ADDIS ABABA UNIVERSITY

ADDIS ABABA INSTITUTE OF TECHNOLOGY

SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING

TELECOMMUNICATION NETWORK ENGINEERING PROGRAM

Optimal Multi-Objective Capacity Enhancement and Energy Efficient HetNet Planning and Deployment Approach: The Case of Addis Ababa, Ethiopia

By

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Approval by Board of Examiners

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Declaration

I, the undersigned, declare that this thesis is my own work and does not incorporate without acknowledgment of any material previously submitted for a degree or diploma in any other university or institute of higher learning. To the best of my knowledge, it does not contain any material previously published or written by another person except where the acknowledgment is made in the text.

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Addis Ababa ________/____/2020

Place Date of Submission

The above candidate has carried out research for the master's thesis under my supervision.

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Abstract

Following growth in infrastructure, number of subscribers and availability of smart devices and applications, the aggregate cellular data traffic in Addis Ababa city's cellular network is increasing exponentially. Moreover, traffic growth follows non-uniform distribution both in space and time. To accommodate this non-uniformly growing data traffic, ethio telecom, for now, the sole telecom service provider in the city, deploy single-layer homogeneous macro base stations (MBSs). Macro-cell densification has been used to increase capacity of the radio access network (RAN). However, excess densification increases the RAN energy consumption, which is becoming a concern for cellular network operators like ethio telecom.

Deploying small cells overlaid with macro BSs, named as the heterogeneous network (HetNet), is an energy-efficient (EE) approach capable of meeting the high capacity demand and also keeps network deployment costs low. Many studies have analyzed the HetNet planning and deployment scenario. However, user usage scenarios and their mobility pattern based on realistic data are not considered for the selection of initial small cell candidate locations. Their results differ from one another depending on the environment, cell size, data set, and technology, or the methodology on which the research is made.

This research investigates a genetic algorithm (GA) based multi-objective optimization based on system capacity and EE maximization to provide a set of optimal solutions for HetNet selection. In doing so, based on a dataset collected from Addis Ababa cellular network, existing macro BSs data traffic, user usage scenarios, and spatial data traffic demand distribution are generated to identify hotspot areas, and are given as input parameters for the GA for optimal small cell selection. Then, layered planning and deployment is carried out in an interference-limited Long-Term Evolution (LTE) network based on the target requirement. Finally, performance gain of the optimized layered approach is evaluated with system capacity and EE as performance metrics and compared with a uniform topology which is resulted from unplanned small cell deployment through network simulation tool. The simulation results mainly show that both EE (up to 22%) and up to 16% capacity gain with cell edge performance gain (52%) of the target area are, improved by the deployment of optimized small cells, over the uniform (unplanned) deployment.

Keywords: *HetNet, energy efficiency, hotspot localization, capacity, deployment scenario, multi-objective optimization, spatial traffic distribution.*

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Contents

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Abbreviations, Definitions, Acronym

3G	Third Generation
3GPP	3rd Generation Partnership Project
4G	Fourth Generation
BSs	Base Stations
CA	Carrier Aggregation
CAGR	Compound Annual Growth Rate
CAPEX	Capital Expenditure
CDF	Cumulative Distribution Function
CDMA	Code Division Multiple Access
CoMP	Coordinated Multi-Point
CRE	Cell Range Expansion
CSG	Closed Subscriber Group
DL	Downlink
EIRP	Effective Isotropic Radiation Power
eNB	Evolved NodeB
ET	ethio telecom
GA	Genetic Algorithm
GB	GigaByte
GSM	Global System for Mobile Communications
HeNB	Home Evolved Node B
HetNet	Heterogeneous Network or Heterogeneous Cellular Network
ICIC	Inter-cell Interference Coordination
ICT	Information and Communications Technology
IMPEX	Implementation Expenditure
KPI	Key Performance Indicator
KWh	Kilowatt hour
LPN	Low Power Node
LTE	Long Term Evolution
MBS	Macro Base Station
MIMO	Multiple-Input and Multiple-Output

MoGA	Multi-objective Optimization Genetic Algorithm
MOO	Multi-objective Optimization
MWh	Megawatt hour
NSGA	Non-dominated Sorting Genetic Algorithm
NSGA-II	Non-dominated Sorting Genetic Algorithm II
OFDMA	Orthogonal Frequency Division Multiple Access
OPEX	Operational Expenditure
PDF	Probability Distribution Function
PRB	Physical Resource Block
PRES	Pareto-Achieved Evolution Strategy
QoS	Quality of Service
RAN	Radio Access Network
RE	Range Expansion
RF	Radio Frequency
RRH	Remote Radio Head
SC	Small Cell
SC-FDMA	Single Carrier Frequency Division Multiple Access
SINR	Signal to Interference plus Noise Ratio
TB	Terabyte
TDD	Time Division Duplex
TS	Time Slot
TTI	Transmission Time Interval
TWh	Terawatt hour
TX	Transmission
UE	User Equipment
UL	Uplink
UMTS	Universal Mobile Telecommunication System

1 Introduction

In this Chapter, the motivation and background of the thesis topic are presented. Moreover, the problem statement, objectives and outline of the thesis are introduced.

1.1 Background

Over the last many years, global mobile data traffic has grown exponentially. The overall global mobile data traffic is expected to increase a seven-fold between 2017 and 2022 with a compound annual growth rate (CAGR) of 46%, reaching 77 Exabytes per month by 2021. Along with this growth, energy consumption in mobile networks has increased considerably [1, 2]. Studies indicate that mobile radio networks alone have consumed about 0.5% of the world energy [3, 4]. Driven by growing environmental awareness and increasing electrical cost, energy-efficient green mobile networks have become an active area of research [4, 5]. The greenness of cellular networks is characterized by economic benefits (lower energy costs) and practical usage. This includes evaluation of energy savings and performance of the system, which subsequently form the basis of energy efficiency metrics.

It is known that conventional cellular networks based on macro base stations (MBSs) suffer from poor signal quality for indoor (where high data traffic is generated) and cell edge users as well as are unable to satisfy the traffic demand in hotspot areas. As an example, the Long-Term Evolution (LTE)-Advanced or beyond standards propose HetNets that consist of a macro cell network overlaid by small (micro, pico or even femto) cells. The macro-tier guarantees the coverage, while the small cells are a means to offload the data traffic from the macro cells on the hotspot (including indoor) areas and to satisfy the area user capacity demand [6].

The small cell deployment in HetNets should be planned with caution, as otherwise the energy efficiency of these networks will be compromised [3].

A classification of the state-of-the-art approaches towards green cellular network solutions is shown in Figure 1-1. As shown, it focuses on four important aspects: identifying green metrics, bringing technical changes in BSs hardware design, network planning and network operation [7]. It has been highlighted that the energy efficiency improvements through the energy-aware network planning by exploring the optimizations on the BS size, location and density not only result in lower overall power consumption but also better overall energy efficiency. From a network operation perspective, the most efficient ways to turn off cells/networks, sleep mode mechanism, and load balancing techniques while maintaining a good quality of service are emphasized, in order to bring more energy efficiency.

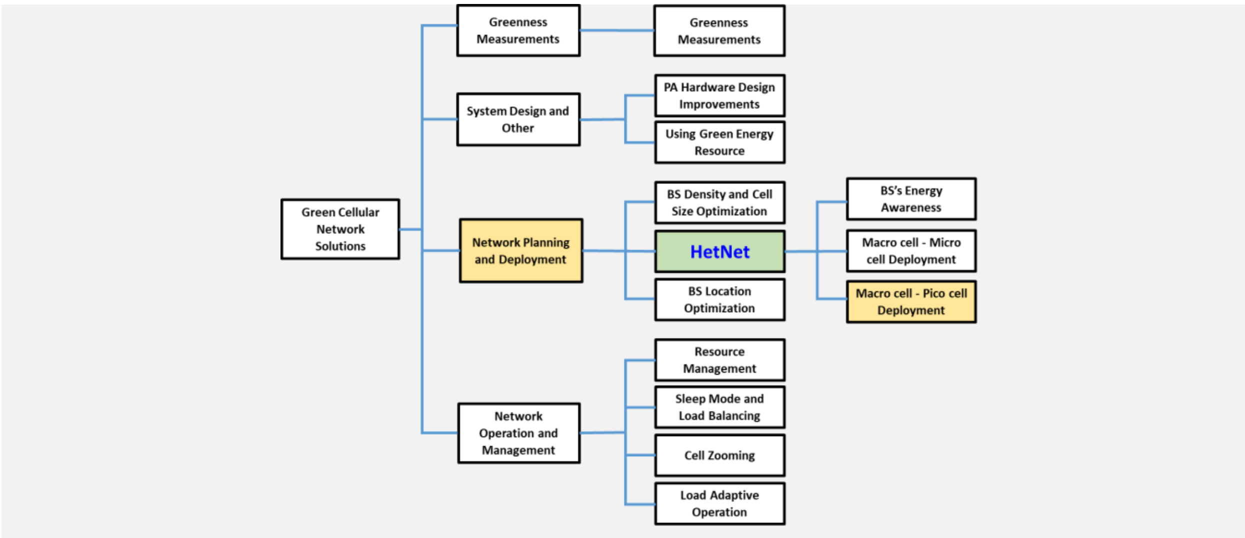
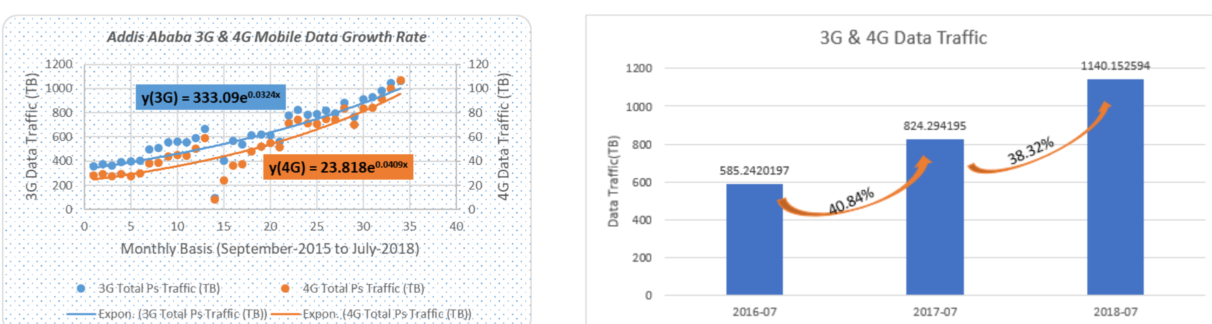


Figure 1-1 Classification of approaches towards green cellular network solutions [7].

In the Ethiopia context, ethio telecom is the sole service provider in the country and provides integrated telecommunication services. As in the global, the data traffic grows exponentially. Moreover, it is non-uniformly distributed and varies in time. Figure 1-2 shows the cellular network data traffic collected from 332 LTE and 742 Universal Mobile Telecommunications Service (UMTS) BSs that are operating in the city of Addis Ababa, Ethiopia. One can note that the download volume reaches 1140TB per month in the year 2018. Similarly, in this figure, for the past three years CAGR of Addis Ababa city's data traffic is on the average 39%, which is close to the global data growth trend.



a) Monthly (2015 – 2018) b) Annually (2016 – 2018)

Figure 1-2 Mobile data traffic growth of Addis Ababa City (2015 – 2018) [8].

The data traffic growth is the result of mobile services tariff reduction, penetration, and type of different high-end mobile devices. Figure 1-3 shows the mobile device type distribution among 41.1 million active mobile devices in ethio telecom cellular network as of November 15, 2018 [9, 10]. From the figure, 31% of the devices are high-end mobile devices which are smartphones and tablets generating high speed and large volume data.

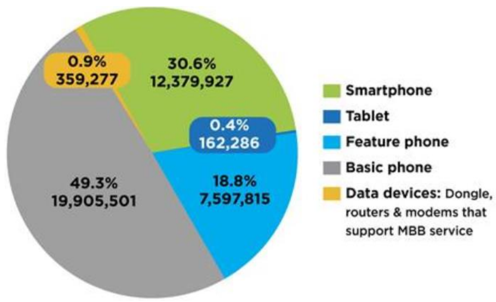


Figure 1-3 Active device type distribution in ethio telecom network [10, 11].

To improve user experience and absorb the exponential data traffic growth, the approach ethio telecom follows are radio network optimization (done via drive test and parameter fine-tuning); resource expansion (which includes carrier addition/aggregation, board expansion, sectorization and antenna split for the existing BSs); and macro BS densification. Currently, the operator owns over 7000 BSs to support the 41.1 million subscribers, from a population of 110 million. The BSs number will be double to reach the total population. The dense deployment is causing (and will cause) high energy consumption and increase ethio telecom's operational expense (OPEX).

Therefore, saving the power of BSs is the primary focus of green cellular network design and also designing green power strategies should be started at ethio telecom too. Thus, among the above-mentioned approaches, this research followed HetNet planning and deployment based on a real traffic density map. Intending to produce this result, motivated by the high traffic demand variations over space and time, optimal small cell location selection based on the real spatial traffic distribution and user's usage scenarios is performed for HetNet deployment as a promising approach to overcome the above-stated problems.

1.2 Statement of the Problem

With the growing availability of smart devices and applications, increasing subscriber, and new pricing scheme [12], Addis Ababa city's mobile data traffic demand is increasing exponentially. The traffic follows a non-uniform distribution in both space and time.

To capture this non-uniform traffic density and higher data rate demand, the most widely used approach by ethio telecom is macro base station densification. The main drawback of this approach is its planning with hexagonal grid and homogeneous data traffic usage distribution assumptions, and also its main concern is about coverage and capacity problems. So, this densification should be done in an energy-efficient aspect.

As shown in Figure 1-4, the average energy consumption for the currently deployed 332 LTE and 742 UMTS macro BSs is about 22MWh/day or 8,030MWh/year. Considering that on average, one BS will consume 7.6MWh per year [8] and taking an average energy bill of 87 million Birr, the local currency ethio telecom pays 13.3 million Birr, for the 1074 BSs. It is also noted that though LTE BSs are almost one half in number and one-tenth less in carrying data traffic than 3G BSs, they consume on average 25.7 KWh more energy per day. With the increase in data traffic demand and hence, the BS densification and introduction of new technology, energy consumption is expected to rise.

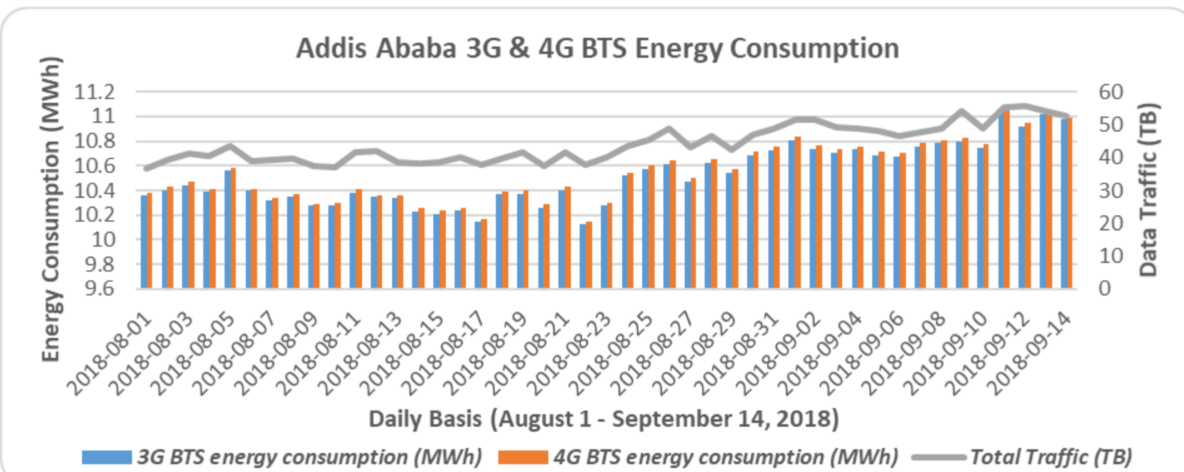


Figure 1-4 Daily basis BS energy consumption trend due to data traffic only [8]

Keeping the energy consumption at a minimum while fulfilling the rising data rate demand via densification is an issue that shall be addressed at different levels, where the concern in this research is during the initial network planning phase.

In response to these problems, the optimal number and placement of small cells have an impact on the energy consumption of the network. So, this research investigates the energy-efficient planning and deployment approach of multi-tier, small cells along with the existing macro BSs, HetNet. Spatial data traffic demand, usage scenarios, and active mobile data user density are inputs for the analysis of simulation results.

1.3 Objectives of Thesis

1.3.1 General Objective

The main focus of this research is to plan and investigate performance gain of system capacity and energy efficiency with HetNet deployment approach in a realistic case scenario of Addis Ababa city LTE network. For that, the multi-objective GA optimization problem is formed and applied.

1.3.2 Specific Objectives

To achieve the general objective of the study, the following specific objectives are identified:

- To review related works from literature;
- Data collection from performance reporting system (PRS) and ethio telecom working documents such as low-level and high-level design (LLD and HLD);
- To analyze the dataset based on active mobile data users and their usage scenarios, and data traffic distribution;
- To divide the target area into small grids and illustrate the area's spatial data traffic distribution, and then to plan the location of the small cells for the hotspot under the specified grids;
- To perform LTE radio access HetNet deployment scenario;
- To select the optimal small cell BS density and transmit power based on multi-objective GA optimization problem;
- To evaluate the performance gain of the planned HetNet with system capacity and energy efficiency as performance metrics.

1.4 Literature Review

Mobile operators are deploying HetNet to meet capacity, coverage, and quality of service (QoS) targets [13]. Some of the key challenges associated with HetNet deployment are energy consumption, hotspot identification, accurate demand forecasting, spectrum allocation, the coexistence of increased interference levels and availability of high capacity backhaul link. The next paragraphs present energy efficiency in HetNet's perspective.

Motivated by the ICT's high carbon emission rate, authors in [2] have identified HetNet deployment, resource allocation and user association as a drive for the concept of green HetNet.

The authors argued due to the non-uniform traffic distribution, placing the small cells at the center of the macro cell coverage area doesn't guarantee the optimal energy efficiency placement in a HetNet. In the end, the authors concluded an optimal BS density, transmission power level, and placement can improve energy efficiency and network throughput in HetNets with optimal joint user association and resource allocation.

