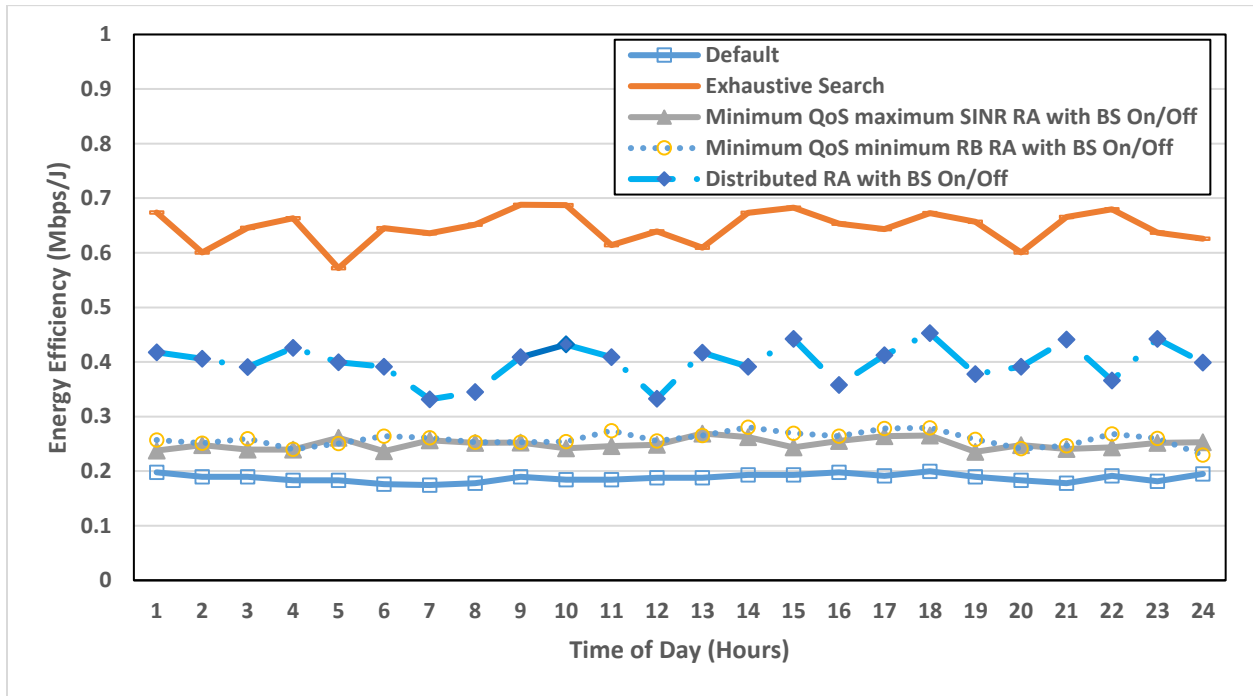
### 4.3.3 Network Energy Efficiency Performance given similar Distributions of Femto-Cells and UEs

First and foremost, it can be deduced from **Figure 22** and **Figure 23** that despite the default/base-line algorithm providing the maximum possible throughput to all UEs by using maximum SINR as resource allocation strategy, it has the highest power consumption, given it does not employ Cell On/Off. On the other hand, the “Minimum QoS using Minimum RBs” as Resource allocation given uniform distribution of UEs and femto-cells will have the least power consumption. The scenario of uniform distribution of UEs and femto cells ensures that the UE per femto-cell ratio is relatively low. This ensures lower power consumption given that the overall total number of RBS given out in the network will be low. The RBs’ allocation for the “Minimum QoS using Minimum RBs” is based on associating a UE with a cell giving it the least number of RBs to satisfy demanded QoS, hence the total number of distributed RBs being low.

The exhaustive search algorithm, despite having higher power consumption than the sub-optimal algorithms, will experience the highest NEE performance regardless of UEs and Cell distribution. This is because the UE-cell association, and resource allocation thereafter, are based on ensuring the allocation of RBs to any UE does not result into reduction in energy efficiency of that given cell or overall network. It is also worth noting that the exhaustive search yields a very high throughput for all UEs and employs exhaustive search Cell On/off. The default/base-line algorithm, despite giving high throughput to all UEs, will experience the least NEE performance. This is because the resource allocation is based only on maximum SINR and there is very high-power consumption when using this scheme. The high-power consumption as seen in the power

consumption performance results is due to the fact that all the cells in the network are always active and the high total number of RBs given to the UEs.

In both **Figure 22** and **Figure 23**, fluctuations in NEE performance for all algorithms throughout the day can be observed. This is largely due to two reasons. One; the change in UEs per cell ratio as UEs change positions and Two; the constant change in average UE demanded data rate,  $R_k(t)$ , throughout the day which impacts the number of RBs given out. Therefore, due to these two reasons, we get fluctuations in total network throughput, overall network power consumed and hence, NEE.



