A Planning and Optimization Framework for Hybrid Ultra-Dense Network Topologies

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Abstract

The deployment of small cells has been a critical upgrade in Fourth Generation (4G) mobile networks as they provide macrocell traffic offloading gains, improved spectrum reuse and reduce coverage holes. The need for small cells will be even more critical in Fifth Generation (5G) networks due to the introduction of higher spectrum bands, which necessitate denser network deployments to support larger traffic volumes per unit area. A network densification scenario envisioned for evolved fourth and fifth generation networks is the deployment of Ultra-Dense Networks (UDNs) with small cell site densities exceeding 90 sites/km^2 (or inter-site distances of less than 112 m). The careful planning and optimization of ultra-dense networks topologies have been known to significantly improve the achievable performance compared to completely random (unplanned) ultra-dense network deployments by various third-part stakeholders (e.g. home owners). However, these well-planned and optimized ultra-dense network deployments are difficult to realize in practice due to various constraints, such as limited or no access to preferred optimum small cell site locations in a given service area. The hybrid ultra-dense network topologies provide an interesting trade-off, whereby, an ultra-dense network may constitute a combination of operator optimized small cell deployments that are complemented by random small cell deployments by third-parties. In this study, an ultra-dense network multiobjective optimization framework and post-deployment power optimization approach are developed for realization and performance comparison of random, optimized and hybrid ultra-dense network topologies in a realistic urban case study area. The results of the case study demonstrate how simple transmit power optimization enable hybrid ultra-dense network topologies to achieve performance almost comparable to optimized topologies whilst also providing the convenience benefits of random small cell deployments.

Keywords Small Cells, Ultra Dense Networks, Genetic Algorithms, NSGA-II, Network Planning, Network Optimization, 5G, Transmit Power Optimization, Network Topologies, Multiobjective Optimization

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Hamit Taylan Yüce
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Abbreviations

1G	First Generation
2G	Second Generation
3G	Third Generation
3GPP	Third Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
BW	Bandwidth
BWeff	Bandwidth Effective
CAPEX	Capital Expenditure
CAGR	Compound Annual Growth Rate
CDF	Cumulative Distribution Function
COST	European Cooperation in Science and Technology
CoMP	Coordinated Multi Point
CQI	Channel Quality Indication
CRAN	Cloud Radio Access Networks
CRE	Cell Range Expansion
D2D	Device-to-Device communication
DAS	Distributed Antenna Systems
DC	Dual Connectivity
DL	Downlink
eNB	evolved NodeB
ETSI	European Telecommunications Standards Institute
GA	Genetic Algorithms
HetNets	Heterogeneous Networks
ISD	Inter Site Distance
ITU-2000	International Mobile Telecommunications-2000
ITU-R	International Telecommunication Union-Radiocommunication Sector
LAA	Licensed Assisted Access
LOS	Line of Sight
LTE	Long-Term Evolution
LTE-A	Long-Term Evolution Advanced
LWA	LTE-WLAN Aggregation
MAC	Medium Access Control
METIS	Mobile and Wireless Communication Enablers for Twenty-twenty Information Society
MMC	Massive Machine Communication
mmWave	Millimeter Wave
MOGA	Multiobjective Genetic Algorithm
Multi-RAT	Massive-MIMO and Multi Radio Access Technologies
NMS	Network Management System
NP	Nondeterministic Polynomial Time
NSGA	Non-dominated Sorting Genetic Algorithm

NSGA-II	Non-dominated Sorting Genetic Algorithm II
OFDM	Orthogonal Frequency Division Multiple Access
OPEX	Operating Expenses
PAES	Pareto-Archived Evolution Strategy
PS	Pilot Signals
RACH	Random Access Channel
RAM	Random-access Memory
RRM	Radio Resource Management
RSS	Received Signal Strength
SDO	Standards Development Organizations
SCF	Small Cell Forum
SDN	Software Defined Network
SE	Spectral efficiency
SINR	Signal to Noise plus Interference Ratio
SINReff	Signal-to-Noise-plus-Interference Ratio Effective
SON	Self-Organizing Networks
STD	Spatial Traffic Distribution
UDN	Ultra Dense Network
UE	User Equipment
UL	Uplink
TP	Throughput
TWh	Terawatt hours
QAM	Quadrature Amplitude Modulation
QoE	Quality of Experience
QoS	Quality of Service
WiFi	Wireless Fidelity

1 Introduction

In this section, a brief introduction to motivation and background of thesis topic will be given. Moreover, problem statement, objectives and outline of the thesis will be introduced.

1.1 Motivation and Background

The number of connected devices has been increasing dramatically. In addition to this, personal data requirements and mobile data consumption have been growing rapidly. According to [1], a number of connected devices will be 28 billion by 2021. Moreover, there will be 1 GB data usage per day by 2020 [2]. These data provide insights to observe that data consumption has been increasing expeditiously. Therefore, growth in data demand will increase the burden on the network operators. This will lead to the challenges for network operators in terms of meeting data requirements.