As the spectral efficiency in cellular networks approaches its theoretical limits with the forecasted growing of data traffic, the authors in [14, 15] analyzed the need for an alternative strategy in increasing the macro BS density to further improve network capacity with minimized power consumption. Finally, the authors reached to conclude HetNet is one of the best alternative deployment approaches. To make more energy efficiency, the authors in [16] proposed a grid-based traffic map BS energy saving algorithm. They have investigated large energy waste during low traffic periods in dense cell deployment due to BSs inability to adjust network configuration since traffic loads fluctuate in time and space.

The authors in [17], investigated two-tier macro-micro HetNet planning strategy in terms of energy efficiency, based on a realistic dense urban scenario and spatiotemporal traffic distribution map of existing macro BS in a grid-based approach. The authors concluded as mobile network planning mainly focused on coverage and capacity problems with uniform or log-normal traffic distribution assumption, it is not energy efficiency.

Similarly, the authors in [18, 19], discussed the HetNet deployment approach with small cells initially set and uniformly distributed over the study area and evaluated the performance gain of HetNet in system throughput and area energy efficiency (Watt/km2/Mbps) as a performance metrics. The user mobility pattern is considered for effective macro-cell upgrades and appropriate BS selection. In the end, they have concluded HetNet achieves a higher data rate in an energy-efficient manner than a homogeneous network.

The authors in [20], motivated by drawbacks of cellular network planning input assumptions, uniform traffic distribution over the network coverage area. Then, they have proposed an energy-efficient HetNet planning scheme with a spatial modeling method of scalable, spatially correlated, and Log-normally distributed traffic for the existing macro BSs' cell level traffic data. Finally, they reached to conclude the proposed planning input model well captured BSs' inhomogeneous spatial traffic distributions. They have also measured the level of spatial traffic inhomogeneity with small cell deployment in HetNet and analyze its influence on the performance of energy efficiency.

To summarize the above-stated studies, many of the studies have investigated that the HetNet deployment approach provides an energy efficiency network for mobile operators, specifically in dense urban BS deployment. Each author followed different approaches and input data assumptions to evaluate the performance gain of HetNet over the commonly used approach of a homogeneous network. Their results differ from one another depending on the environment, cell size, data set, initial small cell candidate location selection techniques, algorithms, and technology, or the methodology on which the research is made.

In this research, a realistic user-level data set is used in addition to the cell level data set of BSs. Moreover, active mobile data users and their usage scenarios at cell busy hour condition are generated and applied for hotspot zone identification, and for further initial small cell candidate location selection instead of uniform distribution assumption.

1.5 Methodology

In order to conduct this research, initially, the dataset for Addis Ababa's UMTS network downlink (DL) data traffic demand is extracted from ethio telecom PRS. Then kinds of literature in the field of the HetNet planning and deployment approach and related area were reviewed. With insight from the studies reviewed, the raw dataset was analyzed, and the target area is defined and sub-divided into smaller pixels. After that, hotspot zones in this study area are identified and type and number of initial candidate small cell locations are selected.

With system parameters and assumptions from reviewed literatures, the layered deployment of the existing MBSs and candidate small cells in the area is carried out for simulation, and pathloss information for each cell is computed by using WinProp network simulation tool. Then, a multi-objective optimization problem based on system capacity and energy efficiency maximization is formulated, and genetic algorithm is established and applied to provide a set of optimal solutions (Pareto front). Then, one of the solutions from the given set of optimal solutions is selected and the esteemed random (unplanned) topology is generated based on random user distribution. Finally, the performance gain of optimized topology is evaluated with system capacity and energy efficiency as performance metrics.

1.6 Scope and Limitations

1.6.1 Scope of the Thesis

In this thesis, capacity enhancement and power consumption reduction deployment approaches in HetNet architecture for ethio telecom LTE network are studied and implemented by applying a multi-objective optimization (MOO) GA technique. The study is carried out by considering the UMTS network at busy hour data traffic conditions with minimum QOS requirements in the area of Megenagna to Bole, Addis Ababa, Ethiopia where high data traffic demand is generated.

1.6.2 Limitations of the Thesis

Even though we have applied realistic data for the analysis and simulation, there are some limitations to our study. To highlight some of them, the following were the main limitations in conducting this thesis:

- The dataset collected from the network monitoring system for the analysis and target area selection is limited to Addis Ababa city's UMTS traffic. This is mainly due to currently the city is not fully covered by the LTE network and it is difficult to get the full picture of the data traffic demand. On top of this, the dataset is limited to DL data service only since uplink (UL) to DL ratio is 1:7.5.
- The dynamic part of BSs energy consumption is gained from the network monitoring system while the static part is considered from the standard value.
- The user-level data traffic demand which is collected from ethio telecom's performance monitoring tool is taken with 50 meters grid resolution. But, due to the limitations on the coverage radius of picocells, the grid resolution for their location is set to 100 meters.
- It is limited to the LTE network only, and the effect of dual or tri-band which is available in one antenna is not considered.

1.7 Contributions

To accommodate the growing traffic and the high-speed data rate demand, ethio telecom has to plan and expand the existing cellular network with the concept of energy efficient HetNet. So, by generating the spatial data traffic distribution and user's usage scenarios, small cell planning and deployment approaches along with the existing macro BS in terms of energy efficiency in HetNet architecture will be provided.

Therefore, from the output of this research ethio telecom will get an insight into small cell deployment approaches, to save a significant amount of energy from the mobile network aspects by keeping the required QoS and data rate demand. In addition, cell edge user's SINR and spectral efficiency will be improved, hence their average throughput will be enhanced. Moreover, it will also provide an approach for hotspot identification and small cell localization.

1.8 Outline of Thesis

The rest of this thesis is organized as follows. In Chapter 2, detailed descriptions about HetNets are presented. In Chapter 3, the fundamentals of optimization algorithms based on multi-objective problems are discussed. In Chapter 4, explanations about system models as materials and methods for the research are presented. The Chapter also explained the dataset used for the research and procedures followed to select the target area and deployment scenario, optimization problem formulation for system capacity and energy efficiency analysis. Chapter 5 conducted performance analysis and simulation results obtained from the planned HetNet deployment approach. Finally, the conclusion of the study and future work will be given in Chapter 6.

2 Background on Heterogeneous Networks

In this research, HetNets is a term that represents a network that consists of different LTE BSs with various transmit power levels. This Chapter explains motivations for network densification. In addition to that, the definition, as well as general HetNet research topics, are given. Lastly, background about small cell types, deployment scenarios, and requirements are discussed.

2.1 Motivations for Network Densification

There are environmental, economic and technological motivating factors for the rapid development of HetNets [21]. To mention the key motivations: explosive growth of data traffic, efficient utilization of spectral and network resources, and revenue maximization [21, 22]. These points are discussed in detail in the below sections.

2.1.1 Growth of Data Traffic and Challenges from the Solution

In recent years, mobile internet has witnessed an explosive growth in the capacity of data traffic demand [1]. This is largely fueled by the proliferation of more intelligent mobile devices, such as smart phones and tablets. Market studies have shown that the data traffic volume is a direct function of the device's screen size, the user-friendliness of its operating system and the responsiveness of wireless networks that the device is connected to [21]. For instance, a 3G smartphone on average consumes about 30 times the system capacity of a 2G voice phone; and tablet consumes five times the system capacity of a smartphone. As the mobile devices continue to increase in screen size, image resolution and battery life, the growth in data capacity demand will continue, and often in an asymmetric fashion between the UL and the DL. Hence, the network infrastructures continue to improve in peak data rate [21].

Machine-type communications that require more capacity also add another complexity to the future generations of wireless networks. With mobile internet evolving towards embedded internet, future networks need to scale up in size and complexity in order to accommodate a unique number of connected devices with many different traffic characteristics, usage patterns and service class requirements (very low traffic volume to high speed real-time) [14]. We also start to see network congestion in all aspects of cellular network; from the access network to the core network and even to the backbone network and backhaul links.

A simple and well-known deployment strategy will be vital if operators are to plan and install a network that can cope with this significant traffic increase. Operators can choose from a wide range of deployment options, beginning with full utilization of the existing macro layer and deployment of LTE. But properly managing billions of such connected devices across many different types of networks adds to the complexity of capacity dimensioning. Operators will also need extensive capital investment in new network capacity to meet the growing traffic with energy consumption as one of the key challenges. So, their profitability, energy efficiency, and competitiveness are challenging issues. Therefore, this heterogeneous data traffic growth requires a paradigm shift to HetNet for further increasing from spectral efficiency to the overall network efficiency with service quality and fairness throughout the network coverage areas, particularly at the cell-edge [23].

2.1.2 From Spectral Efficiency to Network Efficiency

The wireless industry has several options for meeting the explosive data traffic growth. After decades of continual air interface innovations, today we are practically reaching the theoretical limit of radio channel capacity, commonly known as the Shannon limit [21]. Although air interface improvement will continue to maximize the benefits of advanced wireless communication research and take full advantage of advanced signal processing technologies for an even higher spectral efficiency, we need several orders of magnitude greater system capacity than the air interface spectral efficiency improvement can offer [24]

Therefore, the increase in future capacity needs to come from a combination of technology solutions, including, in particular, maximizing the overall network efficiency instead of only relying on the spectral efficiency improvement at the radio link level as shown in Figure 2-1. HetNets are a fundamental technology behind most of these solutions.

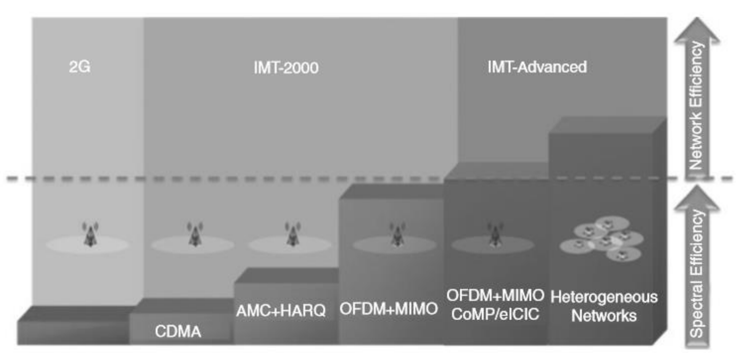


Figure 2-1 Wireless technology evolution [21].

Moreover, we need more proactive solutions to encourage and enable future continued data traffic growth and to satisfy every person's requirement. One such solution is the data offloading or steering strategy in HetNet. This includes facilitating and encouraging subscribers to offload their traffic from macro BSs to the alternative small-cell networks. In addition, more flexible spectrum utilization, including spectrum sharing, dynamic spectrum access and cognitive radio with opportunistic network access is another alternative.

2.2 Key Focuses on Macro BS Utilization

Many operators already have wide-area Global System for Mobile (GSM) coverage and HSPA in densely populated urban areas. They have also deployed LTE in dense urban areas, and some have deployed LTE in rural areas to exploit the digital dividend. One of the key elements to cope with increasing traffic is the higher spectral efficiency provided by LTE compared to HSPA and GSM [23]. Therefore, the first step is to deploy LTE where possible, using the LTE handset penetration in the subscriber base.

As of 2014, there are 497 million LTE subscribers and nearly 838 million new LTE subscriptions in the year to September 2017 and with a global penetration of approximately 7%. LTE and LTE-Advanced are growing rapidly throughout the world with an annual growth of 41%. Operators with high LTE handset penetration can better exploit the LTE layer and spectrum. Many operators are re-farming existing GSM frequency bands to HSPA or LTE, so they can update their equipment gradually to more spectrally efficient radio standards. Some operators are even re-farming HSPA for LTE. GSM, HSPA, and LTE will continue to coexist and evolve in the long term for several reasons, like service type and coverage of technologies, roaming, cost of deployment and energy, availability and affordability of handsets.

a) Macro Cell Splitting and Sectorization

Macro cells carry most of the traffic in today's mobile network, supplemented by small cells in hot zones. One of the key performance multipliers for macro cells is to subdivide each cell into smaller cells, boosting the site capacity significantly.

There are basically two ways to split a macro cell; in the horizontal or azimuth domain and in the vertical domain (tilt or coverage). Combining both horizontal and vertical sectorization provides a narrow beam targeting only a single or a few users. This can be done by deploying active antenna systems and has been standardized in (3rd Generation Partnership Project) 3GPP Release 12.

b) Macro Layer Evolution

Many mobile networks were designed for voice coverage and with the increase in data rates, the coverage area may shrink owing to power limitations in user devices. Therefore, macro BS upgrades may require additional densification, increased BS output power or further cell-splitting or sectorization.

Figure 2-2 Different sectorization options [23].

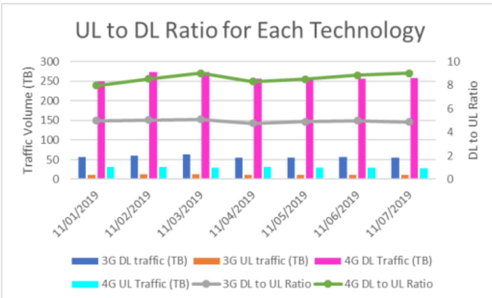
Many operators are facing challenges such as lack of new site locations, operating frequencies with limited coverage and performance and ever-growing demand for a high-quality end-user experience. With multi-sectorization options as depicted in Figure 2-2, operators can improve their rollout and meet the challenge of traffic growth by providing more coverage and more capacity simultaneously. They can also improve end-user service quality without having to invest heavily in new base station sites. But in this deployment approach, the BS's energy consumption and the network energy efficiency are considered as a limiting factor.

c) Outdoor Small Cell Densification

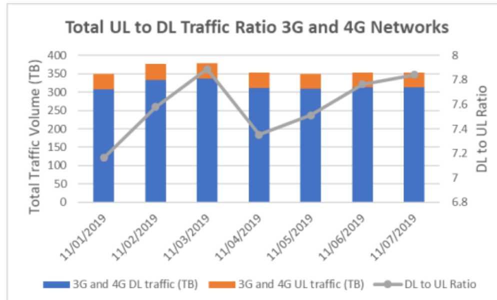
When traffic increases, the capacity of macro cell networks can be increased by the methods explained in the previous sections. Macro cell evolution may still not be sufficient to provide the required improvements in capacity, coverage, and quality of experience. Adding more macro sites is expensive and wastage of energy. So, it becomes cost-effective and energy efficiency via small cell solution to add capacity with limited spectrum and nonuniform traffic demand in hot spot areas.

The ideal network upgrade depends on which link is currently limiting the performance. Some networks are DL performance limited while others are UL performance limited. But the ratio of UL to DL traffic load is about 1:5 [23]. Likewise, as shown in the Figure 2-3, ethio telecom's

Addis Ababa mobile network has the same figure in UMTS network whereas 1:8.5 from 4G network perspective. However, it is highlighted that the total UL to DL data traffic load of the city is about 1:7.5. Hence, we are more concerned with DL traffic load as a key parameter for network upgrade or densification.



a) For each technology traffic ratio



b) Total traffic ratio

Figure 2-3 UL to DL traffic load ratio for Addis Ababa City mobile network [8].

The most efficient deployment of the small cells versus additional macro carriers depends on the spectrum availability, traffic density, and interference level. Therefore, when deploying small cells, operators need to decide which spectrum to utilize for small cells, either shared spectrum with macro cells or dedicated spectrum for the small cells [23].

d) Indoor Small Cell Deployment

In high-traffic density areas, the recommended first step solution is to enhance macro layer capacity with an upgrade and then to deploy outdoor micro or pico cells. But it will not be a solution for indoor coverage problems where most of the operators faced, like ethio telecom, in which indoors are covered by outdoor macro cells though 70% of the total traffic is indoor generated. Moreover, in dense indoor traffic hotspots such as train stations, airports, shopping malls or enterprise buildings, indoor cells provide a very feasible coverage and energy efficiency solution.

2.3 HetNet

Macro networks can be extended through the creation of HetNets with small cells as carriers densify their networks with new sites and associated backhaul. In HetNets, small cells play a key role in offloading user data traffic from congested macro-cells and extending the limited coverage of macro-cells. Thus, operators are also continuing to focus significant amounts of attention on small cells for improving coverage and capacity on a highly targeted basis indoors in addition to outdoors. Offices, shopping malls, and sports arenas are of particular interest [21].

As compared to macro cells, small cells are low-powered base stations with small coverage distances. In addition to coverage, small cells differ from macro cells with their transmit power levels, number of resources, size, weight, and prices.

In general, similarities and differences between small cells and macro cells are basically based on transmit power level, cell radius (coverage), deployment scenario, antenna height, availability of bandwidth and RAN technology options, ease of access, features (like plug and play for small cells) and cost. Some of the mentioned points are discussed in the following sub-sections.

2.3.1 Types and Basic Requirements of Nodes in HetNet

a) Types of Nodes

Low power nodes (LPN), sometimes called small cells, are BS that transmit with very low power compared to a macro BS. Generally speaking, depending on the prices, transmit powers and resources, there are three different types of small cells in the small cell terminology. These are femtocells, picocells, and microcells.

In HetNets the cells of different sizes are referred to as macro, micro, pico, and femto cells; listed in order of decreasing BS power. The actual cell size depends not only on the BS power but also on antenna position, as well as the location environment; e.g. rural or city, indoor or outdoor. Table 2-1 shows more details about HetNet nodes.

Usually, femtocells are the small cells with the lowest resources and the lowest prices as compared to other small cell types while microcells are with the highest prices and the highest resources. In terms of the locations, femtocells or home evolved Node B (HeNB) can achieve better performance inside the buildings while picocells and microcells match the outdoor applications [25]. Figure 2-4 illustrated a typical two-layer HetNet deployment scenario, macro-cell underlaid with pico-cell. Hence, HetNet consists of a mix of nodes, and it is flexible, cheap, and easy to deploy capacity enhancing mechanism introduced in LTE Release 8.

HetNet planning was already used in GSM. The large and small cells in GSM are separated through the use of different frequencies. This solution is still possible in LTE. However, LTE networks mainly use frequency reuse of one to maximize the utilization of the licensed bandwidth.