**Figure 22: Comparison of NEE versus time of day given Uniform Distributions of UEs and Femto-Cells**

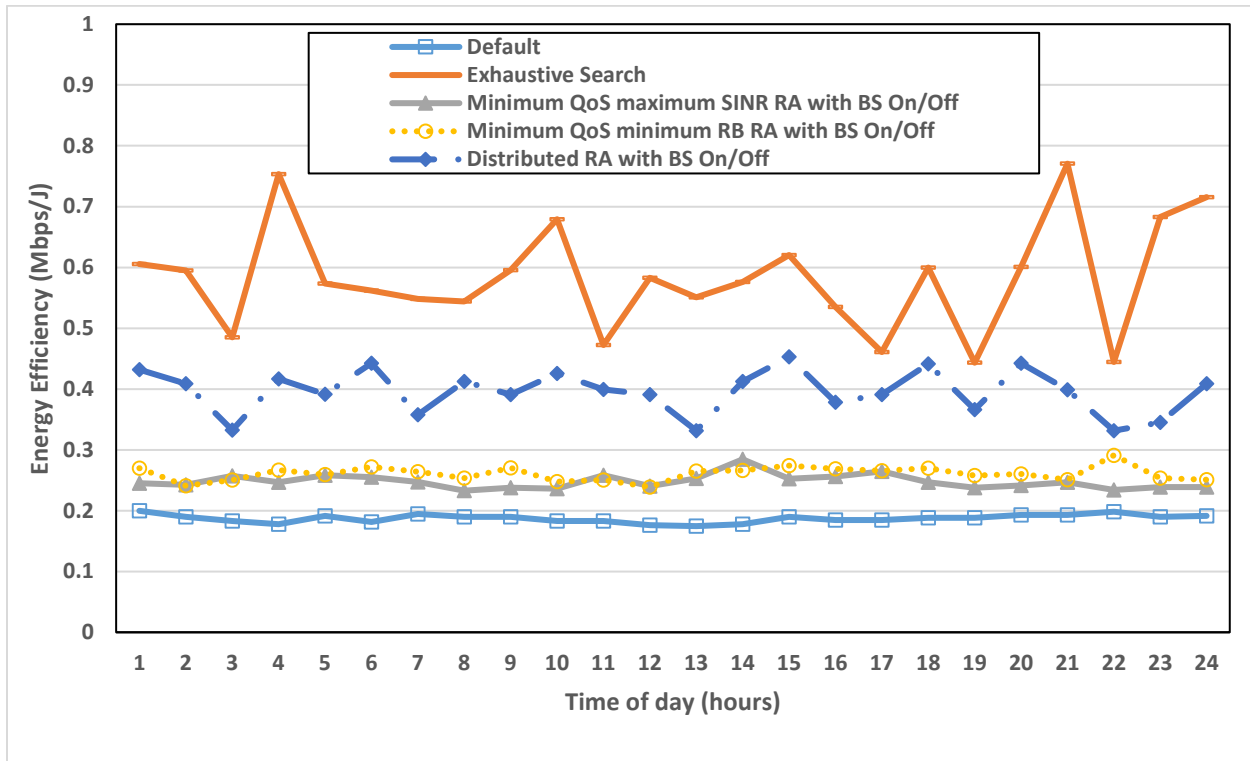


Figure 23: Comparison of NEE versus time of day given Non-Uniform Distributions of UEs and Femto-Cells

#### 4.3.4 Network Energy Efficiency Performance given different Distributions of Femto-Cells and UEs

The NEE performance of all algorithms is higher in the scenarios where both UEs and femto-cells have similar distributions i.e. in *Figure 22* and *Figure 23* as compared to NEE performance shown in *Figure 24* and *Figure 25*. This is inherently because, when both UEs and femto-cells have similar distributions, the overall throughput is higher as a result of the UE per Cell ratio being relatively better than in scenarios having uneven or not similar UEs and femto-cells' distributions. Furthermore, the overall idle BS power consumption would cease to be insignificant if majority of the UEs were to be connected to just a few of the base stations leaving a large number of the cells, especially the femto cells, idle. Therefore, it is due to these two reasons that a scenario with similar UEs and femto cells' distributions enable better NEE performance for all algorithms.

Lastly, the NEE performance of the proposed scheme, as well as that of the 2 sub-optimal algorithms, is similar in both Uniform and Non-Uniform UE distribution scenarios. This is because, given that these schemes are designed to give just enough RBs to meet the Guaranteed bit rate (GBR) for each UE, the NEE performance is not greatly affected by the UE per cell ratio.