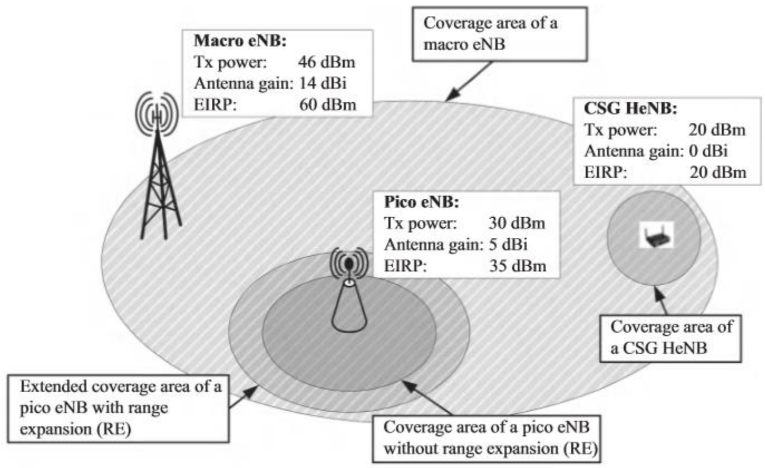


Figure 2-4 A typical two-layer HetNet [17].

In HetNet deployments, the overlay macro cell provides a wide area coverage umbrella while the LPNs are deployed in a more targeted manner to eliminate coverage holes, increase network capacity, and improves the users experience with increased bitrates per watts per unit area at traffic hot zones [17, 25, 24].

Table 2-1 Details about HetNets Nodes [23, 26].

Cell Type	TX Power	Backhaul	Access	Coverage	Solution
Macro	46 dBm	S1 Interface	Open to all user equipment (UE)	Few km	Outdoor
Micro	30-38 dBm	S1 Interface	Open to all UE	≤1.5 km	Indoor/outdoor
Pico	23-30 dBm	X2 Interface	Open to all UE	<300 m	Indoor/outdoor. Planned deployment
Femto (HeNB)	<23 dBm	No X2 as Baseline	Open, Closed, or Hybrid Subscriber Group (CSG)	<50 m	Indoor. Consumer deployed
Relay nodes	30 dBm	Air-interface	Open to all UEs	<300 m	Placed indoor or outdoor

The growing roles of smalls cells have an overlay capability in different sizes. For instance, from the table, outdoor users may be served by a combination of macro, micro and pico cells. Low power remote radio head (RRH) and pico cells may provide both outdoor and indoor solutions in hot zones such as shopping districts, train stations or shopping malls, with a typical cell radius of up to 200 meters. Indoor pico and femto cells are used indoors in cells of no more than 10-25m radius. Pico cells are deployed by an operator whereas femto cells are typically user deployed.

In most 3G and LTE networks today, operators are also seeing some areas of their networks with a much more rapidly growing capacity demand than in others. These former hotspots have effectively evolved into much larger hot zones, outdoor and indoor areas that cannot be covered by a single or a few macro cells. To this end, small cells have a key role to play in supporting capacity and better subscriber performance in these hot zones. Therefore, an optimal network expansion roadmap and type of BS selection are required and it depends on various operator location-specific parameters and assumptions [23].

b) Basic Requirements of Small Cell BSs

The mobile subscribers in wireless communication, the required data demand is provided by BSs. In order to provide data to the subscribers, BSs should be deployed according to rules and regulations. Thus, small cells provide opportunities to high speed and dense networks. However, there are some requirements like energy efficiency, site acquisition and backhauling to be considered for small cell deployments.

Many organizations and governments have put attention to energy efficiency in different fields [2, 5]. Energy efficiency is also important in the field of wireless communication since the number of connected devices will be larger in the future. According to [27], 50 million small cells, which consume 12 Watts each, could lead to 5.2 TWh energy consumption which is half of the power generation of a nuclear plant.

Therefore, vendors and manufacturers follow approaches to reduce the energy consumption of devices. In addition, wireless network topologies could be taken into consideration to increase their energy efficiency because since most of the energy (80%) in the cellular system is consumed in the BSs. Hence, network operators can reduce energy consumption by planning the system with the energy efficiency approaches of considering energy in their initial planning phase. Another requirement is the site acquisition for small cell deployment as one of constraint in network planning and deployment. This situation may increase the expenditures of the network operators, and even leading to poor planning, and thus waste of resources and energy [23]. Moreover, backhauling (wired and wireless) is also considered as an additional requirement in small-cell communication.

2.3.2 HetNet Deployment Scenario

In heterogeneous networks, cells with different sizes can be used in a hierarchical network deployment. The type and location of the base stations (also called evolved Node B (eNB) in LTE/LTE-Advanced systems) controlling these cells will play a significant role in determining the cost and performance of layered deployments.

For example, indoor femtocell deployments using HeNBs can utilize the existing backhaul thereby significantly lowering the cost of such deployments. With outdoor pico cell deployments through pico eNB, the operator will need to provide backhaul capability and manage more critical spectrum reuse challenges. Other deployment models cover indoor enterprise or outdoor campus deployments that may impose different manageability and reliability requirements. Assuming an operating bandwidth of 10 MHz, a typical configuration of the macro eNB is 46 dBm transmission (TX) power per cell. Assuming a 14 dBi antenna gain (including feeder loss), the equivalent isotropic radiated power (EIRP) for the macro eNB is 60 dBm.

For the HetNet shown in Figure 2-4, the pico eNB only has an EIRP of 35 dBm, which naturally results in a significantly smaller coverage than the macro eNB. On the other hand, the HeNB has the smallest EIRP of only 20 dBm.

Due to the higher deployment density of the small cells, it is beneficial to expand the footprint of picocells, that is, offloading UEs from macro cells to picocells, to enable more UEs to connect to the small cells and take the advantage of higher deployment density. This can be achieved through cell range expansion (CRE) [21] as in the above figure. One of the approaches for CRE is a cell-specific bias to the UE measurement of some power applied for pico eNB. In this way, more UEs will be inclined and connected to pico eNBs instead of macro eNBs.

Depending on the small cell deployment strategy followed by cellular telecom operators, LPN can be operator deployed or consumer deployed (CSG). Operator-deployed small cells are deployed in densely populated suburban areas, which are characterized by a lack of fixed lines, energy scarcity, and difficulty in site acquisition. However, CSG, for instance, femtocell, is a cell that only allows its member UEs to access it and provides cost-effective network densification from operators' perspective and affordable connectivity from user perspective [28, 29]. In general, depending on business requirements, various deployment scenarios are implemented in HetNet, and Table 2-2 presents its baseline.

Table 2-2 Baseline deployment scenario for Heterogeneous network [28]

Environment	Deployment Scenario	Non-Traditional node
Macro + Indoor	Macro + femtocell	Indoor femtocell
	Macro + indoor Relay	Indoor relay
	Macro + indoor RRH/pico	Indoor pico
Macro +Outdoor	Macro + outdoor relay	Outdoor relay
	Macro + outdoor RRH/Pico	Outdoor pico

In introducing a mix of cell sizes and generating a HetNet adds to the complexity of network planning and introducing interference problem [24]. Hence, a number of features added to the 3GPP LTE specification can be used to mitigate the interference problem in HetNets with small cells and CRE, such as time-domain Inter-cell Interference Coordination (ICIC) for small cell users which are served at the cell-edge, higher-order MIMO, Carrier Aggregation (CA) and Coordinated Multi-Point (CoMP) [30].

2.4 Trends on HetNet Deployment Approach

With the deployment of HetNets, a large number of research areas are explored. These include, but are not limited to, research in areas such as channel modeling, user association, interference management, techno-economical aspects, energy efficiency, mobility, wireless network planning and optimization [25]. To this end, energy efficiency and network planning and deployment approach, the focus areas of this research are discussed in the following sub-sections.

2.4.1 Energy Efficiency

Energy efficiency can be defined as the ratio of aggregate network throughput to the total consumed energy in the network [17]. Moreover, studies on energy consumption could be motivated by static and dynamic parts of the network. With increased awareness for energy efficiency, different studies are proposed to reduce energy consumption in wireless networks. For example, from the wireless communication equipment perspective, 50% to 80% [4] of the energy is consumed in the BSs. Therefore, concentrating on the topology side is crucial to reduce consumed energy because reducing the number of cells can reduce overall energy consumption.

In [16], the authors proposed a cell switch-off framework for cellular networks, switching off a large set of small cells without affecting the QoS of the subscribers. Deploying more relay nodes or picocells in a service area could enhance capacity and coverage. However, it also increases energy consumption. In [31, 32], authors evaluate the energy efficiency of relay nodes and picocells in both uplink and downlink. In this work, they investigate the effect of more small cells that are deployed in a service area on reducing the area power consumption of a network. According to the results, both relay nodes and picocells reduce the area power consumption in the UL, whereas picocells reduce the area power consumption in the DL.

2.4.2 Network Planning and Deployment Approaches

The HetNets will be different from traditional networks in terms of network planning. In traditional networks, the approach consists of dimensioning, detailed planning and optimization phases. In dimensioning phases, the number of BSs to cover the location with a certain QoS is estimated. Then, the detailed planning phase is started to evaluate the wireless network deployment in the service area in more detail. After these two phases, network operators maintain network optimization according to requirements [25, 33]. However, because of the presence of a large number of BSs in the HetNets this approach may be more challenging for network operators.

The HetNets deployment can be carried out in grid-based approach [17]. In this approach, the number of macro BSs are estimated, and the service area is divided into the sub-regions with almost equal traffic distribution. After evaluating path losses, spectrum allocations and QoS, the same procedure is followed for the small cells. The number of small cells is estimated first as an initial candidate location and then they are distributed to the location with almost equal traffic distribution. Similarly, a method is proposed to analyze the deployment scenarios of the HetNets in an energy-efficient manner with a multi-objective optimization genetic algorithm for optimal topologies that satisfy system objectives.

In [33], the authors proposed a network framework for planning and optimization of the HetNets by the multi-objective genetic algorithm. According to their proposal, they have explored that the boundary between planning and optimization will not exist, and they would rather be considered at the same time in the network design phase. These studies show that there is an emerging need for new approaches to future wireless network planning and optimization.

In addition, current research in this area also considers the time-varying nature of mobile wireless networks. Depending on the time in a day, population density in an area would be high and it would lead to different load or congestion situations and different interference levels [34]. In terms of the HetNets, the number of access nodes is extremely high and therefore there would be different inter-cell interference scenarios depending on the time during the day.

2.5 LTE Basics

LTE, developed by 3GPP, is a wireless broadband technology designed to support roaming Internet access via cell phones and handled devices. It is the successor to 3G UMTS and HSPA providing much higher data download speeds and setting the foundation for LTE Advanced with further additions of technology. It meets baseline requirements of increased speed, Multiple Input Multiple Output (MIMO), IP-based network and new air interface which is Orthogonal Frequency Division Multiple Access (OFDMA). In the following, we give an overview of LTE physical layer features, focusing on the scheduling and resource allocation.

LTE radio transmission is based on OFDMA for downlink communications and Single Carrier Frequency Division Multiple Access (SC-FDMA) for uplink communications. OFDMA allows to exploit multiuser diversity and to provide more flexibility in radio resources allocation [35].

An LTE frame is divided into 20 timeslots (TSs) with 0.5ms duration of each TS (TDD mode). Two adjacent TSs are grouped into a sub-frame of length 1ms, corresponding to a Transmission Time Interval (TTI). Each TS corresponds to 7 OFDM symbols, which is preceded by a cyclic prefix to avoid inter-symbol interference.

The bandwidth corresponding to a slot (7 OFDM symbols) is subdivided into several blocks of 12 subcarriers, each of which is called Physical Resource Block (PRB). The smallest resource unit that can be allocated to a user covers a TTI of 1ms and a PRB (bandwidth of 180khz), called scheduling block (SB), and shown in Figure 2-5.

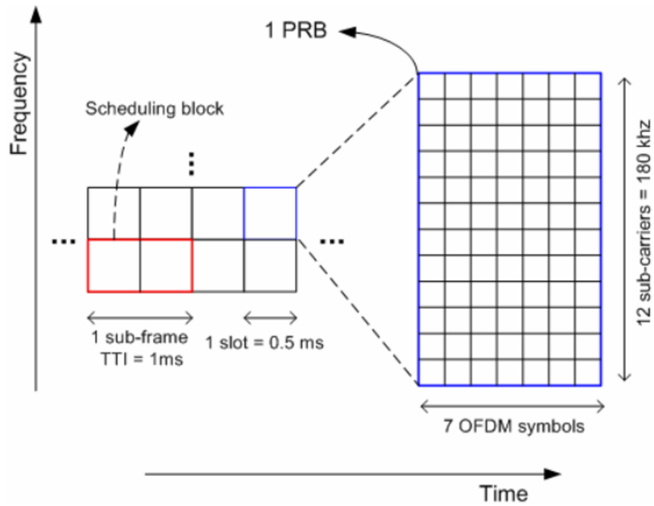


Figure 2-5 An illustration of resource element in LTE [35]

Given a bandwidth available for the backhauling network, the goal is to find an optimal schedule within a minimum time frame to maximize the capacity. In this thesis work, for each base station, the optimal number of SB in order to send its own traffic and to route the traffic of the other nodes will be allocated based on the number of active users attached to it and SINR value.

3 Genetic Algorithm-based Multi-Objective Optimization

3.1 Background on Genetic Algorithm

Genetic algorithms are a type of optimization algorithm, that are used to find optimal solution(s) that maximizes or minimizes a particular function that represents a computational problem. Genetic algorithms represent one branch of the study called evolutionary computation [36], in that they imitate the biological processes of reproduction and natural selection to solve for the 'fittest' solutions.

Like in evolution, many of a genetic algorithm's processes are random; however, this optimization technique allows one to set the level of randomization and the level of control. These algorithms are more powerful and efficient than random search and exhaustive search algorithms, which are a type of traditional optimization methods [36], yet require no extra information about the given problem. This feature allows them to find solutions to problems that other optimization methods cannot handle due to lack of continuity, derivatives, linearity, or other features.

Researchers found that genetic algorithms were a way to find solutions to problems that other methods could not solve. Moreover, they can simultaneously test many points from all over the solution space, optimize with either discrete or continuous parameters, provide several optimum parameters instead of a single solution, and work with many different kinds of data [36]. In this case, Genetic algorithms take advantages over traditional optimization methods by producing stunning results when they fail. With "traditional" optimization methods, we are referring to three main types: calculus-based, exhaustive search, and random [36].

Calculus-based optimization methods come in two categories: direct and indirect. The direct method 'jumps onto' the objective function and follows the direction of the gradient towards a local maximum or minimum value. This is also known as the hill-climbing or gradient ascent method [36]. The indirect method takes the gradient of the objective function, sets it equal to zero, then solves the set of equations that results. These calculus-based techniques have two drawbacks. First, they only search for local optima and finish the searches, and this would cause the wrong solutions. Second, these methods require the existence of derivatives, and this is virtually never the case in practical applications.

Exhaustive search algorithms perform exactly that - an exhaustive search. These algorithms require a finite search space or a discretized infinite search space of possible values for the objective function. Then they test every single value, one at a time, to find the maximum or minimum. While this method is simple and thus attractive, it is the least efficient of all optimization algorithms [36].

In practical problems, the search spaces are too vast to test every possibility one at a time and still have a chance of using the resulting information to some practical end. So, random search algorithms became increasingly popular as people realized the shortcomings of calculus-based and exhaustive search algorithms. This style of algorithm randomly chooses some representative sampling from the search space and finds the optimal value in that sampling. While faster than an exhaustive search, this method can be expected to do no better than an exhaustive search [36]. Using this type of algorithm means that we leave it up to chance whether we will be somewhat near the optimal solution or miles away from it.

From the above discussions, it can be seen that the genetic algorithm differs substantially from more traditional search and optimization methods [37]. The four most significant differences are:

- Genetic algorithms search a population of points in parallel, not a single point.
- Genetic algorithms do not require derivative information or other auxiliary knowledge; only the objective function and corresponding fitness levels influence the directions of search.
- Genetic algorithms use probabilistic transition rules, not deterministic ones.
- Genetic algorithms work on an encoding of the parameter set rather than the parameter set itself (except in where real-valued individuals are used).

It is important to note that the genetic algorithm provides a number of potential solutions to a given problem and the choice of the final solution is left to the user [37]. In cases where a particular problem does not have one individual solution, for example, a family of Pareto-optimal solutions, as is the case in multi-objective optimization and scheduling problems, then the GA is potentially useful for identifying these alternative solutions simultaneously.

Unlike calculus-based methods like hill-climbing, genetic algorithms progress from a population of candidate solutions instead of a single value. This greatly reduces the likelihood of finding a local optimum instead of the global optimum. They do not require extra information that is unrelated to the values of the possible solutions themselves. The only mechanism that guides their search is the numerical fitness value of the candidate solutions, based on the creator's definition of fitness [36]. This allows genetic algorithms to function when the search space is noisy, nonlinear, and derivatives do not even exist. This also makes genetic algorithms applicable in many more situations than traditional algorithms, and they can be adjusted in each situation based on whether accuracy or efficiency is more important.

Moreover, genetic algorithms can solve problems that are stochastic, highly non-linear and discrete. To this end, GAs use population selection instead of point selections and make them parallel in nature. Parallelism property provides an ability to work with different points simultaneously [25, 36].

Since genetic algorithms are designed to simulate a biological process, much of the relevant terminology is borrowed from biology. However, the entities that this terminology refers to in GAs are much simpler than their biological counterparts [36]. The basic components of all GAs are: a fitness function for optimization, a population of chromosomes, selection of which chromosomes will reproduce, crossover to produce next generation of chromosomes, and random mutation of chromosomes in the new generation.

The $fitness\ function$ is the function that the algorithm is trying to optimize [36]. It is used here because the fitness function tests and quantifies how 'fit' each potential solution is. Hence, the fitness function is one of the most pivotal parts of the algorithm and discussed in detail later.