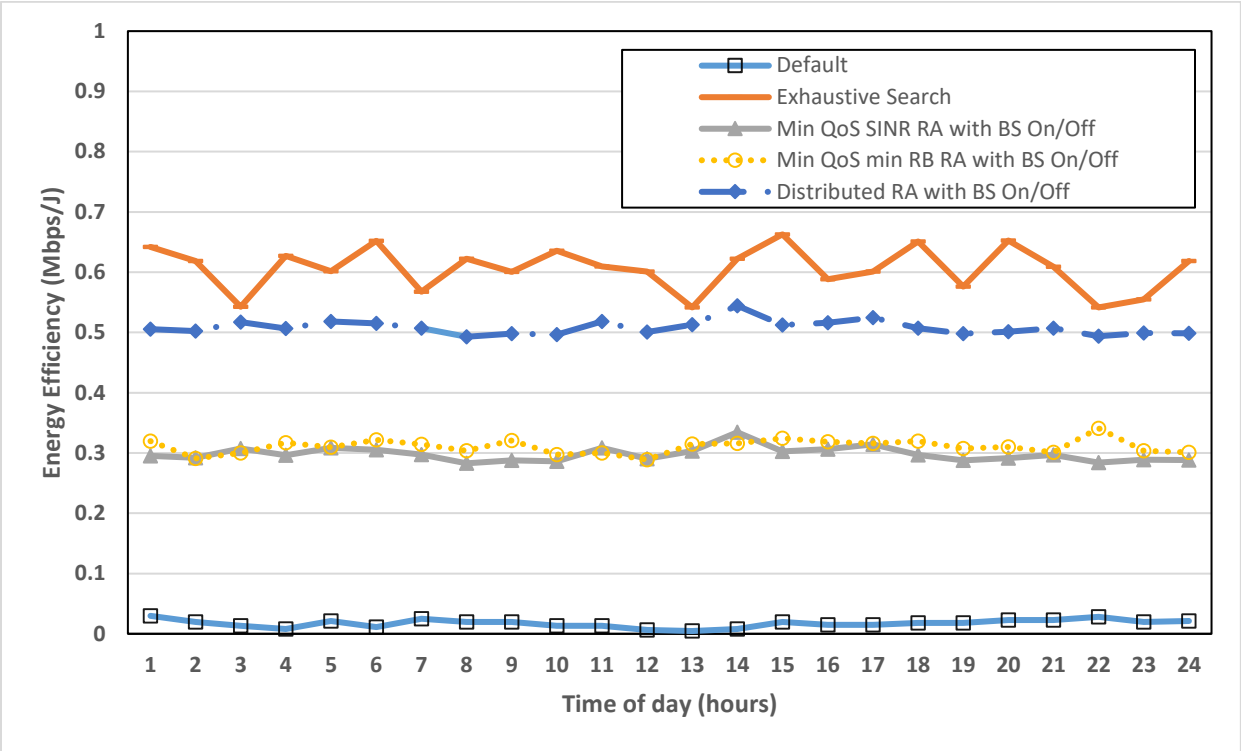


Figure 24: Comparison of NEE versus time of day given Non-Uniform Distribution of UEs and Uniform Distribution of Femto-Cells

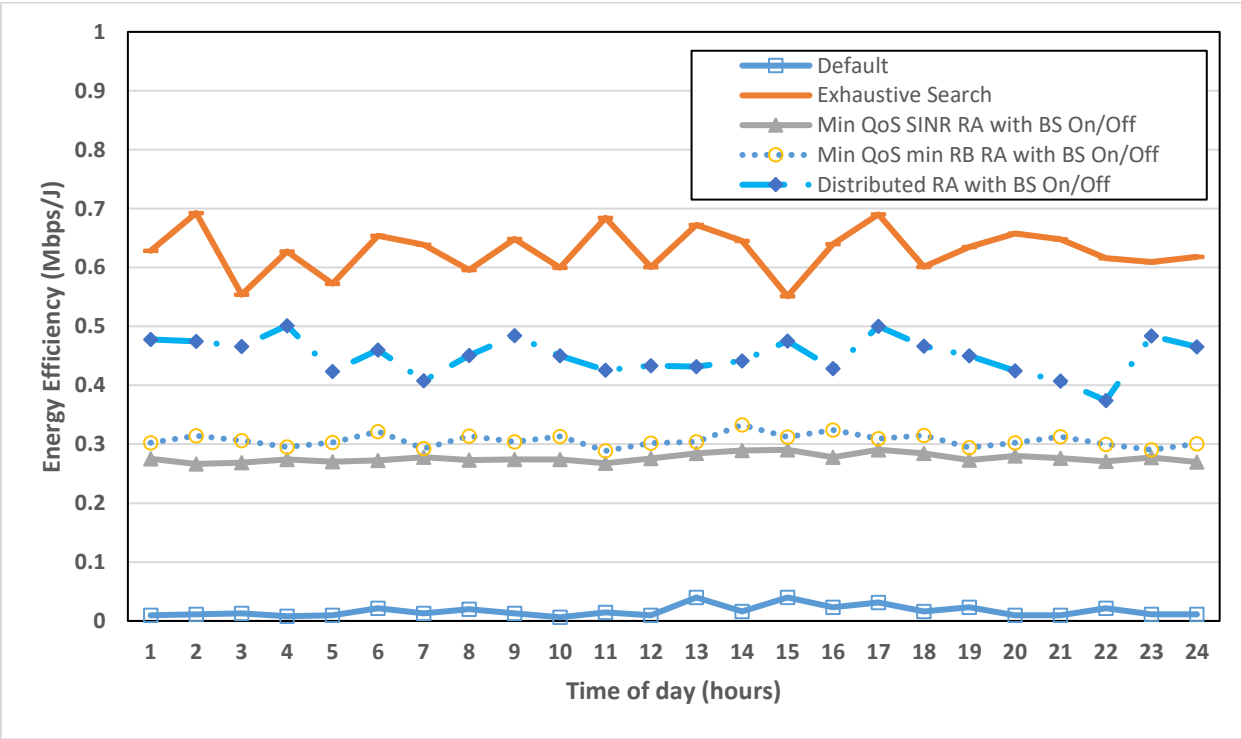


Figure 25: Comparison of NEE versus time of day given Uniform Distribution of UEs and Non-Uniform Distribution of Femto-Cells

### 4.3.5 Network Energy Efficiency performance given an increasing UE density under Non-Uniform Distribution of UEs and Femto-cells

This scenario aims at evaluating and comparing the effect/impact of UE density or Average UE number,  $N(t)$ , on NEE performance. A scenario with Non-Uniform UEs distribution is considered for 2 reasons, one being; This is the most probable and realistic UE distribution especially in urban areas and Two; the overall NEE performance results in **Figure 22, Figure 23, Figure 24, and Figure 25** show that all algorithms experience better NEE performance when both UEs and the Cells have similar distributions.

It can be seen in **Figure 26** that, as the UE number increases from zero, so does the NEE for all the algorithms. The reason for this being that, as the average UE number increases, so does the UE per Cell ratio and hence utilization factor of each cell, which implies increase in NEE. However, it can also be seen that as average UE number increases from 60 onwards, the step-increase in NEE reduces for all algorithms. This is because the increase in UEs leads to UE per Cell ratio surpassing the optimum point and causing the overall throughput, as well as QoS and hence NEE, to drop.

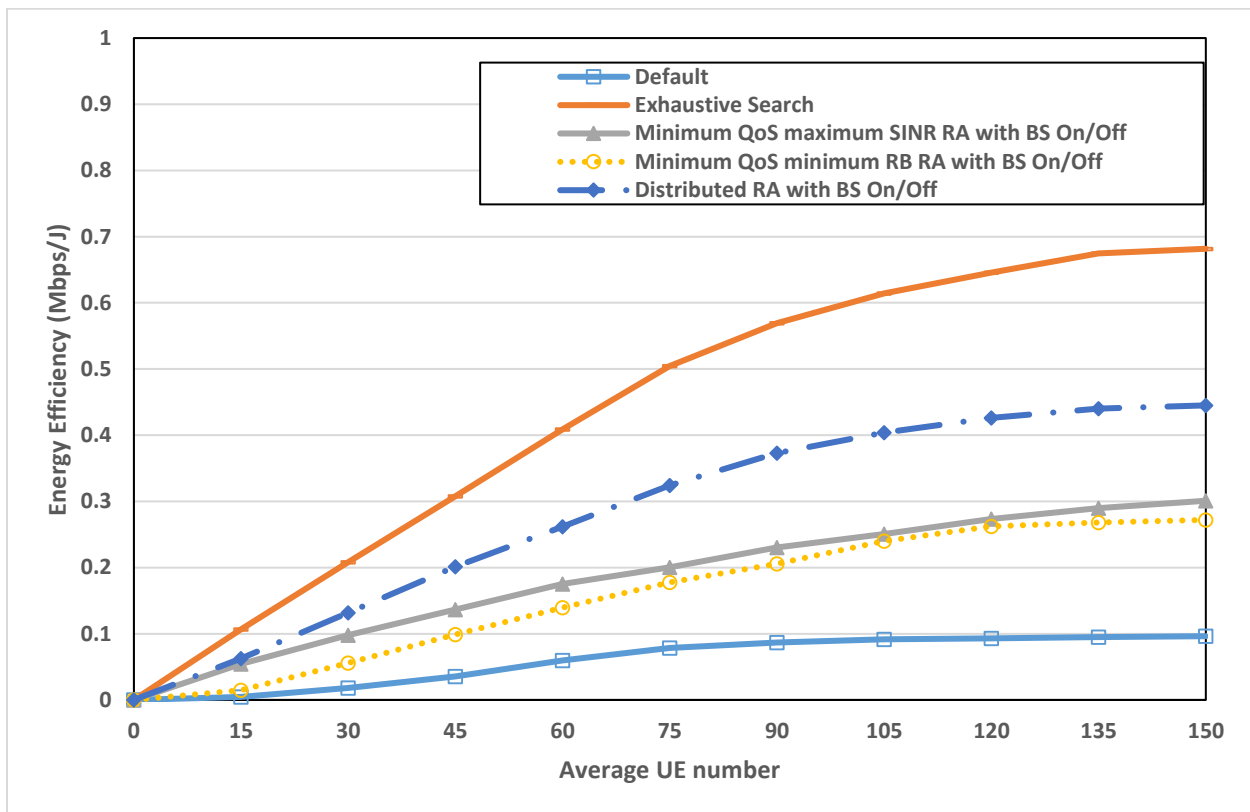
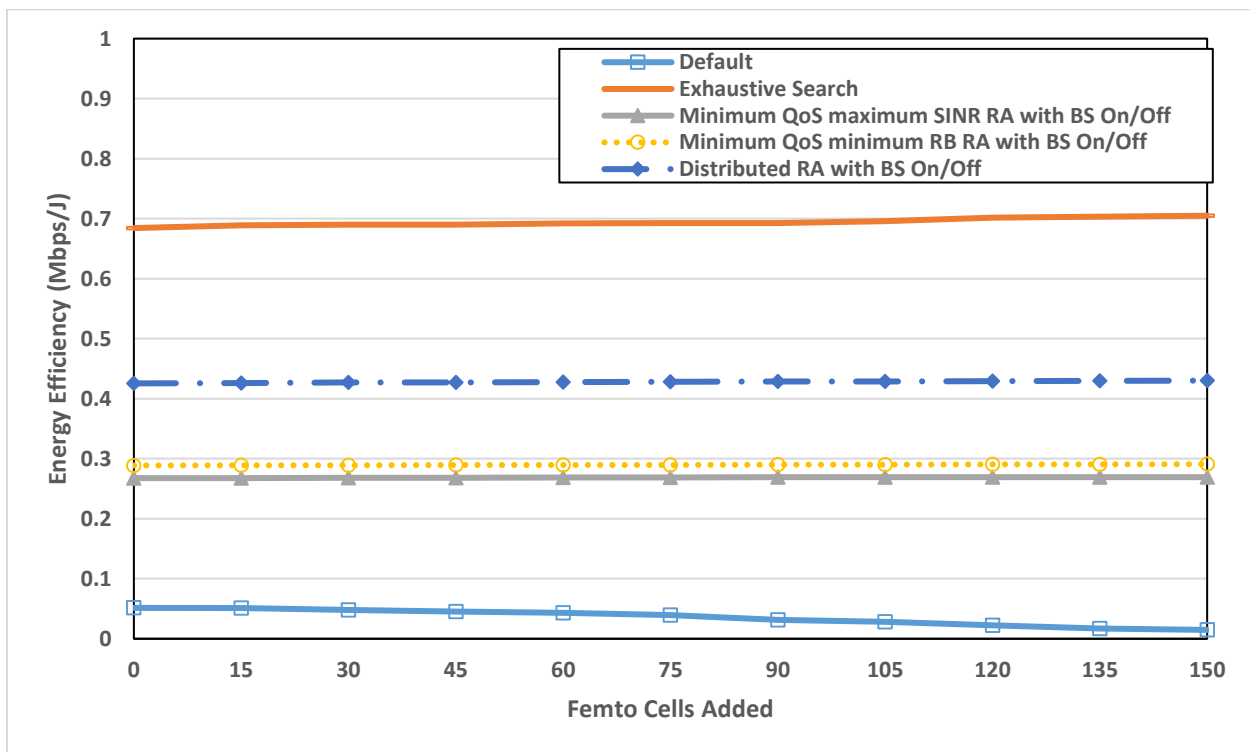