The term $chromosome$ refers to a numerical value(s) that represent a candidate solution to the problem that the genetic algorithm is trying to solve. Each candidate solution is encoded as an array of parameter values, a process that is also found in other optimization algorithms. If a problem has N_{par} dimensions, then typically each chromosome is encoded as an N_{par}-element array:

$$chromosome = \left[p1, p2, \dots, p_{N_{par}}\right]$$

where each p_i is a particular value of the i^{th} parameter. It is up to the creator of the genetic algorithm to devise how to translate the sample space of candidate solutions into chromosomes. One approach is to convert or encode each parameter value into a bit string (sequence of $1's$ and $0's$), then concatenate the parameters end-to-end like genes in a DNA strand to create the chromosomes [38, 36], and it remains a suitable method for discrete solution spaces.

Modern computers allow chromosomes to include permutations, real numbers, and many other objects. However, our thesis work is also based on a bit string type, we will focus on binary chromosomes type. A simple genetic algorithm flow chart is depicted in Figure 3-1. In this figure the selected individuals N_p during the selection process are a sub-set of populations N which are initially created and $N \gg N_p$.

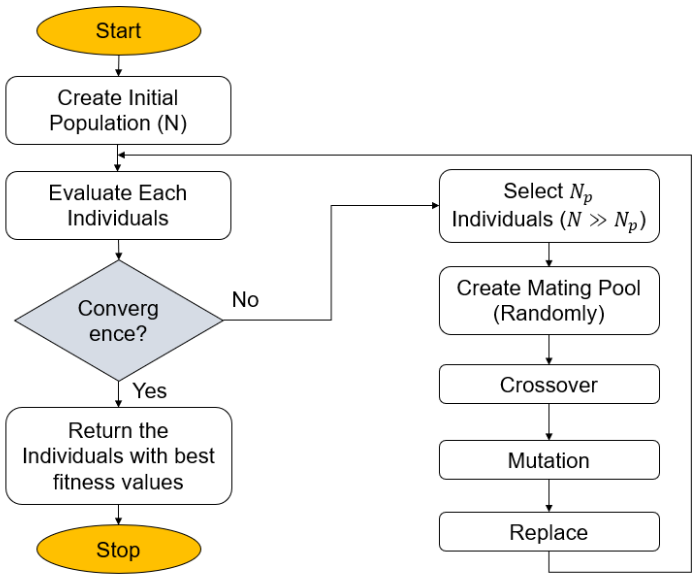


Figure 3-1 Simple genetic algorithm process [25, 39].

A genetic algorithm begins with a randomly chosen assortment of chromosomes, which serves as the first generation (initial population). Then, each chromosome in the population is evaluated by the fitness function to test how well it solves the problem at hand.

Now the $selection\ operator$ chooses some of the chromosomes for reproduction based on a probability distribution defined by the user. The fitter a chromosome is, the more likely it is to be selected. For example, if f is a non-negative fitness function, then the probability that chromosome C_X is chosen to reproduce might be:

$$\mathrm{P}(\mathrm{C_X}) = \left| \frac{\mathrm{f}(\mathrm{C_X})}{\sum_{\mathrm{i}=1}^{\mathrm{p}_{\mathrm{N_{pop}}}} \mathrm{f}(\mathrm{C_i})} \right| \qquad (3\text{-}1)$$

Note that the selection operator chooses chromosomes with replacement. So, the same chromosome can be chosen more than once which adds complexity. This situation is eliminated in NSGA-II which is discussed in the following sub-sections later.

The $crossover\ operator$ resembles the biological crossing over and recombination of chromosomes in cell meiosis. This operator swaps a subsequence of two of the chosen chromosomes to create two offspring. For example, if the parent chromosomes

$$\text{P1}: [11010111001000]\ and\ \text{P2}: [01011101010010]$$

are crossed over after the fourth bit, then the following two of their offspring are created:

$$\text{Offsping1}: [01010111001000]\ and\ \text{Offsping2}: [11011101010010]$$

The $mutation\ operator$ randomly flips individual bits in the new chromosomes (turning a 0 into a 1 and vice versa). Typically, a mutation happens with a very low probability, such as 0.001. Some algorithms implement the mutation operator before the selection and crossover operators; this is a matter of preference. At first glance, the mutation operator may seem unnecessary. In fact, it plays an important role, even if it is secondary to those of selection and crossover.

$Selection$ and $crossover$ maintain the genetic information of fitter chromosomes, but these chromosomes are only fitter relative to the current generation. This can cause the algorithm to converge too quickly and lose potentially useful genetic material ($1's$ or $0's$ at particular locations). In other words, the algorithm can get stuck at a local optimum before finding the global optimum. The mutation operator helps protect against this problem by maintaining diversity in the population, but it can also make the algorithm converge more slowly.

Typically, the selection, crossover, and mutation process continue until the number of offspring is the same as the initial population so that the second generation is composed entirely of new offspring and the first generation is completely replaced. However, some algorithms let highly fit members of the first generation survive into the second generation.

Now the second generation is tested by the fitness function, and the cycle repeats. It is a common practice to record the chromosome with the highest fitness (along with its fitness value) from each generation, or the best-so-far chromosome [31, 25, 36]. Genetic algorithms are iterated until the fitness value of the best-so-far chromosome stabilizes and does not change for many generations. This means the algorithm has converged to a solution(s). The whole process of iterations is called a run. At the end of each run, there is usually at least one chromosome that is a highly fit solution to the original problem. Depending on how the algorithm is written, this could be the most fit of all the best-so-far chromosomes or the fittest of the final generation.

The last step of the algorithm is $termination$. Repeat the above selection, crossover and mutation process until the fixed number of generations is reached or the best fitness value is no longer increasing.

There would be two major problems in GA applications. One is the achievement of the fitness function that provides fitness values of individuals. It should be formulated in detail since it may cause extra computational complexity for GA. Another problem is that there is a need for a diverse population because premature convergence is risky for the well-distributed set.

The performance of a GA depends highly on the method used to encode candidate solutions into chromosomes and the particular criterion for success, or what the fitness function is actually measuring. Other important details are the probability of crossover, the probability of mutation, the size of the population, and the number of iterations. These values can be adjusted after assessing the algorithm's performance on a few trials runs, else the running time will be too large and might be impossible to compute in the local machine.

The larger the population sizes would cause computational complexity whereas the smaller sizes might not provide optimal solutions. Therefore, the size of the population should be considered very carefully. Crossover and mutation are applied to keep variation in the population to have randomness and increase the performance of a GA.

Genetic algorithms are used in a variety of applications. Some prominent examples are automatic programming and machine learning. In terms of telecommunication engineering, GAs have been used by researchers for various purposes such as coverage, QoS, and energy efficiency. In [40, 32, 17], authors have proposed a method where they used GA for the wireless network design in order to reduce energy consumption. In their study, they considered energy efficiency from the beginning of their network design and they succeeded energy saving between 10% and 30%, and network traffic coverage ratio between 5% and 20% in the simulations.

In [25, 33], GA is used to optimize the locations of base stations. Authors considered the trade-off between system capacity maximization and the number of base stations, and between cell-edge performance maximization and number of BSs. Similarly in [17], the energy-efficient GA algorithm (more capacity to the zones of the service area where the traffic is more likely to appear) is proposed for BSs location problem, instead of traditional planning strategy, which is placing small cells at the center position of the hotspot.

Therefore, there are various GA based algorithms in the literature. Some of these algorithms are Multi-objective Genetic Algorithm (MOGA), Pareto-Archived Evolution Strategy (PAES), Non-dominated Sorting Genetic Algorithm (NSGA) and NSGA-II. In the following sections, NSGA and NSGA-II are introduced as one of the most efficient algorithms for multi-objective optimization problems, and since we have applied in this thesis work.

3.2 Non-Dominated Sorting Genetic Algorithm

Non-Dominated Sorting Genetic Algorithm (NSGA) is a type of genetic algorithms for multi-objective optimization. It is the ancestor of NSGA-II which is used in this thesis. NSGA is different from the other GAs in terms of the selection process. At the beginning of NSGA, the algorithm ranks individuals based on their non-dominations. Afterward, the first group from the current population is identified to define the first nondominated front and they are assigned dummy fitness values. It is good to note that dummy fitness values are assigned to all of the non-dominated individuals. The efficiency of the NSGA is the usage of dummy fitness values because it does not use the objective functions for each iteration to create new generations.

As mentioned earlier, diversity is an important factor for GAs. In order to handle the diversity in the NSGA, selected non-dominated individuals are shared with their dummy values. Fitness sharing is a term used to maintain a stable population. It is based on the approach where individuals in the same sub-population should share available resources. When a number of individuals are in a certain area, fitness value is degraded more. After the sharing step, the first group of non-dominated individuals is ignored in order to process the next non-dominated individuals in the same way. For each processing step of non-dominated individuals, NSGA changes dummy fitness value that is smaller than values of previous fronts.

These steps are repeated until all population is classified into different fronts. After all members of the population are classified into different fronts, NSGA reproduces population depending on the dummy fitness values. Then, crossover and mutation are applied to the population.

Reproduction, crossover, and mutation are done until the end of the iterations to find the optimal values [41].

3.3 Fast NSGA Improvements

Different algorithms have been developed for many years to improve the quality of previous algorithms. In [25, 41], the authors proposed fast NSGA, called NSGA-II, by improving the NSGA. Mainly, NSGA-II is a searching algorithm for finding non-dominated solutions or Pareto front of the multi-objective optimization problems.

Although NSGA is a good algorithm, it has different disadvantages. First, NSGA has high computational demand because of considering the number of populations in detail and its non-dominated sorting of individuals after every new generation. NSGA has $O(MN^3)$ complexity where M is the number of objectives and N is population size. Secondly, NSGA is lack of elitism. As in evolution theory, the survival chance of the best genes is higher than other genes. This situation is protected by elitism that combines a new generation with the old generation to create better solutions (keeping the best individuals from the parent and child population). Thirdly, the NSGA uses a sharing approach to maintain diversity by using the sharing parameter. On the other hand, the sharing parameter is not demanded and diversity should not depend on parameters [25, 41]. Hence, NSGA-II has been introduced to take the advantages over NSGA.

NSGA-II starts with the population initialization that has size N. Afterwards, objective functions are used to evaluate the fitness values of individuals in the population. Depending on fitness values, the algorithm sorts individuals. In order to select individuals from the population, NSGA-II uses crowding distance selection. The next step is to evaluate objective functions after crossover and mutation are operated to create a new generation.

As mentioned before, NSGA-II has elitism to preserve good solutions. NSGA-II combines old and new generations to preserve elitism and ranks non-dominated individuals. The algorithm selects N individuals to continue the process. If the termination criterion is not met, the algorithm continues until the termination criterion is matched [41, 42].

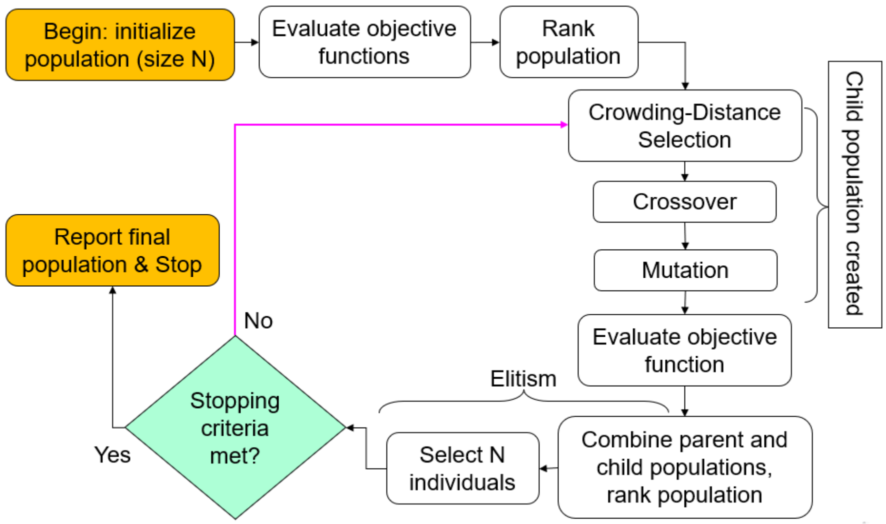


Figure 3-2 NSGA-II flow chart [41].

NSGA uses sharing function to maintain diversity in the population. In sharing function, a user can define the sharing parameter that identifies the extent of sharing between members. The sharing parameter is related to a distance metric that is used to find proximity measure between two members. Within the distance metric, two solutions share each other's fitness value. However, sharing function has difficulties where it depends on the sharing parameter defined by the user.

Moreover, all solutions have to be compared to each other and it causes complexity of the sharing function which is $O(N^2)$. In NSGA-II, the sharing function method is removed, and a crowded distance is proposed. A particular solution has a crowding distance value that is calculated by using the difference of neighborhood solutions around a particular solution, and it is calculated for each solution in the front.

In general, since the nature of the objectives in this research are opposing each other, optimization of individuals (from candidate locations) to the global solution is required. Unlike another optimization algorithms, genetic algorithms search parallel from a population of points. So, it is less complex, and it is more accurate to provide global optimal solution than local optimal since it progresses from a population of candidate solutions instead of a single value. Therefore, genetic algorithm is used in this thesis for optimization of the esteemed multi-objective problems.

4 Methods for Energy Efficiency and Capacity Enhancement

In this Chapter, the proposed approach, system model and performance metrics used in this thesis are presented. In addition, optimization problems are given.

4.1 System Model

Modeling is a simplified representation of a system as methods or materials at some particular point in time or space intended to promote understanding of the real system [20]. The representation could be physical, mathematical or otherwise logical. In addition to a system, the representation could be for an entity, phenomenon or process. Thus, in order to achieve the thesis objective, the system (or process) is organized as a methods and materials as in Figure 4-1, and has been followed step by step.

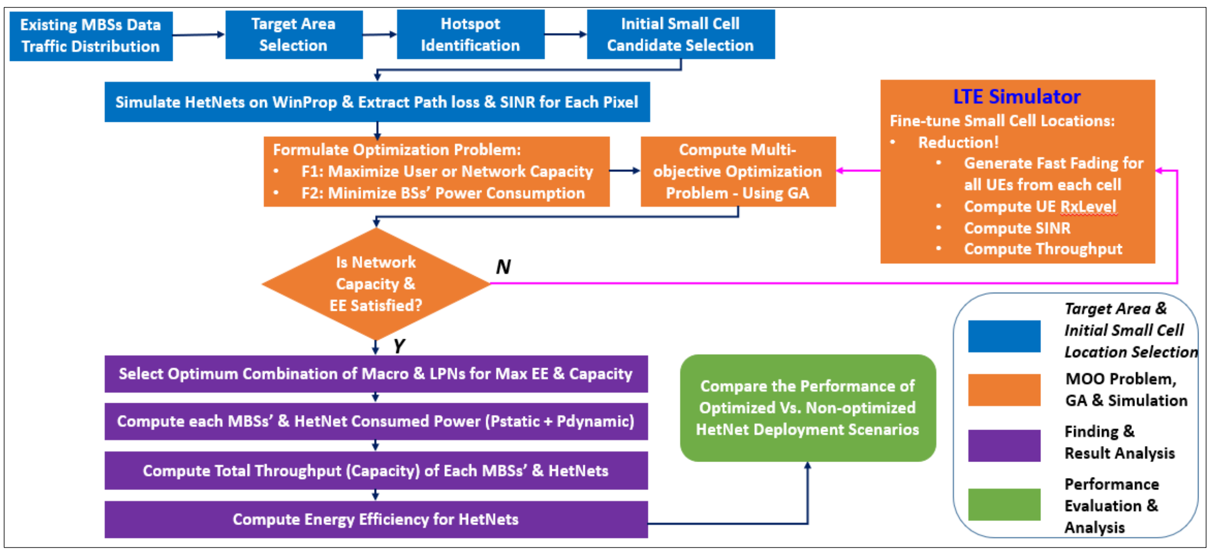


Figure 4-1 Proposed approach

4.1.1 Methods

In this research, the real data traffic from the existing BSs of Addis Ababa UMTS network is collected. In order to ensure that the network can carry the maximum volume of expected traffic while planning, simulations for further optimization are carried out by considering the busy hour peak data traffic and some of the basic system models as a methods, and optimization problems are discussed in detail below.

The growing interest in new, reliable and non-uniform data service demands in mobile telecommunications has resulted in an increased number of installed BSs [26], which is done through the commonly used approach of macro BSs densification. This deployment has contributed to the significant growth of the total energy consumed by BSs, which leads to energy inefficient in non-uniformly distributed and growing mobile data traffic.

Therefore, the goal is to provide and investigate an energy efficient HetNet in a service area $'\mathcal{A}'$ composed of existing macro BSs with higher TX-power (for larger coverage) and small-scale BSs with lower TX-power (for the hotspot areas with high data rate demand). So, to handle the user's high data rate demand and improving the target area network efficiency, the service area is divided into smaller grids $'\mathcal{g}'$ which are also known as pixels. Then, hotspot identification, small cell location selection, and thus optimal small cell deployment are carried out for the solution. It is based on current macro BSs' traffic (active user) density map, users' usage scenarios and spatial data traffic distribution.

In the case of HetNet architecture, the macro BSs ensure permanent coverage, while the localization of smaller cells depends on current (and forecasted) traffic load. Hence, the implementation of small cells in the HetNet architecture can increase the energy efficiency of cellular networks while keeping the minimum required QoS.

The system output is affected by many of the system input parameters, such as the target area, grid size, cell area, the radius of hotspot area, inter site distance, the distance between the macro BS and the hotspot, the BS power level, and the traffic volume of each area. In this case, under each grid, a set of user equipment (UEs) are referred and each has a certain amount of traffic demand and can be served by either macro or small cell for the resource.

The fundamental system resources include the number of users, bandwidth, site location, energy, information, time and capital. So, the aim is to use (and provide) those resources as efficiently as possible. The efficiency is measured by performance metrics, such as system throughput and network energy efficiency defined as throughput per power consumption (Mbps/Watts or Mbits/Joule) [17].

The study area has considered downlink OFDMA with system bandwidth B. It also has a maximum of L predefined candidate small cell locations based on combined analysis of collected data sets. Each candidate location represents a possible location for placement of a small cell with maximum transmit power $P_{\max}$.