Figure 26: Comparison of NEE given increasing UE density under Non-Uniform Distributions of Femto-Cells and UEs

### 4.3.6 NEE performance given increasing femto cells density under Non-Uniform Distributions of UEs and Femto-cells at Peak Hour

Peak hour in this study is that time when  $N(t)$ , the average number of UEs in this area, is highest during the day. **Figure 27** shows the NEE performance of all algorithms versus addition of femto-cells at this peak hour given the Non-Uniform distribution of UEs. The Exhaustive search experiences a slight increase in NEE with increase in femto-cells. This is due to the fact that the exhaustive search's RBs' allocation is solely based on NEE improvement each time for any given BS allocating a resource block (RB). This, coupled with the use of Exhaustive Search Cell On/Off, means the network will experience an insignificant change in power consumption combined with increased throughput, hence the slight increase in NEE. The default/base-line algorithm suffers decrease in NEE performance under this scenario. The increase in femto cells leads to increase in both the overall power consumption as well as signal interference, which lowers throughput. These two combined leads to lowering the overall NEE performance.

It can also be seen that adding extra femto-cells has no significant impact on NEE performance for all minimum QoS algorithms. The nature of the minimum QoS algorithms is to always give just enough RBs to guarantee QoS as defined by each UE's class and switch off all BSs with zero load. Therefore, adding or deploying more femto-cells at peak hours does not lead to an increase in throughput nor a more than significant increase in overall power consumption either, hence, the insignificant change in NEE performance.



**Figure 27: Comparison of NEE given increasing femto-cells at peak hour under Non-Uniform Distributions of Femto-Cells and UEs**

### **4.3.7 Comparison of number of Active Macro-cells and Femto-cells given increasing UE density under Non-Uniform Distribution of UEs and Femto-cells**

It can be seen from *Figure 28* that the Minimum QoS using maximum SINR as RBs allocation with Cell On/off algorithm and the Minimum QoS using minimum RBs as Resource allocation with Cell On/Off algorithm have no active macro-cells at any point in time even with increase in UE density. The reason for this is, given that these two algorithms are designed to give the minimum required QoS to any UE and also ensure reduction in power consumption, the decision making in UE-Cell association only considers the low power femto cells and does not factor in the high power consuming macro-cells.

The “Distributed Resource Allocation Algorithm” on the other hand, despite being a minimum QoS algorithm because it uses a multiplier combined with using minimum RBs on each iteration in determining UE-Cell association, takes into consideration both macro and femto cells. This balance of using both femto and macro cells as also seen in the exhaustive search results into a better overall NEE performance for these two algorithms.

In both figures, as the UE density increases, so does the number of active cells needed. The “Minimum QoS using maximum SINR as RBs” allocation with Cell On/off algorithm and the “Minimum QoS using minimum RBs” as Resource allocation with Cell On/Off algorithm use more femto cells as the UE number increases. On the other hand, the proposed scheme and exhaustive search also use more cells but create a balance between the macro and femto cells.

Finally, the default/base-line algorithm has no Cell On/Off hence the reason why all the cells are always active when using that scheme even with no UEs. This also partly explains why this scheme experiences the highest power consumption and least NEE performance of all algorithms.

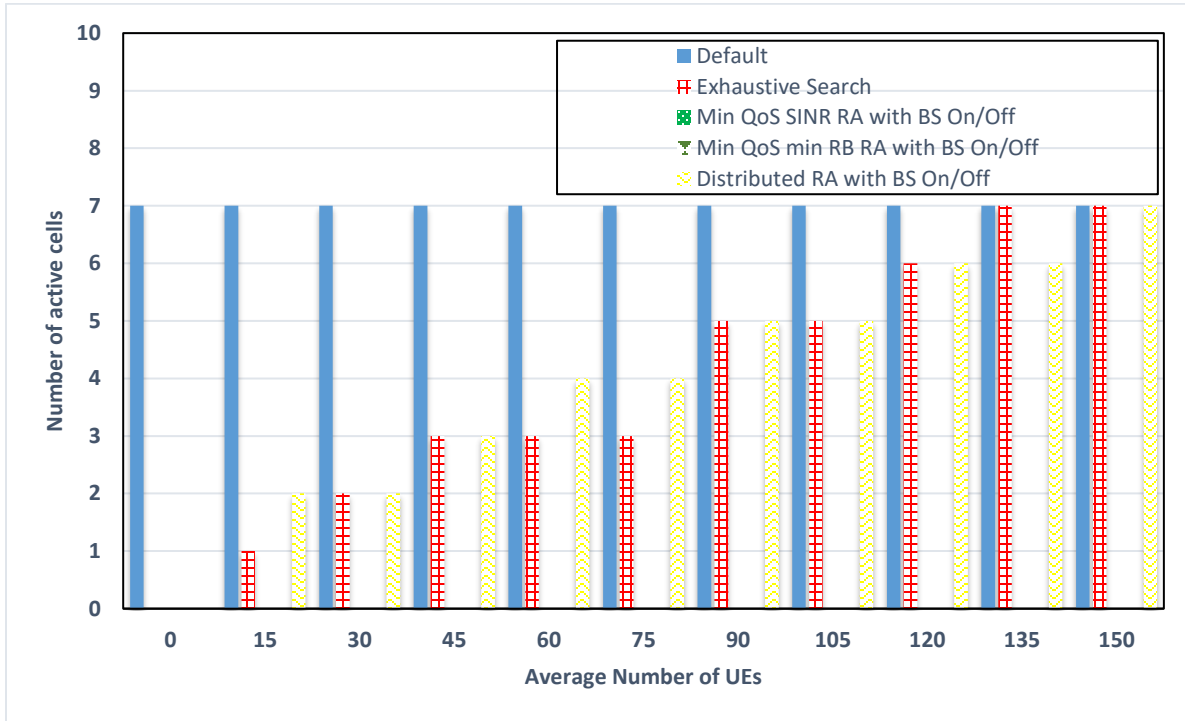


Figure 28: Comparison of Active Macro-cells given increasing UE density under Non-Uniform Distribution of UEs and Femto-cells

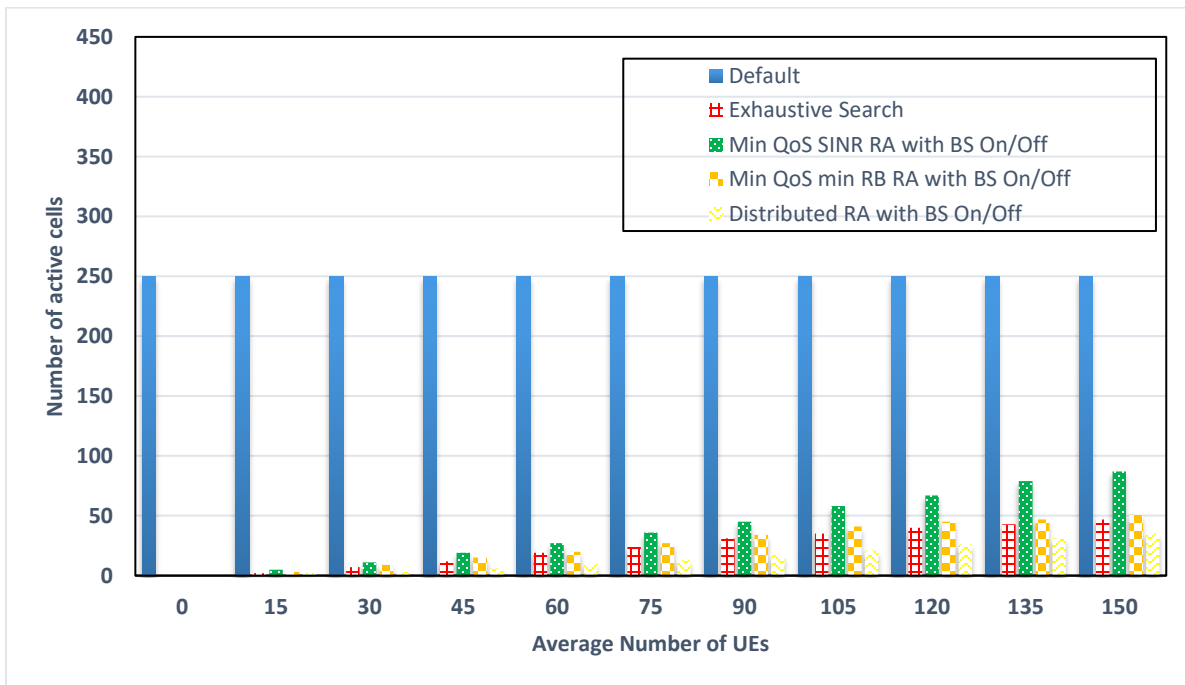


Figure 29: Comparison of Active Femto-cells given increasing UE density under Non-Uniform Distribution of UEs and Femto-cells

### 4.3.8 Comparison of algorithm Average Execution time versus increase in UE density under Non-Uniform Distribution of UEs and Femto-cells

From *Figure 30* it can be seen that the Exhaustive search has the longest execution time, while the “Minimum QoS using minimum RBs” as Resource allocation with Cell On/Off has the least execution time even as the UE numbers increase. The Exhaustive search computes the overall network energy efficiency on each iteration and uses this in the decision to assign RBs to any UE. This, coupled with the fact that it also uses greedy search cell On/Off to determine which cells are left active or idle, explains why its execution time exceeds 10 minutes when the UE number increases to 150. On the other hand, the “Minimum QoS using minimum RBs” as Resource allocation with Cell On/Off has the least execution time because it’s designed to give the least number of RBs to satisfy QoS demanded.