The radio frequency propagation path loss matrix, which is resulted from the WinProp for a given service area can be represented by the matrix $\mathcal{L} \in \mathbb{R}^{\mathcal{A}\times L}$, whereby, $\mathcal{L}(a,l)$ represents the path loss between the a^{th} pixel and the small cell deployed in the l^{th} candidate location. The selection of serving small cell in each pixel is based on the maximum received signal power in that pixel. Thus, the received signal power at the a^{th} pixel of the signal from the small cell deployed at the l^{th} candidate location is given by:

$$\mathrm{P_{rx}(a,l)} = \left(\mathrm{P_{max}} - \mathcal{L}(\mathrm{a,l})\right) \cdot \mathrm{x(l)} \tag{4-1}$$

where the vector $x \in \{0,1\}^L$ indicates whether a small cell is deployed at the l^{th} candidate location.

$$x(l) = \begin{cases} 1, & if\ the\ small\ cell\ is\ deployed\ at\ the\ candidate\ location \\ 0, & otherwise \end{cases}$$

In fact, the row vectors of x could refer to the network topology since they represent the actual cellular layout and therefore the main network planning variable.

The average signal-to-interference-plus-noise-ratio (SINR) at a^{th} pixel is given by

$$\gamma(\mathrm{a}) = \frac{\mathrm{P_{rx}(a,l)} - \mathcal{F}(\mathrm{a,l})}{\sum_{\mathrm{i=1,\ l \neq l^*}}^{\mathrm{L}} \mathrm{P_{rx}(a,l)} + \sigma^2} \tag{4-2}$$

where σ^2 is the noise power, l^* is the serving cell for that pixel and $\mathcal{F}(a,l)$ is the fast-fading between the a^{th} pixel and the small cell deployed in the l^{th} candidate location. Subsequently, the throughput $\tau(a)$ achievable in the a^{th} pixel is obtained through mapping the above SINR results using a modified Shannon formula [25]:

$$\tau(\mathrm{a}) = \begin{cases} \mathrm{B(a)} \cdot \mathrm{B_{eff}} \cdot \mathrm{log2}(1 + \gamma(\mathrm{a})\ \mathrm{SINR_{eff}}), & \mathrm{if}\ \gamma \geq \gamma_{\min} \\ 0, & \mathrm{otherwise} \end{cases} \tag{4-3}$$

where $B(a)$ is bandwidth allocated at ath pixel, γ_{min} is the minimum required SINR, and the constants $SINR_{eff}$ and B_{eff} are effective SINR and effective bandwidth values used to adjust the model to account for realistic implementation inefficiencies.

4.1.2 Materials

In addition to the above-stated parameters in our system, some of the related models as materials are discussed as follows.

a) Spatial Traffic Model and User Distribution

In this research, the network traffic load is simulated in terms of the number of active mobile data users. Within the network area, the location of where users are added is based on the spatial traffic density map, which is generated based on existing macro BSs real data traffic statistics from the actual network, and also based on randomly generated spatial user density map [43, 44].

The spatial user density map was derived from the user-level packet switched traffic measurements, for instance, High-Speed Downlink Packet Access (HSDPA) averaged for busy hour traffic conditions. Thus, it is used as a tool for identifying the hotspot and blind spot zone for small cell initial candidate location selection.

It is assumed that each user in a pixel generates the averaged same amount of traffic. Similarly, carried traffic per cell is equivalent to traffic density generated by the number of simultaneously active users per cell.

The users can be distributed within the network in two ways: uniform and non-uniform (hotspot). In uniform distribution, UEs are randomly and uniformly distributed in the geographic coverage area of macro cells whereas in the hotspot, a fraction of the total UEs are randomly placed within the coverage area of small cells and the remaining UEs are randomly and uniformly distributed within the macro cells [45].

The hotspot is a more realistic approach than purely uniform distribution since mobile users are not uniformly distributed in real life. In which, areas such as schools, shopping malls & hospitals are densely populated. Some hotspots may periodically turn on & off, depending on the time of the day. For instance, a hotspot may occur in a business center between 8am - 5pm, whereas another may operate in a shopping mall between 10am - 10pm. Therefore, cell busy hour traffic is critical and hence considered for hotspot zone identification and further network dimensioning.

b) Propagation Model

The research presented in this thesis is based on a real, dense urban Addis Ababa city LTE cellular network. This means that the location, antenna height, orientation and configuration of all BSs in the area have been made available for the research. A clutter map of the area representing the type of terrain is also used to compute the path loss value of both macro cells and small cells by using the WinProp simulation tool.

Then, for every pixel which has 5m resolution within the area, the SINR is computed. This is used to allocate users to their serving BS. As stated earlier, the SINR is also used to calculate the achievable throughput of a user in a particular pixel [44].

c) Coverage Model

Cellular coverage is designed based on an average received power $P_{rx}(R)$ at the cell boundary with cell radius R. The cell coverage area can be defined as the fraction of the cell area where received power is above a given level P_{min}, which is also referred as receiver sensitivity at which a throughput requirement is fulfilled [32]. Thus, network coverage ratio is expressed as the ratio of carried traffic and total expected traffic (demand) of the service area:

$$\text{Coverage Ratio } (\eta_{\text{Traffic}}) = \frac{\text{Carried traffic}}{\text{Total expected traffic}} \tag{4-4}$$

Moreover, the outage probability of the cell is defined as the percentage of the area within the cell that does not meet its minimum power requirement P_{min}; namely

$$\mathrm{P_{out}} = \mathrm{p}(\mathrm{P_{rx}}(\mathrm{r}) < \mathrm{P_{min}}) = 1 - \eta_{\text{Traffic}} \tag{4-5}$$

In other words, it can be expressed in terms of cell-edge user throughput (example, 10th percentile), achieved < minimum required data rate ($R_{min} = 512\ kbps$). Hence, the coverage area of a cell is a function of receiver sensitivity P_{min}, carrier frequency f, transmitted power P_{tx}, path losses exponent and shadowing standard deviation. Therefore, by limiting R_{min} to a certain value, the network performance in terms of achievable throughput and EE for the target area is estimated.

d) Resource Allocation

When more than one user is present within a cell, available physical resource blocks (PRB) need to be shared. In the LTE simulation tool which is used in this research, user scheduling is performed as follows [44]. All users within a specific cell are sorted according to their SINR. Then, available PRBs to guarantee their R_{min} are first allocated to the users with the highest SINR, thus requiring the least amount of resources. Finally, any remaining resources are shared in a round robin fashion.

In addition to the above resource allocation procedures, small cells are biased with the values ranging between *(3~10dBm)* to be more attracted and selected by the active users than the nearby macro cells, which are supposed to serving hotspot zones in the study area [17, 25].

e) Spectrum Allocation Strategy

Two frequently used spectrum allocation schemes between macro BSs and small cells are a co-channel assignment, where two layers of BSs share the same frequency and on contrary, orthogonal assignment, where two layers of BSs use orthogonal spectrum. In this thesis work, it is assumed that there is no limitation on the spectrum, and thus orthogonal assignment is considered.

f) Base Station Selection Strategy

This technique is mainly applied to avoid frequent vertical handoffs between the layers [17]. The received power of grid i from sector σ of macro BS m is given by

$$\mathrm{P}(\mathrm{i},\mathrm{m},\sigma) = \mathrm{G}_{\mathrm{im}\sigma} * \mathrm{g}^{\mathrm{m}\sigma}_{\mathrm{macro}_{\mathrm{ant}}} * \mathrm{Los}_{\mathrm{Pen}} * \mathrm{Tx}_{\mathrm{m}} \tag{4-6}$$

where, $G_{im\sigma}$ is the path loss from grid i to sector σ of macro BS m, $g^{m\sigma}_{macro_{ant}}$ is the antenna gain of sector σ of macro BS m, Los_{Pen} is an additional 20dB penetration loss and Tx_m is the transmission power of the macro BS. Similarly, the received power of grid i from small cell BS j is given by

$$\mathrm{P}(\mathrm{i},\mathrm{j}) = \mathrm{G}_{\mathrm{ij}} * \mathrm{g}^{\mathrm{j}}_{\mathrm{SC}_{\mathrm{ant}}} * \mathrm{Los}_{\mathrm{Pen}} * \mathrm{Tx}_{\mathrm{SC}} \tag{4-7}$$

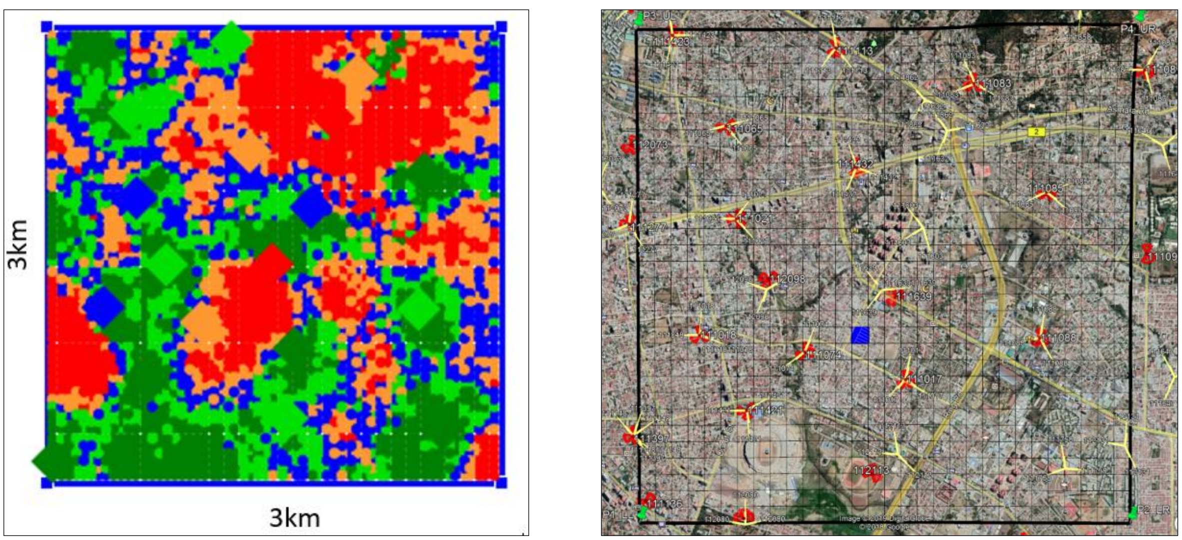
where, G_{ij} is the path loss from grid i to small cell BS j, $g^{j}_{SC_{ant}}$ is the antenna gain of small cell j, similarly Los_{Pen} is an additional 20dB penetration loss and Tx_{SC} is the transmission power of the small cell. In this thesis, the study area which is 3kmx3km is divided into a smaller grid with 5m resolution, which has a total of 360, 000 pixels.

Therefore, BS, either macro or small cell is selected based on the highest SINR of each pixel and their throughput is computed by using the previously stated technique of SINR to throughput mapping. To this end, the target area system capacity is formulated as the sum of all pixel's throughput.

4.2 Target Area Selection and Geographic Observations

As we have discussed in the previous sections, the target area is selected based on peak hour downlink data traffic demand offered by the serving BSs, their receiving power level (RSCP), active number of data users and their downlink traffic demand, which are collected from ethio telecom performance monitoring tool. Distributions for the collected data set, both user level, and BS level, are carried out over the network coverage area of Addis Ababa city UMTS network. Then, the area generating higher data traffic demand is selected as the target area for the study as depicted in Figure 4-2.

This figure shows the traffic distribution of data users under each grid with a resolution of 100 meters and the existing 19 macro BSs located in the target area of covering 9km^2 wide. Then, the aggregate or average values of each data set under each grid is set to the centroid of that grid.



a) Traffic demand distribution b) Geographic top view

Figure 4-2 Target area's macro BSs and user demand distribution and geographic observation

The colors indicate the traffic density of each user in the pixels and serving BSs (in the diamond square). Deep green, light green and blue colors indicate the area with user throughput of 0.7Mbps and above (which is considered as hotspot zones), whereas the red and orange colors specify the area with low data traffic demand in which users achieved 0.2Mbps to 0.6Mbps DL throughput.

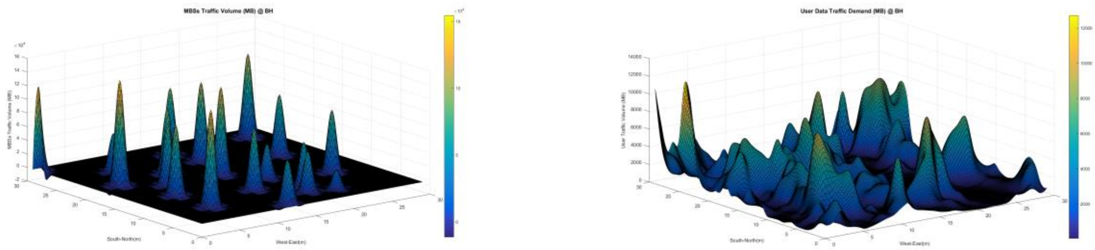
4.3 Initial Candidate Small Cell Location Selection

The spatial dynamics of cellular traffic usage over the spatial domain (i.e. geographic area), is closely associated with network performance. Mobile users, the number of BSs and traffic distribution are three elementary parts in the service chain of cellular networks, especially in the RANs [46]. Humans with similar social behaviors tend to live together, which leads to various traffic hotspots and causes BSs to be deployed densely as clusters in a certain area. Intuitively, the BS spatial distribution would be heavy tailed just like the spatial traffic dynamics.

Under the usual assumptions of homogeneous traffic density, the capacity of a cell under a given area is trivial to compute. On the other hand, the homogeneity assumption implies that all cells reach their capacity limits simultaneously. This cannot be expected when traffic is nonhomogeneous. Therefore, if area capacity is defined as the maximum traffic load such that the required blocking probability is not exceeded in any cell, the cell capacities will usually not be fully exploited except in a single cell [47]. This should be felt particularly in systems with only a few channel resources like GSM systems with small bandwidth. In this thesis, we reveal the heterogeneity of BSs deployment and traffic demand on spatial dimensions at a busy hour, based on realistic data records from Addis Ababa city UMTS cellular network.

To get an impression of capturing the cellular data traffic distribution, the spatial traffic distribution of the target key performance indicators (KPIs) are analyzed. Possible areas of application with this distribution are hotspot identification, capacity estimation, and potential candidate small cell location selection. Normally, the actual deployment of BSs in the long term is highly correlated with human sociality and traffic demand distribution [20].

Therefore, the target KPIs, which are DL traffic volume, DL throughput, RSCP, and the active number of data users are collected from the ethio telecom performance monitoring tool at a busy hour. Then, the distribution of each KPIs is carried out by using MATLAB. This is very helpful to characterize the target area's traffic behavior, identify the hotspot zones and then localize small cell locations by using a combinatorial condition of the specified KPIs. The presence of hotspots drives the operators to provide more capacity in those areas by deploying cells of smaller sizes. The spatial distribution of each KPIs and the tailored model are given as follows:

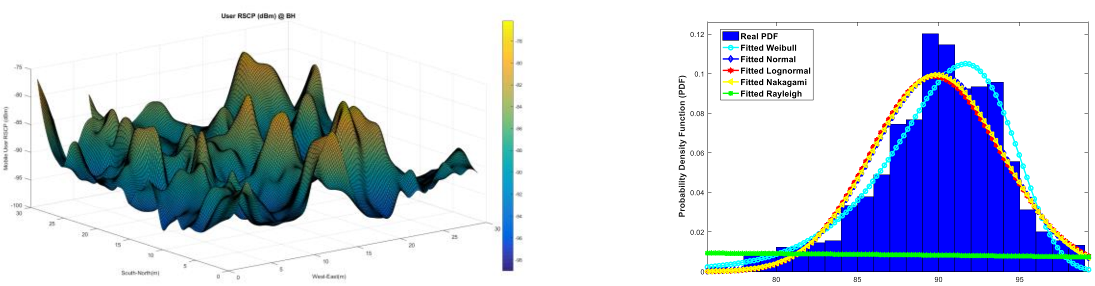


a) BS Level (MB) b) User Level (MB)

Figure 4-3 User and BS level DL traffic demand Distribution

The average data traffic demand distribution of the area serving BSs and user level distribution over the defined grids are depicted in Figure 4-3. According to this figure, the users are offering the downlink traffic ranging from 34 MB to 12 GB, on average 1.6 GB per day. It is also observed that there is 2GB to 12 GB/hour and 35Gb to 255 GB/day traffic demand offered by each BS as shown in Figure 4-6.

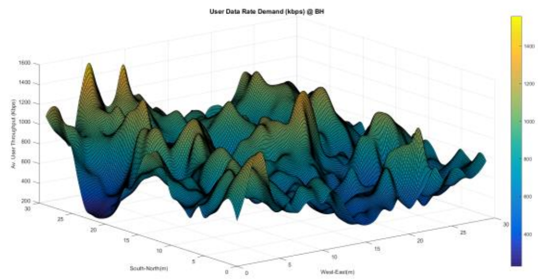
Similarly, the distribution for the rest of KPIs is made and their best fitting model is indicated. For instance, the average received power level distribution is depicted in Figure 4-4 and it is best fitted to Weibull distribution, which is done via maximum likelihood estimation method. In this figure, the area average signal receiving power level in order to guarantee the users offered traffic is about -90 dBm.



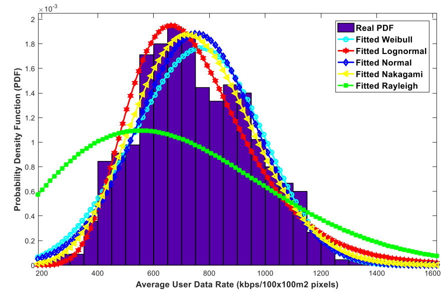
a) RSCP (dBm) b) PDF

Figure 4-4 Distribution of RSCP to achieve user demand and its PDF (fitted to Weibull)

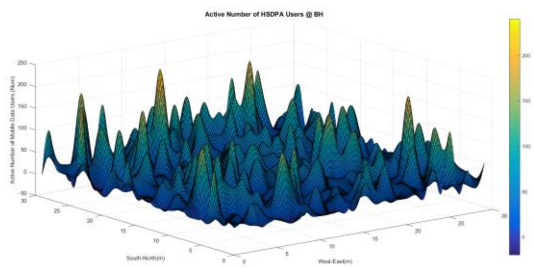
In addition, the active number of data users and their average achievable throughput over each grid of the study area based on the above receiving power level are distributed as shown in Figure 4-5. According to this figure, the distribution of the active number of data users is fitted to Lognormal whereas their achieved DL throughput is fitted to Nakagami. In this study area, on average there is about 32 active number of data users with their average throughput of 0.75 Mbps.



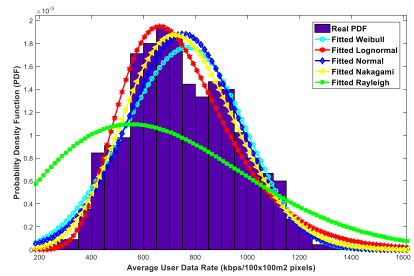
a) Average DL user throughput (kbps)



b) PDF (fitted to Nakagami)



c) Active number of data users



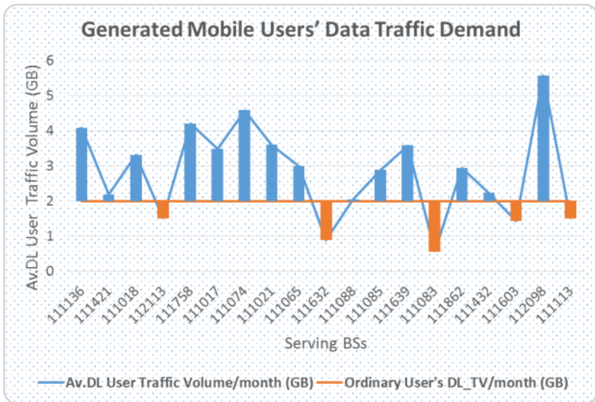
d) PDF (fitted to Lognormal)

Figure 4-5 Distribution of the active number of data users and their average throughput

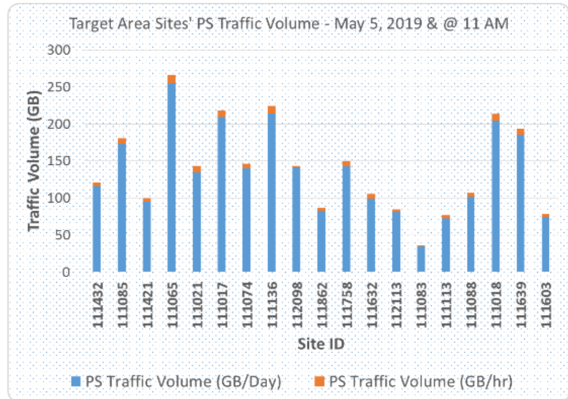
As I have mentioned earlier, studying the spatial distribution of BSs over the territory has a dual purpose. First, it is essential to characterize and to understand the BS deployment in current operators' networks. Secondly, to provide insights into the evolution of the network, such as small cell densification. Therefore, by considering the above real data traffic distributions as a guideline for identifying the hotspot and poor coverage areas, the KPIs combinatorial method has been applied to select the initial candidates of potential small cell locations.

In addition to the above KPIs, I also have considered the active subscriber density and monthly usage scenarios of the mobile user's data traffic demand for the candidate selection [48]. In this case, the user's usage scenario is classified in two ways, that is under heavy user scenario with consuming 5GB/month, which indicates the business area and under ordinary user scenario, in which users consume 2GB/month and tells us residential area.

The activity factor for heavy user's scenario is 25% (assuming 4 busy hours/day or all data users are active for 4 hours/day) [48], and for the ordinary user's scenario it is 12.5% (assuming 8 busy hours per day). To this end, Figure 4-6 indicates the two usage scenarios under the study area. So, almost 75% of BSs are under heavy user scenario which indicates 75% of the target area is business area whereas the rest of it is residential area due to the existence of BSs generating ordinary user's usage scenario.



a) Usage scenarios



b) Day busy hour data traffic volume

Figure 4-6 Target area BSs user usage scenarios and carried busy hour data traffic volume [8]

To this end, initially predefined candidate small cell locations, which are resulted from the above stated method and considerations are shown in Figure 4-7. The colors in this figure indicate the location of a different kind of BSs and intended solutions. The black diamonds or three-sectored points indicate the location of existing macro BSs. The yellow points indicate the small cell locations, in which deep green pyramids are locations for type1 ($P_{tx} = 2W$) small cells (which is for coverage and capacity solution). Similarly, light green pyramids are locations for type1 small cells (but for a capacity solution only) whereas blue and pink pyramids are locations for type2 ($P_{tx} = 0.2W$) SCs (for capacity solution).

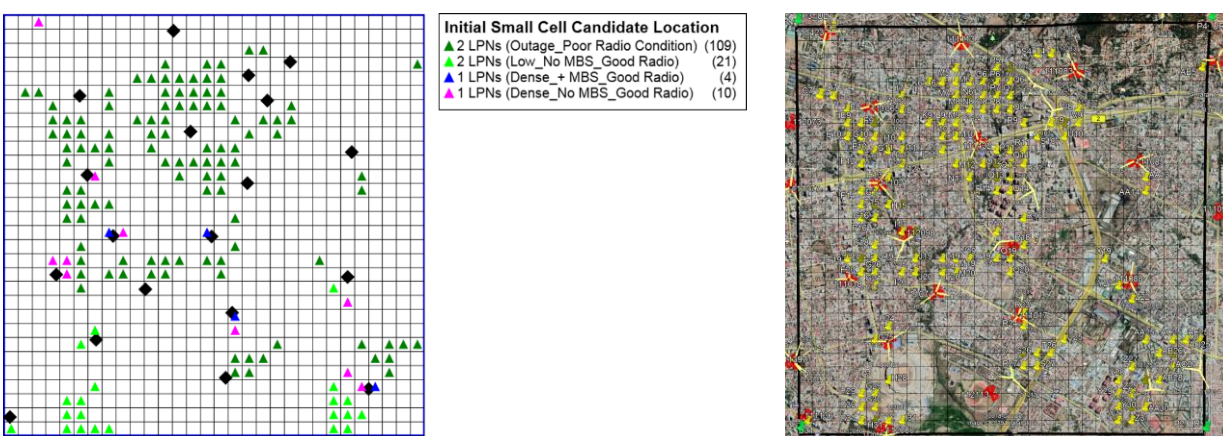


Figure 4-7 Geographic observation of small cell candidate locations

4.4 Performance Metrics for Network Planning

In order to achieve the best solutions in wireless system design, different metrics are taken into consideration. Generally, the goal of network operators is to maximize capacity and coverage in a service area. Moreover, network operators are also willing to minimize their power consumption as a primary concern. In order to reduce power consumption, or maximize energy efficiency, they use a smaller number of BSs in their service areas. However, more BSs can provide more capacity and coverage.

This situation creates a trade-off for network operators, such as ethio telecom. In order to address this trade-off in simulations, four different metrics are considered in this research. These metrics and their explanations are given below [33]:

- $Number\ of\ base\ stations\ (f1)$: It represents the number of base stations in the wireless system design for the study area.
- $Network\ capacity\ (f2)$: It represents the target areas' total aggregate throughput.
- $Energy\ efficiency\ (f3)$: This metric represents the rate of total aggregate throughput and total power consumption in a cellular system of the target area.
- $Cell - edge\ performance\ (f4)$: It represents cell-edge areas user's performance. These areas are the weakest places of the target area network, it is represented in terms of all pixel throughput 10th percentile.

In addition to these four metrics, coverage ratio and outrage are used to elaborate on the idea of cell edge performance. From here, we can witness that $f3$ is a weighted sum of $f2$. In other words, both metrics are linearly interrelated. So, maximizing energy efficiency is also maximizing system capacity for a given limited number of BSs with their configured heterogeneous transmission power. In general, all the above-mentioned system performance metrics are used in the simulations in order to investigate the performances of different topologies resulted from the genetic algorithm.

4.5 Multi-Objective Optimization Problem Formulation

Network operators deploy base stations in order to achieve maximized capacity and coverage in service areas. In order to find locations of BSs maximizing capacity, coverage and energy efficiency in the service area, network operators investigate the area to find possible BSs locations.

However, the large number of BSs locations would complicate investigation for network operators. Thus, optimization algorithms can be used to find optimal locations.

Optimization problems are concerned about the targets as aggregate capacity $f2$, energy efficiency $f3$, and cell edge performance $f4$. If the target is to maximize the aggregate capacity of the system, network capacity metric $f3$ can be selected to design the network otherwise network energy metric $f2$ is selected to maximize and design EE wireless system. However, cell edge performance may have priority in wireless system design. Therefore, cell-edge performance metric $f4$ can be selected to design the wireless system. In this thesis, two different network optimization problems are considered, maximize system capacity and energy efficiency, and they are discussed in the next sub-sections. Hence, operators can select one of them depending on their requirements.

Generally speaking, denser wireless networks can provide more capacity because of high-frequency reuse. On the other hand, a large number of BSs increase the power consumption of wireless systems. So, to maximize system capacity while minimizing the number of BSs, $f2$ or $f4$ can be optimized with the number of BSs $f1$. Similarly, to maximize energy efficiency while minimizing the number of BSs, $f3$ can be optimized with the number of BSs $f1$.

We have seen that there can be a trade-off between those metrics. This trade-off creates multidimensional optimization and it is called multi-objective optimization [38]. Actually, this trade-off can be represented by the Pareto optimal set (front) that addresses the possible solutions for multi-objective optimization. It is the set of optimal solutions that are not dominated by any other solution in the search space. In Figure 4-8, an example of the Pareto front is given. Objective 1 and objective 2 are two dependent variables. An increase in one of them causes a decrease in the other.

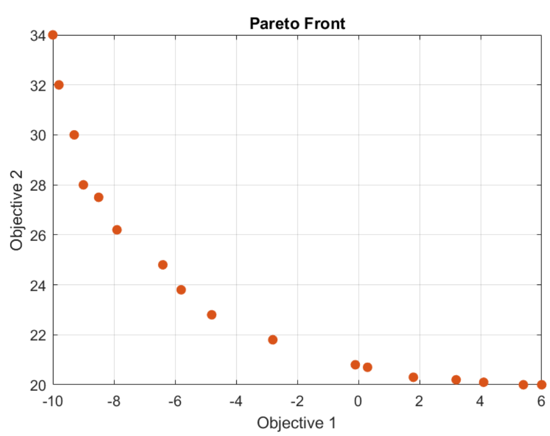


Figure 4-8 Two-dimensional, non-dominated front of MOO example [25]

4.5.1 System Capacity Optimization Problem

In order to find the best trade-off between the number of base stations and aggregate capacity, following the multi-objective optimization problem, is proposed as follows:

$$\mathrm{minimizef} \; = [\mathrm{f1}, -\mathrm{f2}] \quad (4\text{-}8)$$

As it is stated earlier, the aggregate system capacity is formulated as the sum of all pixels' throughput in the study area. Moreover, each grid aggregate throughput is formulated below$\mathrm{r_i} = \sum_{\mathrm{n=1}}^{\mathrm{N}} \mathrm{R_n}$:

$$\mathrm{r_i} = \sum_{\mathrm{n=1}}^{\mathrm{N}} \mathrm{R_n} \quad (4\text{-}9)$$

where, R_n is n^{th} user throughput (capacity), r_i is i^{th} grid throughput and N is the total number of grids. The n^{th} user throughput with in a specific base station i is given as:

$$\mathrm{R_n} = (\eta_\mathrm{i} \mathrm{N_{RBn}}) * \log_2\left(1 + \frac{\mathrm{P_{tx}} - \mathrm{ALF_n}}{\mathrm{IN_n}}\right) \quad (4\text{-}10)$$

where R_n is from modified Shannon:

$$\mathrm{R_n} = (\eta_\mathrm{BW} \eta \mathrm{BW_{RB}}) * \mathrm{N_{RBn}} \log_2\left(1 + \frac{\mathrm{P_{tx}} - \mathrm{ALF_n}}{\mathrm{IN_n}}\right) \quad (4\text{-}11)$$

where, $BW_n = \eta_i * N_{RBn}$ and N_{RBn} are of n^{th} user bandwidth and number of the resource block, $\eta_{BW} \eta BW_{RB} = \eta_i$ is i^{th} BS G-factor, which is defined as a function of interference in the cell. It is an indicator of the cell topology and the relation between the received power from the dominant cell. The value varies from one BS to another BS and evaluates the coverage of the network.

In this regard, the capacity maximization problem is formulated as the system fitness or objective function $f1$ as follows:

$$\mathrm{f_1}\!: \max \sum_{\mathrm{i=1}}^{\mathrm{K}} \sum_{\mathrm{n=1}}^{\mathrm{N}} \mathrm{R_{n,i}} = \sum_{\mathrm{i=1}}^{\mathrm{K}} \mathrm{r_i x_i} \quad (4\text{-}12)$$

where, $R_{n,i}$ is the n^{th} user achievable throughput under grid i, and x_i is a decision variable, indicates whether grid i is covered by BS or not:

$$x_i = \begin{cases} 1, & \text{if } x_i \text{ is covered by BS} \\ 0, & \text{otherwise} \end{cases}$$

From the above equations, it is observed that the aggregate capacity in a cell depends on the number of users associated with it, scheduling algorithm, distribution of the G factor (η_i) and the bandwidth of each user (BW_n).

4.5.2 Base Station Power Consumption Optimization Problem

In order to find the optimum values of system capacity and energy efficiency with a limited minimum number of base stations, the topologies containing the best the trade-off between the system throughput and the power consumption performances can be found by the below proposed formulation as follows:

$$\text{minimizef } = [\text{f1}, -\text{f3}] \tag{4-13}$$

Similarly, for the cell-edge performance which is 10th percentile of all pixel throughput, can be found by the proposed formulation as follows:

$$\text{minimizef } = [\text{f1}, -\text{f4}] \tag{4-14}$$

The cell-edge performance will be enhanced or improved with the improvement of SINR values of cell edge pixels with the addition of optimized small cells.

The target of the energy model is mainly to provide the optimum achievable data rate per minimized power consumption. Therefore, the network energy efficiency is defined as the ratio of the network total throughput R_T (which is f_1 as stated earlier) to the network total power consumption PC_T (which is equivalent to the sum of both the macro cell and small cells) [17, 32], which is expressed as:

$$\text{f}_2 = \text{ EE} = \frac{\text{System Throughput}}{\text{Total Power Consumption}} = \frac{\text{R}_\text{T}}{\text{PC}_\text{T}} = \frac{\text{f}_1}{\sum \text{P}_{\text{macro}} + \sum \text{P}_{\text{SC}}} \tag{4-15}$$

Initially, a set of candidate locations for small cells is predefined based on real cellular network DL data traffic. Then, optimal locations will be selected from the provided set of candidate locations $L = \{1, 2, 3, \dots, L_{SC_{candidate}}\}$ in the study area. Each candidate location $l \in L$ contains two decision variables, which indicates grid i is covered by BS or not, namely the selection variable a_l and transmission power of the small cell p_l.

$$a_l = \begin{cases} 1, & \text{if location } l \text{ has small cell} \\ 0, & \text{otherwise} \end{cases}$$

Therefore, the second optimization problem of network EE maximization can be re-written as:

$$\max_{a_l, p_l} EE = \max_{a_l, p_l} f_2 = \max_{a_l, p_l} \left(\frac{f_1}{\sum P_{macro} + \sum P_{SC}} \right) \tag{4-16}$$

In this optimization problem, the two objective functions of network capacity f_1 and network EE f_2 are linearly interrelated, where f_2 is a weighted sum of f_1. Therefore, in this study, we have considered the network EE maximization problem as the multi-objective optimization problem. Moreover, because of the mathematical structure of $f2$ and $f3$, search space is highly non-linear $(2^L - 1)$ and full of discontinuities [38]. Therefore, NSGA-II is used for multi-objective optimization to address the above-stated two conflicting objectives. The total power consumed by each type of BSs is based on their components' power consumption. So, their components and power model are given below.

a) Components of a macro and small cell BSs

In this section, the power consumption for each radio site BSs is determined. These reflect the situation in the currently deployed study area mobile networks. The distribution of power consumption of the various components of BSs is summarized in Figure 4-9. The largest energy consumer in BSs is the radio frequency equipment (i.e. power amplifier and transceivers) [49], which consumes approximately 65% of the total energy. Among the other components of the BS, the important energy consumers are air conditioning (17.5%), signal processing (10%), and the alternating current (AC) to direct current (DC) converter (7.5%). If we take the sum of all those components, we can determine the BS power consumption.

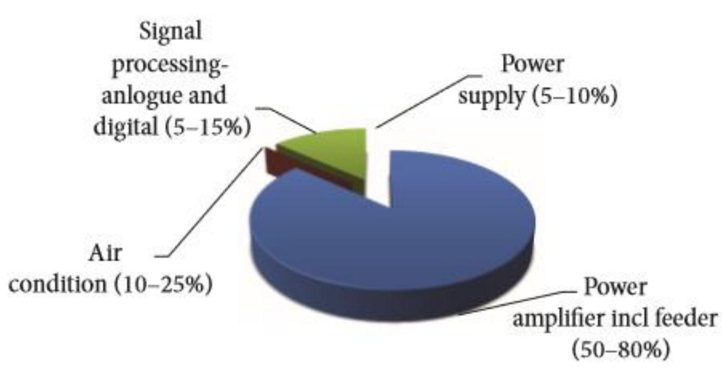


Figure 4-9 Energy consumption for the components of BSs [49]

Table 4-1 summarizes the typical power consumption of different components. These values are retrieved from data sheets of various network equipment manufacturers.