The default algorithm, despite having no Cell On/Off, has the second lowest execution time because it is designed to first give the minimum required RBs to satisfy QoS, and then give the remaining RBs to each UE associated in a given cell using the round robin scheduler.

The “Distributed Resource Allocation Algorithm” has the second highest execution time given that it uses not only the minimum demanded RBs but also multipliers to determine resource allocation. The multipliers, which are stored in multipliers vector, are updated using the gradient descent method as shown in Equation (32) after finding the association indices for all UEs in the network.

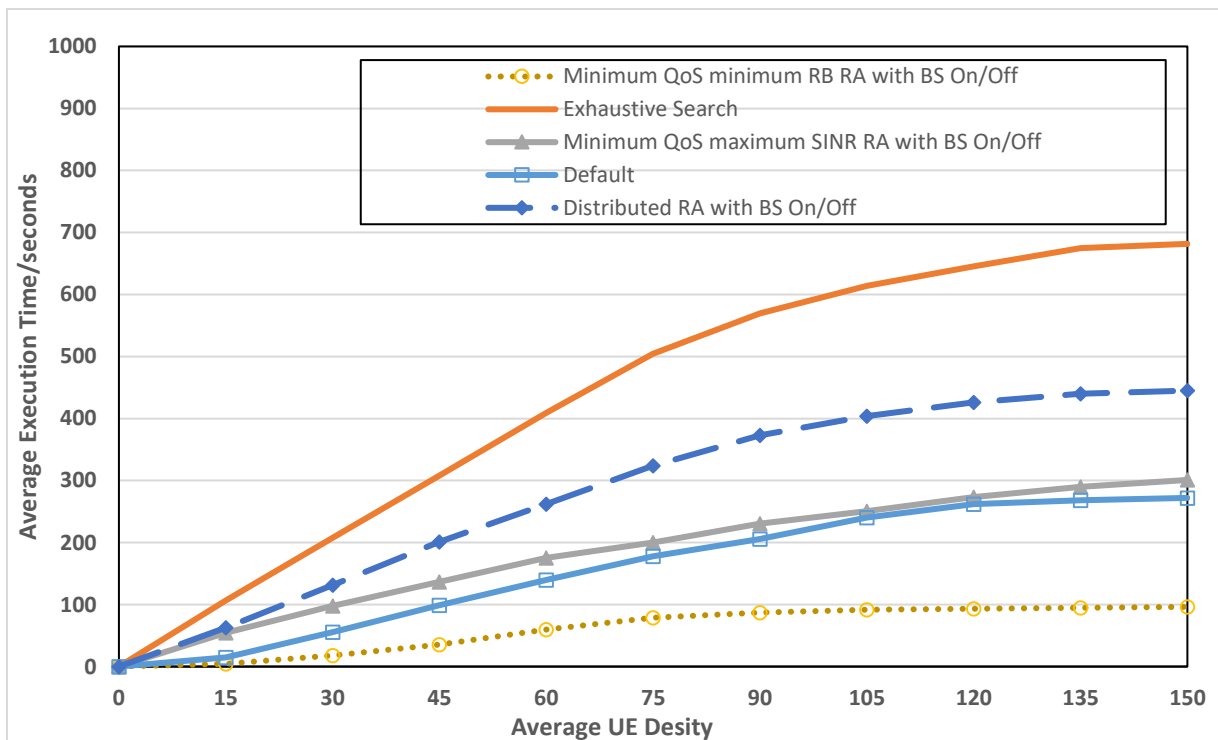


Figure 30: Comparison of Average Execution time versus increase in UE density under Non-Uniform Distribution of UEs and Femto-cells

## 4.4 Chapter Summary

This chapter looks at the “Distributed Resource Allocation Algorithm” performance compared to four other algorithms namely; the default/base-line algorithm, the Minimum QoS using maximum SINR as RBs allocation with Cell On/off algorithm, the Minimum QoS using minimum RBs as Resource allocation with Cell On/Off algorithm, and the Exhaustive search with greedy search Cell On/Off scheme.

The parameters used in the simulation are shown in tabular form and the algorithms’ power consumption performance, network energy efficiency performance and other performance metrics are analysed, and the results graphed under a number of different scenarios. The different scenarios considered in this study have to do with the different UEs and femto-cells distributions as well as different movements of UEs throughout the day. These algorithms are put through these various scenarios to find out how they affect the algorithms’ performance metrics.

The results of the power consumption and network energy efficiency performances for all algorithms under four scenarios are presented to determine how each algorithm impacts these two network performance metrics. Not only the algorithm results for energy efficiency with respect to the most common urban area scenario are shown but also how these algorithms would respond when certain parameters such as femto-cells and average UE number are varied..

The last performance metrics looked at are the overall utilization of cells, i.e. which of the macro-cells or femto-cells each scheme uses most, and the average execution time of each scheme to associate and allocate RBs to each UE in the network.