Table 4-1 Power consumption of the components of the different base stations types [49, 50]

Component	Macro cell	Micro cell	Femto cell
Number of sectors (n_{sector})	3	1	1
Number of transmitting antennas per sector (n_{Tx})	1	1	1
Signal processing (P_{proc})	100 W	100 W	7.9 W
Power amplifier (η, P_{amp})	12.8%, 24.7W ($P_{Tx} = 35dBm$) 12.8%, 156.3W ($P_{Tx} = 43dBm$)	12%, 16.6 W	12%, 2.4 W
Transceiver, (P_{trans})	100 W	100 W	1.8 W
Rectifier [AC-DC], (P_{rect})	100 W	100 W	----
Air conditioning (P_{airco})	225 W	60 W	----
Microwave link (P_{link})	80 W	----	----

In general, the above components of BSs are categorized in load dependent (which are signal processing, power amplifier & transceiver) and load independent components. Load dependent components fluctuate during the time with traffic load whereas load independents kept constant.

b) Base Stations Power Consumption Model

In order to assess the energy efficiency of the BSs, power consumption models are used for expressing instantaneous power consumption of macro and small cell BSs. Power consumption of BSs in the RAN contains two parts; fixed power ($P_{constant}$), which is independent of traffic load and dynamic power ($P_{dynamic}$) which varies according to traffic load (F_i). Hence, power consumption per radio site (P_{BS}) for the macro and small cell can be modeled as the linear sum of the two parts [51, 50, 52]. So, the power consumed by macro cell BS is:

$$P_{macro} = P_{constant} + P_{dynamic} * F_i \quad (4\text{-}17)$$

$$where, P_{constant} = n_{sector} * P_{rect} + P_{link} + P_{airco} \text{ and}$$

$$P_{dynamic} = n_{sector} * \left(n_{Tx} * \left(P_{amp} + P_{trans}\right) + P_{proc}\right)$$

Therefore, macro BSs power consumption will have the following form:

$$P_{macro} = n_{sector} * \left(P_{rect} + F_i * \left(n_{Tx} * \left(P_{amp} + P_{trans}\right)\right) + P_{proc}\right) + P_{airco} + P_{link} \quad (4\text{-}18)$$

where n_{sector} the number of sectors, F_i ($i = 0 \dots 23, 0 \le F_i \le 1$) the load factor, n_{Tx} the number of transmitting antennas, and P_{rect}, P_{amp}, P_{trans}, P_{proc}, P_{link}, and P_{airco} the power consumption (in Watt) of the rectifier, the power amplifier, the transceiver, the digital signal processing, the microwave link, and the air conditioning, respectively.

The load factor is defined to correlate power consumption and load variation. So, the power consumption of the load dependent components, which are signal processing, transceiver, and power amplifier should be multiplied by this load factor. Similarly, power consumption for small cell BSs (for instance, pico cells) is given as:

$$P_{pico} = P_{airco} + P_{rect} + F_i * \left(P_{amp} + P_{trans} + P_{proc}\right) \quad (4\text{-}19)$$

Therefore, based on the above power models, power consumption for each type of cell is computed by referring Table 4-1 for their components typical power consumption.

c) Measurements for calculating load factor (F_i)

As we have mentioned earlier load factor (F_i) is defined to correlate power consumption and load variation. It will multiply the load dependent components' power consumption while computing the total power consumption for each type of BSs.

To determine the load factor F_i, measurements are performed for an actual macro BS in the study area of Addis Ababa, Ethiopia. The BSs power consumption measurement due to traffic load is collected from PRS. The group of load-independent components (i.e. the rectifier, the air conditioning, and the microwave link), was not included in these measurements. Then, from the collected dataset the hourly basis average BSs power consumption on the study area is computed. Hence, it is observed between 871 W (at low traffic hour) and 1214 W (at peak traffic hour).

Finally, the load factor for the area serving macro BSs is computed as the ratio of each hour's power consumption to the maximum power consumption of the given day. Therefore, the average load factor F_{av} is identified to be 0.96, which is resulted from generating 10 GB data traffic and 93 Erlang voice traffic demand per BS/hour with the average power consumption of 1165 W.

4.6 Deployment Scenario, Parameters, and Assumptions

In order to investigate the performance of different topologies, 800 users are dropped randomly in different 5x5 m2 pixels in the service area following the uniform or nonuniform spatial traffic distribution. To increase the statistical quality of the study, the 800 random users are dropped repeatedly for 3000 times. This means that 3000 snapshots are used in static system level simulator. Details of system simulation parameters and assumptions are given in Table 4-2.

Table 4-2 Simulation parameters and assumptions [33]

Parameters	**Value/assumptions**
Number of Sites	(19 MBSs + 274 LPNs) or 57+274 = 331 cells
Average Macro inter site distance	250m
Operating Frequency	LTE_Band3_18000 MHz – 20 MHz BW
Duplex Separation	1765/*95MHz:* F_{DL}=1861.5, F_{UL}=1766.5
Antenna Height (Macro/Small cell)	Variable / 5 meters
Propagation Model (Macro)	COST 231
Propagation Model (Small cell)	3GPP Micro Model
Indoor Penetration Loss	20 dB
Antenna Pattern (Macro)	Katherine (H-Plane only) (18 dB gain)
Antenna Pattern (Small cell)	Omni-directional (5 dBi gain)
Number of small cells	331
Number of UEs	800
Number of Monte Carlo iterations	100
Traffic Model	Full buffer (full load)
Tx Power (Macro/Small cell)	40W / 2W & 0.2W:
	Pico Type1: Ptx=2W (1SC/100x100m), 260 cells
	Pico Type2: Ptx=0.2W (1SC/50x50m), 14 cells

In order to contextualize the HetNet planning and deployment mechanism, a real case scenario of a highly populated area in Addis Ababa city is considered. In this thesis, Bole to Megenagna area is assumed as a place where the HetNet is deployed.

According to the 2007 census [53], the total population of Addis Ababa city is 3,384,569. However, the annual growth rate of the city has been estimated in recent years to be 3.8%, and population counts as of 2017 are growing closer to 4 million. The city holds 527 square kilometers of area. The population density is estimated to 7,590 individuals per square kilometer.

Similarly, the study area covers 9 square kilometers area and embraces 19 macro BSs. So, the area is estimated with the total population closer to 68, 000, and the average BS density of 2.11 BSs per square kilometers. Moreover, most of the heights of the buildings are in the range of 3 to 6 m. Two-dimensional representation of the HetNet deployment scenario of the study area is given below.

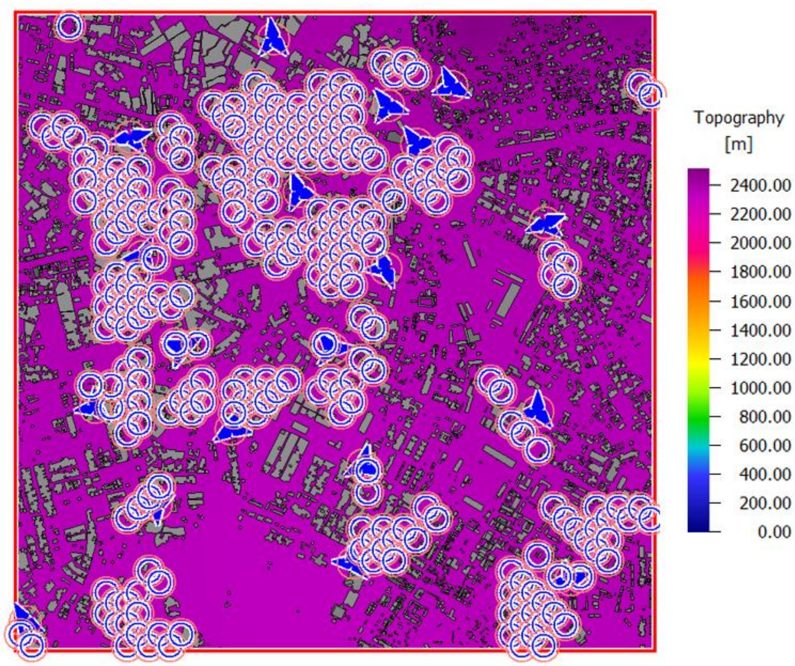


Figure 4-10 HetNet deployment scenario

There are a totally of 331 serving cell locations for both macro and small BSs. Out of which, there are 274 initially predefined candidate locations for small cell BSs, and the remaining 57 locations are for the existing three-sectored macro BSs. As shown in Figure 4-10, these small cell candidate locations are represented with hollow orange-blue circles, whereas the existing BSs are represented with blue three-sectored triangles.

In order to compute the pathloss, the appropriate configuration parameters from ethio telecom's HLD and LLD document from [54] and simulation parameters and assumptions from Table 4-2 for both existing macro and small cells are considered. Moreover, the outdoor building & terrain databases also are applied. Finally, by using the Altair WinProp simulation tool the pathloss value for each of 57 macro BSs and 274 Pico cells, in which 260 of them area type 1 and the remaining 14 pico cells are type 2, is computed. The resulted pathlosses have been converted to ". mat" file using pathloss convertor tool in MATLAB. Then, this converted pathloss of each cell is given to the formulated multi-objective genetic algorithm for optimization in MATLAB LTE simulator.

5 Simulation Results and Discussions

In this Chapter, random (unplanned) and optimized network topology types from the pareto front (which addresses the set of optimal possible solutions), that are resulted from the multi-objective GA based on the user distributions are compared. In order to compare those topologies, key system performance metrics of aggregate capacity (f_2), energy efficiency (f_3) and cell-edge performance (f_4) are used. Moreover, all pixels SINR, cell-edge user's spectral efficiency, average user throughput, and system performance gains (based on energy and cell-edge) also are discussed.

The set of possible solutions for multi-objective optimization is depicted in Figure 5-1 and the two types of topologies are compared in terms of aggregate capacity, energy efficiency and network outage with their respected number of small cells. In this figure, there are about 35 optimum solutions or topologies (topology1 to topology35).

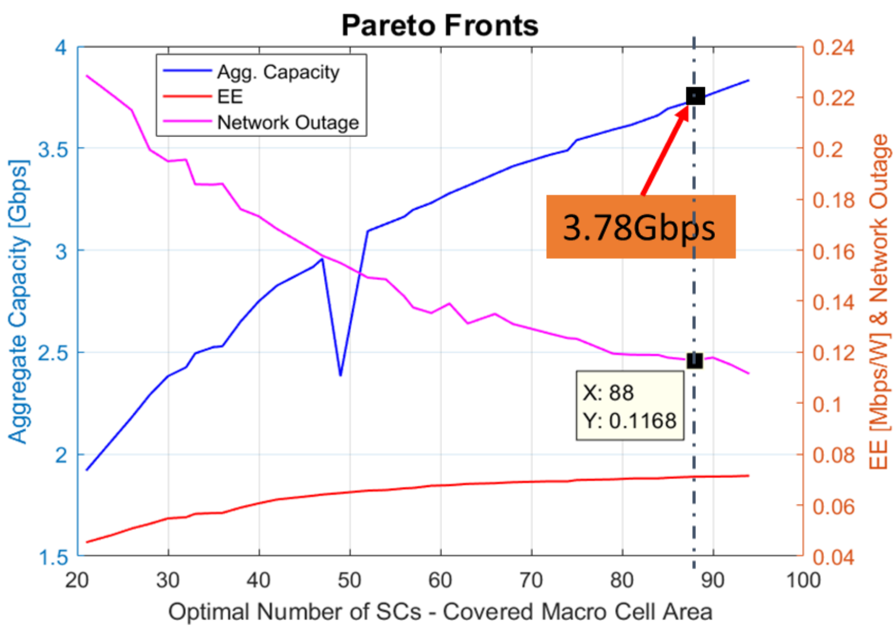


Figure 5-1 Pareto Front

So, the decision to select the optimum topology is the operator's desire based on the sated target requirements. Then, after selecting the required topology, random topology based on users' random distribution is created, and then network performance comparison is carried out. For instance, let us consider topology10, from the above Pareto frontier, with network layout having 88 number of small cells, and 3.78Gbps aggregate capacity, network outage of around 12% and network energy efficiency of 0.07Mbps/Watts.

Then, in Figure 5-2, the summary of one of the selected optimum solutions is shown, and onwards all the comparisons are carried out based on this topology, which is supposed to meet the esteemed requirements. Therefore, as shown in this figure, the target area is served by a total of 145 number of cells, composed of both macro and small cell BSs from the specified topology.

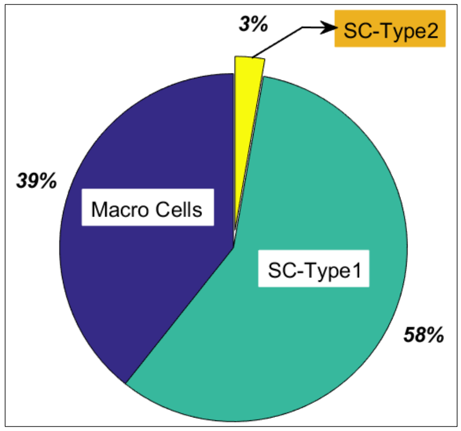


Figure 5-2 Summary of topology10 (88 number of small cells)

In other words, 39% of the cells (i.e. 57 cells) are macro BSs, and 61% of the cells (88 cells) are small cells. These small cells are two kinds based on their transmission (TX) power level, type1, and type2 pico cells. For this result, 58% of small cells are type1 pico cells, with its Tx power is equivalent to 2 watts, whereas the remaining 3% of them are type2 pico cells, in which its Tx power is equivalent to 0.2 watts.

As mentioned before, improving or optimizing SINR values of each pixel in the target area, will, in turn, result in the improvements in the SINR achievable by the UEs. Thus, one of the purposes of providing optimized topology is to serve users with better performances.

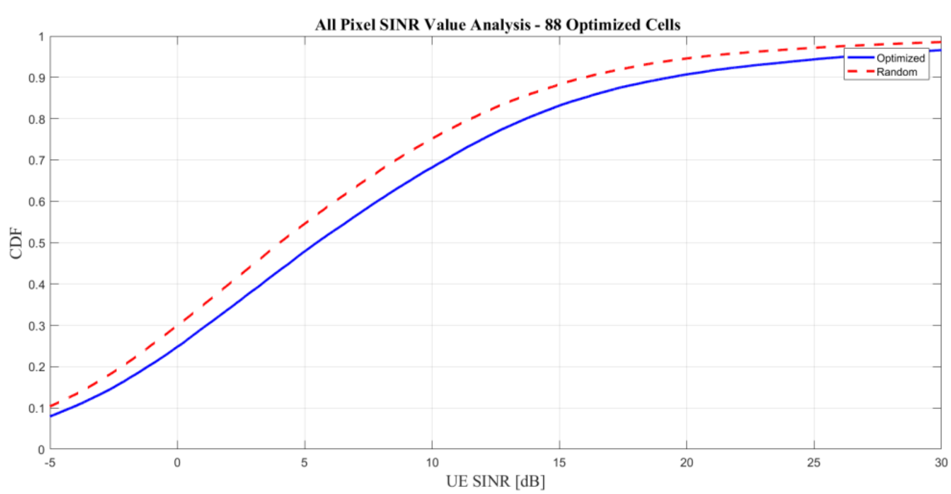


Figure 5-3 All pixels SINR value

In Figure 5-3, the cumulative distribution function (CDF) of all pixel SINR value is shown. In this figure, there are 88 small cells on network layout and the locations of small cells are selected in an optimized and random fashion based on the user's distribution, either random or optimized. Therefore, it is observed that optimized topologies provide improvement in pixel SINR, and it can easily be seen that CDF of all pixel SINR values is increased in the optimized topology than random topology. From this point of view, it can be concluded that the user density-based optimization method provides better system performance gain.

In Figure 5-4, the spectral efficiency (SE) gain comparison of a random and optimized topology is given. The throughput by definition is the maximum data rate transmitted by the communication system. In the theoretical limit, it is equal to the Shannon channel capacity (i.e. $Throughput = Bw * log2(1 + SINR)$).

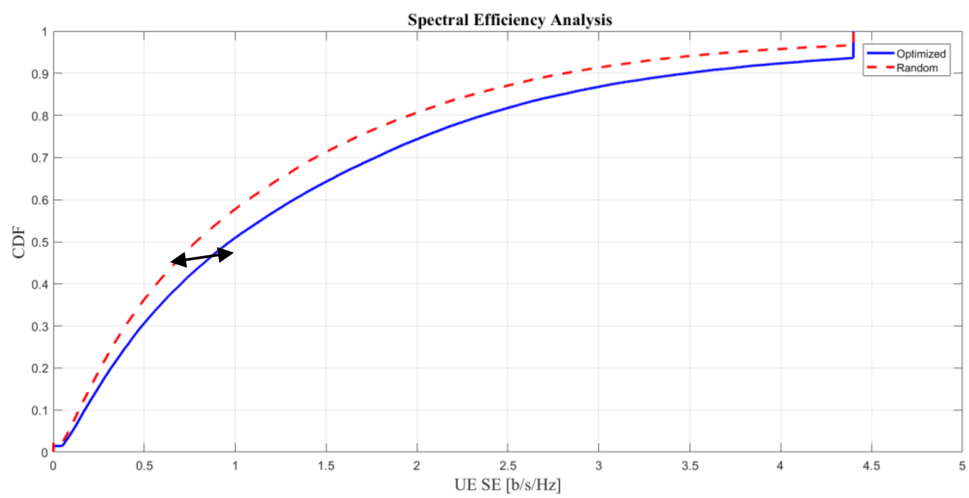


Figure 5-4 Spectral efficiency

Moreover, according to Shannon, the spectral efficiency has a linear relation with throughput and linear logarithmic relation with SINR value (i.e. $SE = log2(1 + SINR)$), this is because the spectral efficiency is the ratio of the transmitted data rate $Throughput$ and channel bandwidth Bw, that is, $SE = Throughput/B$ bits/Hz [55]. Therefore, it can be easily observed that in order to increase spectral efficiency for a given system one has to increase its SINR.

So far, we have seen that SINR values of all pixels are improved with the optimized topology. Therefore, from Figure 5-4, we can see that the UE spectral efficiency is increased in optimized topology.

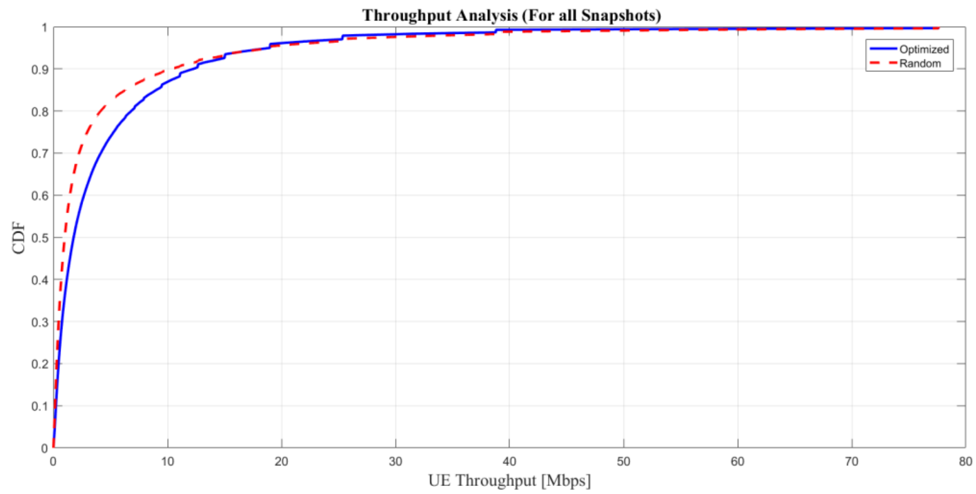


Figure 5-5 User capacity for all snapshots

The CDF of achievable UE throughput (user capacity) values for all snapshots are given in Figure 5-5. Similarly, the average user throughput per each snapshot also is shown in Figure 5-6. As stated earlier, if pixel SINR values are increased, the SINR values of UEs can also be increased. Thus, we can accept that the throughput value of the UEs is also increased because of the increase in SINR values; and the SINR relations to throughput in Shannon capacity.

For this reason, according to the above figure and Figure 5-6, the average UE throughput values of the optimized topology has increased over the non-optimized (random) topology. Numerically, on average there is a 23% improvement of average user throughput from the optimized topology of the target area network. With this improvement, for instance, 50% of the users on the service area will get up to 4.6 Mbps from the optimized network while 3.7 Mbps and less from the non-optimized network.

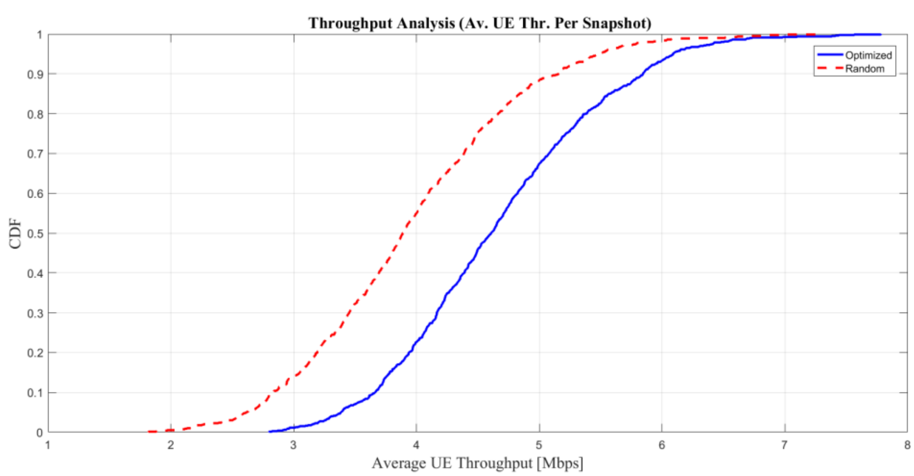


Figure 5-6 Average user capacity per individual snapshot

On the other hand, if the average user throughput values achieved by all UEs in the target area is increased, consequently the aggregate capacity of that service area is also be increased.

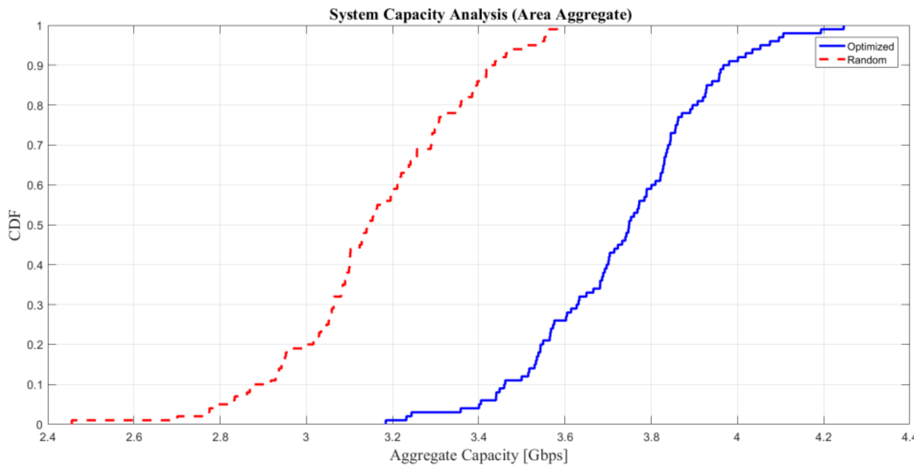


Figure 5-7 Network Capacity Plot

In Figure 5-7, aggregate capacity (f_2) performance of both random and optimized topologies is shown. As in the previous performance metric case, the average UE capacity, optimized topology has better performance as compared to the random topology. Therefore, it is also observed that the optimized topology in the study area has a better aggregate capacity than random topology.

Moreover, it should be noted that optimized topologies in Figure 5-7 are optimized by GA (NSGA-II) in terms of aggregate capacity (f_2). It means that (f_2) the performance metric is used for optimization. In other words, optimized topologies generated in terms of aggregate capacity of (f_2) and optimized topologies generated in terms of energy efficiency (f_3) could be different from each other. Hence, it is the operators' interest to select the optimization methods for the requirements.

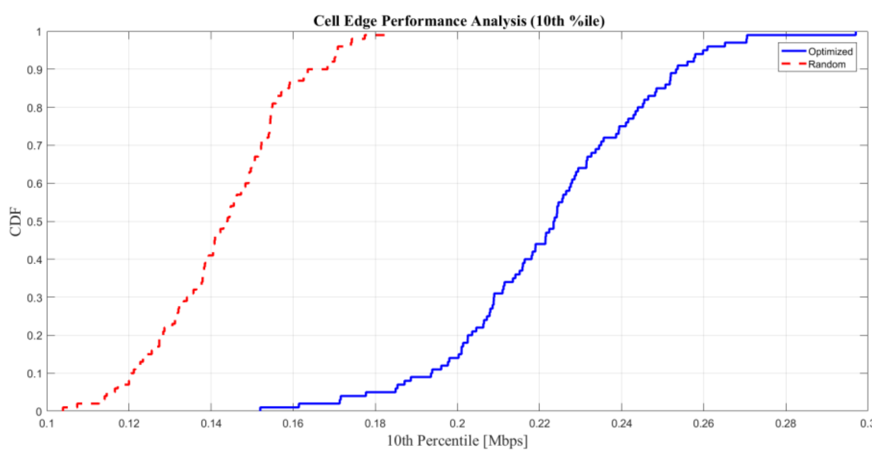


Figure 5-8 Cell Edge Performance (10th percentile)

In Figure 5-8, optimized topologies are compared in terms of cell edge performance (f_4). In this figure, 50% and less of 10th percentile cell edge users are provided less than or equal to 0.143Mbps with random topology whereas with the optimized topology they are provided up to 0.223 Mbps, which is increased almost 56%.

This is attributed to the fact in the non-uniform spatial distribution case, the higher small cell deployment density closely followed the areas with a higher concentration of users, unlike the uniform distribution case. Therefore, with the same number of small cells, it is quite possible that optimized topology gains much better cell-edge performance (f_4). Its average cell-edge performance gain comparison over the random topology is given in Figure 5-9, and the optimization in the non-uniform (optimized) case increases the average gain by 52%.

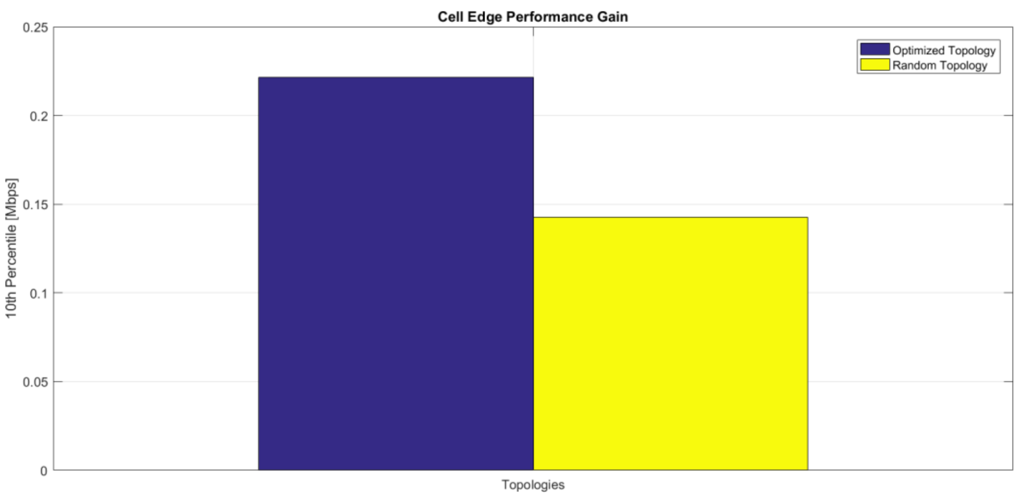


Figure 5-9 Cell Edge Performance Gain

This gain comparison is done by considering the average value of each topologies' CDF of 10th percentile cell-edge value which has 88 small cells. As stated above, UEs in the non-uniform distribution case are mostly in certain areas while UEs in uniform distribution case are distributed uniformly. From these results, it can easily be seen that optimized topology has much better cell-edge performance gain as compared to the random topology. Therefore, to summarize, simulation results show that around 56% improvement to cell-edge areas user throughput, and 23% gains to the cell throughput or average user throughput, as shown in the previous figures.

The system energy efficiency (f_3) is another key metric to compare different topologies resulted from spatial traffic distributions. In Figure 5-10, CDF values of energy efficiency considering both static and dynamic power consumption for comparing the performance enhancement of random and optimized topologies are given. In this figure, the overall energy efficiency of optimized topology has increased.

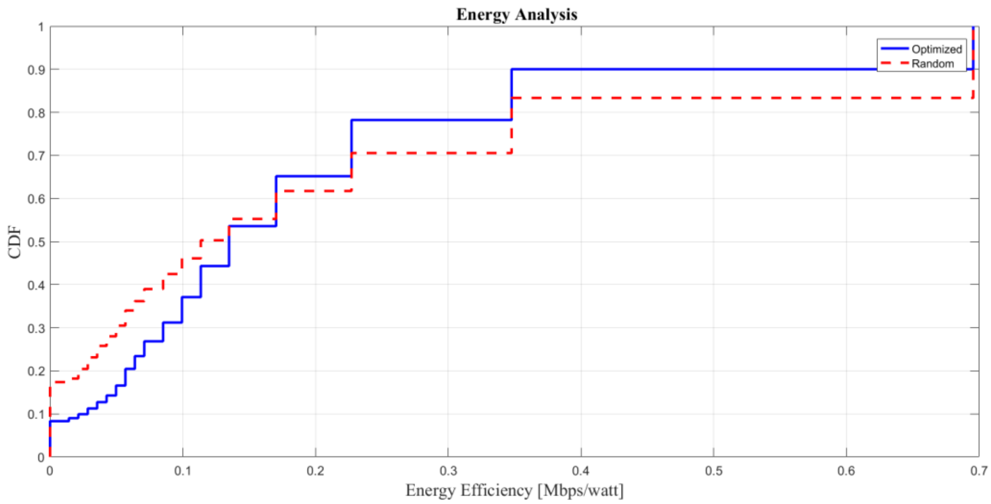


Figure 5-10 Energy Efficiency

From Figure 5-11, we can investigate the impact of users utilizing the resources more from the cell-edge (with lower user throughput) or towards the cell center (higher user throughput) on the performance of energy efficiency. To examine the effects, lets us consider 60% CDF of energy efficiency result as the reference. To the left of the reference, optimized topology is not more energy efficient (i.e. 7% to 15% gain) due to more users are towards cell edge, whereas to the right of the reference, the system has more energy efficiency gain which is 15% to 22% from optimized topology. This higher energy efficiency gain is because the users are utilizing more resources towards the cell center. In general, there is about 7% to 22% energy efficiency gain from optimized topology than random topology for the service area.

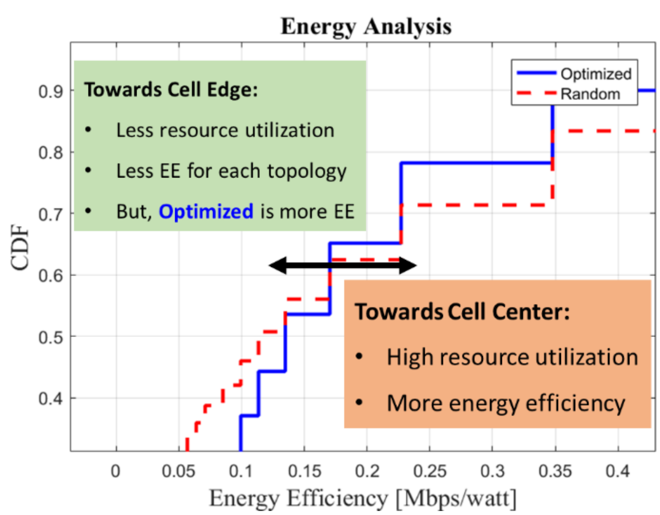


Figure 5-11 Energy Efficiency towards cell center and towards cell edge from 60% CDF

In general, from the above analysis of the two cases, it can be concluded that as the traffic load or the number of connected users increased and has non-uniform spatial data traffic distribution, the spectral efficiency gain, cell edge users' pixel SINR and throughput, average user throughput, system capacity and energy efficiency of the target service area from the optimized topology have increased.

6 Conclusion and Future Work

6.1 Conclusion

The exponential growth of mobile data traffic and high-speed data service demand in Addis Ababa city of ethio telecom cellular network has been a key driver for BS densification. Accordingly, ethio telecom has followed the usual approach of macro cell BS densification with uniform user distribution and hexagonal grid planning assumption. However, the data traffic and the user distributions follow the non-uniformity.

As a result, this approach is failed to capture the non-uniform user distribution and high-speed data traffic demand. This leads to poor network dimensioning and deployment, which provide underutilization and wastage of resource, the low performance of the network and quality of service and specifically it is a waste of energy, and hence provided energy inefficient network. Therefore, energy is one of the key concerns and must be considered during the planning phase. While doing so, the optimization problem of maximizing capacity and minimizing power consumption or maximizing energy efficiency is formulated. Further, the LTE simulator and genetic algorithm are used to generate a set of optimal solutions.

In this thesis work, one of the main contributions is to investigate and provide the HetNet planning and deployment approaches. In particular, to maximize system capacity and energy efficiency in the LTE HetNet deployment scenario has been considered and evaluation of different topologies based on user distribution is undertaken.

Initial candidate small cell locations are selected based on the realistic spatial data traffic distribution and the locations of existing macro BS. In order to optimize different metrics, such as small cell locations and their transmission power, the NSGA-II algorithm is used in a system level static simulator. The algorithm can produce a set of optimum solutions by carefully selecting algorithm parameters. Then, the set of best optimal solutions which are esteemed to maximize the network energy efficiency while satisfying the required minimum QoS, average user throughput and cell edge performance gain have been generated.

From the results of this thesis, it can be concluded that the optimized network topologies increase the average user throughput and the network capacity compared with random topologies. In addition to the improvements in the system capacity, it increases the network energy efficiency, measured in Mbps/Watts, by 22%, and the cell edge user performance by 52%. Thus, the proposed optimal HetNet increases the capacity of the network while consuming the energy more efficiently. This is mainly due to the HetNets capability in absorbing the growing data traffic, the uneven user and traffic distribution, and even high-speed data traffic demand.

6.2 Future Work

Although the provided analyses and methodologies are quite good and constitute a set of powerful tools to guarantee the real-time requirements of the mobile users' high speed and non-uniform data traffic demand, and network energy efficiency from HetNet perspective's, there are some improvements that can still be made in order to make more energy efficient. Unfortunately, they have been left for the future due to scope, limitation, and lack of time (i.e. the simulations with real data & parameters assumption are usually very time consuming, requiring even weeks to finish a single run). In this context, we will survey some of the provided results which can be improved or extended further. This section also briefly describes some interesting research topics, which are worth investigating further. Here are these points:

- Consider smart sleep strategy on the operator deployed pico nodes during off-peak hours to enter sleep and active modes for energy efficiency.
- It could be interesting to consider the spectrum allocation for the betterment of both energy efficiency and spectral efficiency: the energy efficiency of the two-tier networks with orthogonal spectrum deployment is better than that with co-channel spectrum deployment. Thus, it is better not to allocate the same frequency to small cells and macro cells, but not spectrally efficient. As a result, we may apply the co-channel spectrum deployment by exploring the co-channel interference mitigation techniques, like ICIC to improve both SE and energy efficiency.
- Deployment with different larger spectrum band, which creates load balancing with multi-band small cell deployments and provide both SE and more energy efficient deployment.
- Consider mobility management, which can affect signaling and data transmission (i.e. handover and link rate adaptation) at the cell edge. A full alignment of user distributions in both idle and connected modes also avoids the ping-pong effect between the layers. It can be used to further offload traffic from macro-cells to pico-cells layer.

- Another important observation that we must take into account is the coordination in small cell networks (SON), the need for coordination and management of multiple layers of the HetNets, specifically in an interference limited LTE network. Thus, the active/sleep scheduling strategy for BSs as an effective way to match capacity to demand and also improve energy efficiency. Coordinating the low-power layer of small cells with the macro network improves performance across the entire network while also further increasing efficiencies in spectrum use and power consumption, automating network configuration and optimization.
- We will take into account the reasonable traffic steering strategy. In this work, the positive biasing of small cells that have been systematically located in hotspots is to take full advantage of the existing pico-cells by offloading as much traffic as possible from the macro-cells. In addition to increasing energy efficiency, spectral efficiency will also be increased.
- Incorporate the idea of dynamic pricing to improve the BSs' resource utilization and maximize network energy efficiency. Further, the mobile operator's data traffic and revenue gain will be coupled even in the data dominant system.
- Consider the backhaul network; in my thesis work, the total network power consumption is restricted to the sum of the power consumption of all BSs. Thus, the backhaul contribution to the total power consumption is usually overlooked due to its limited impact compared to that of the radio base stations [56, 30]. Therefore, for SE and energy efficiency analysis of HetNet CoMP, the energy and bandwidth consumption of the backhaul is also be considered.

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