## Chapter 5      Conclusions and Recommendations

### 5.1 Introduction

In this the last Chapter we present the summarized findings from the research done as well as conclusions from the performance results of the algorithms in comparison to the Distributed Cell Association and Resource allocation combined with Sub-optimal cell On/Off scheme. Due to the demand for higher data rates and more network capacity, Mobile Wireless Networks (MWNs) have evolved from being largely Heterogeneous Wireless Networks (Het-Nets) to being Ultra-Dense Networks (UDNs). However, these Ultra-Dense networks (UDNs) do come with their challenges due to the large number of femto-cells deployed to supplement the macro-cell coverage. One the major challenges brought about by deploying femto-cells in large numbers is the issue of efficient energy usage which not only impacts the operating costs of Mobile Network Operators (MNOs), but also has significant impact on the carbon dioxide (CO<sub>2</sub>) emissions from the Mobile and Telecommunications industry.

Following an extensive and qualitative literature review in this study, a scheme labelled the Distributed Cell Association and Resource allocation combined with Sub-optimal cell On/Off was proposed to solve the energy inefficiency issue in an LTE Ultra Dense network. This scheme was proposed to tackle some of the issues that other energy efficiency strategies and related works did not factor in or consider. The extensive and qualitative literature review covered in Chapter 2 entails what constitutes the power consumption of an LTE Ultra-Dense Network (UDN), the highest consuming parts of said LTE UDN, the difference between reduction in power consumption and attaining energy efficiency, the various techniques/strategies used to reduce power consumption as well as achieve optimal network energy efficiency and why said techniques work and their limitations. The analysis of the general context and the state of the art presented in Chapter 2 shows that despite the wealth of existing work, much remains to be done in terms of technical optimization and design of UDNs. This is due to the continuous evolution of network technologies and architectures, services offered and the high penetration of mobile users.

In Chapter 3, a system model is proposed to factor in some of the elements that were identified as missing in the related works, and also to factor in issues such as cell interference as well as user mobility throughout the day. The problem formulation of the network energy efficiency issue is also shown in this chapter. The algorithm design and flow as well as tools used to solve the formulated problem are clearly laid out using a set of equations and mathematical models.

Then, using a number of different network scenarios, the proposed scheme' performance is compared to other four algorithms/schemes. The performance metrics used are overall network power consumption and overall network energy efficiency. The different scenarios involve changing the positions of UEs as well as the distributions of both UEs and femto-cells. Then

using a set of simulation parameters, the tests are done, graphed and analysed in detail in Chapter 4.

## 5.2 Conclusions

From the power consumption performance results under all four scenarios in Chapter 4, it was observed that the proposed scheme outperformed the Exhaustive search and default/base line algorithm. The design of the “Distributed Resource Allocation Algorithm” therefore achieves its goals with regards to reduction in power consumption. The exhaustive search’s resource allocation, despite using cell on/off will use a lot of power, given that it gives more RBs to the UEs than demanded, hence the very high throughput.

The “Distributed Resource Allocation Algorithm” of all schemes compared in this paper when it comes to overall network energy efficiency is the closest in performance under all scenarios to the Exhaustive search, which is designed to find the optimum solution regardless of execution time. The Distributed Resource Allocation Algorithm’s base station and UE pairing is found to be more balanced and similar to the Exhaustive search compared to the two other sub-optimal minimum QoS schemes, which associate UEs with only the femto cells rendering the macro cells idle.

The “Distributed Resource Allocation Algorithm” was also found to outperform the other sub-optimal schemes with regards to overall network energy efficiency even with increase in UE number and increase in femto-cells. Despite having a long average execution time second to only that of the Exhaustive search, the proposed scheme’s overall performance is much superior to that of the other sub-optimal schemes compared to it in this study and it has the closest network energy performance to the exhaustive search. Therefore, it is in order to conclude from the simulation results, that the proposed Distributed Cell association and Resource allocation with sub-optimal Cell On/Off scheme can reduce power consumption while guaranteeing UE QoS, as well as a relatively high overall NEE, especially when the UEs are Non-Uniformly distributed, which is the most probable UE distribution in urban areas with UDNs.

## 5.3 Recommendations

In this study, we are interested in the energy consumption optimization problem in the field of ICT, and more particularly, Ultra-Dense Wireless access networks. This work is part of studies and works aimed at minimizing the carbon dioxide emissions from our activities, and to preserve natural wealth for future generations.

The objective of this study is concerned with the minimization of base station energy while ensuring the demanded guaranteed bit rate for each user in Ultra-Dense Networks (UDNs). In Chapter 3, a Distributed Resource Allocation with Cell On/Off scheme was proposed to handle cell association and resource allocation in a manner that allows to best preserve the energy of the network, while respecting the constraints related to QoS as well as Resource Blocks. The network model used is based on a spatial point process as a tool of stochastic geometry. Therefore, further research should be conducted on how to accurately use Voronoi

tessellation along with network model used in this study.

The key principle in improving network energy efficiency in Ultra-Dense Networks (UDNs) is the increasing the Throughput per Joule of energy consumed. The “Distributed Resource Allocation Algorithm” is designed to give the minimum amount of demanded throughput so as to limit the number of RBs given out, hence save more energy. However, further research can be done on how to simultaneously improve the network energy efficiency (NEE) while not limiting UEs to the minimum number of RBs demanded, hence, increasing the overall network throughput.

The “Distributed Resource Allocation Algorithm” can be analysed further to determine the impact on the other factors affecting customer network experience like delay, jitter and packet losses. This is important since Mobile Network Operators are interested in maximizing the income from their deployed infrastructure and customer experience directly affects their revenue.

Another line of research that requires consideration concerns the combination of several of the solutions proposed to minimize energy consumption simultaneously on UEs and Ultra-Dense Networks. This solution will combine dynamic user association, Downlink and uplink scheduling. It will certainly require architectural proposals and signage.

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