In order to deliver data to increasing number of connected devices effectively, network operators started deploying 4G technologies in their systems almost a decade ago. Indeed, most of the network operators have been operating Long Term Evolution (LTE) in their existing services [3]. However, current infrastructure will not be sufficient enough to manage data demand efficiently [4]. It means that network operators should modernize their telecommunication infrastructures to respond to data demand which arises from the increasing data consumption. Therefore, next phase in telecommunication evolution which is Fifth Generation (5G) standard will be introduced to advance the telecommunication industry.

5G will be the next standard that is expected to be widely adopted beyond 2020. Actually, the main target of this standard is to provide 1000x fold increase in the capacity [5]. In order to provide an unprecedented increase in capacity, 5G mobile standard will introduce Ultra Dense Networks (UDNs) which are extremely densified with more base stations as compared to current telecommunication networks.

UDNs will provide excellent opportunities to network operators by densifying existing infrastructure. In order to densify existing network infrastructure, network operators are supposed to deploy a large number of base stations in their existing networks. Because of the increased densification in the UDNs, base stations will be so close to users so that users will take advantage of more seamless and more ubiquitous telecommunication services. However, a large number of base station deployments will also be the source of the compelling challenges. Indeed, some of those challenges will be interference management, energy efficiency, expenditures, network planning and optimization. In order to reduce the expenditures, network operators could take advantage of small cells instead of taking macro base stations into account. Therefore, small cells could be the key players in terms of efficient solutions for the network planning. However, network planning and optimization with a large number of small base stations will require intensive workload for the network operators since identifying the locations of each of the small base stations will stand in need of a lot of effort.

In this thesis, challenges of network planning and optimization of the UDNs will be investigated. Therefore, new approaches will be studied in order to decrease the burden of planning and optimization of the UDNs. In order to investigate the UDN networks, only small cell layer will be taken into consideration.

1.2 Problem Statement

Among the key network planning decisions that confront network operators deploying the UDNs is determining the UDN topology (number and location of the small cells) for a given service area, such that the spatiotemporal traffic profiles are met. These decisions are influenced by both the network operator constraints on the cost of network deployment and the need to meet pre-determined system performance targets, as well as co-existence with existing infrastructure. Indeed, the previous context presents two extreme possibilities from network planning perspective, evaluating optimized UDN topologies versus completely randomly deployed topologies [6]. The optimized UDN topologies are based on a precise network planning approach whereby the optimum topologies are obtained from optimization framework with given criteria of interest to the operator (e.g., maximizing overall system capacity). Therefore, the optimized UDN topologies are usually the best from the perspective of meeting performance targets. However, the evaluated optimum site locations usually do not consider practical complexities of site acquisition encountered in real-world deployments. The alternative approach of optimized UDN topologies is the random topologies that are obtained from user deployed open access small cells. This approach primarily motivated by the inherent benefits (in terms reduced deployment cost, simplified site acquisition, etc.) over traditional operator-planned small cells deployments [7]. However, the unplanned nature of random topologies would result in poor performances compared to optimized topologies [6].

The main idea is to address a case where network operators leverage the benefits of both optimized UDNs and randomly deployed topologies in the same service area. Therefore, in order to take advantage of both deployment types, hybrid topologies could be a case to investigate as a study. This hybrid deployment creates a network planning and optimization problem that is of interest from both research and practical perspective. The corresponding research problem can be stated as follow: investigating a planning and optimization framework for hybrid topologies that could provide results to analyze the performance of hybrid topologies with pre-defined network performance metrics (e.g., cell-edge performance).

1.3 Objectives of Thesis

In this thesis, a detailed survey of UDNs will be investigated in order to understand the characteristics of telecommunication networks in the future. In order to have much deeper perspectives about UDNs, differences between traditional networks and UDNs will be researched to obtain background knowledge. Moreover, future challenges and current trends of UDNs will also be examined so that a solid foundation for the UDNs will be constructed.

As stated, the main focus of this thesis is to investigate the performance of hybrid UDN topologies with different pre-defined metrics. To investigate the hybrid topologies, optimized UDNs should also be visited. In order to obtain the performance results of both optimized and hybrid topologies, a multiobjective optimization framework will be developed. For this reason, a realistic case scenario will be considered. Thus, a corresponding static system level simulator will be developed. After that, the performance results of different topologies will be compared to each other. At the end of this stage, different network topologies will be ready to deploy in a service area.

After deployments of different topologies, post enhancement approaches will be investigated. For this reason, new optimization approach for transmit power will be introduced to improve the service of hybrid and random topologies.

1.4 Outline of Thesis

This thesis is organized as follows:

- Chapter 2 will introduce fundamentals of Ultra-Dense Networks,

- Chapter 3 will present optimization algorithms and optimization frameworks,
- Chapter 4 will introduce deployment scenario, performance analysis, and simulation results,
- In chapter 5, the conclusion of the study and future work will be given.

2 Ultra-Dense Networks (UDNs)

In this part, the motivation for the network densification will be explained. In addition to that, the definition of the UDNs will be given as well as general UDN research topics. Lastly, information about small cell deployments trends will be investigated.

2.1 Wireless Network Developments and Standards

2.1.1 The Growth in Number of Connected Devices

In wireless telecommunications market, demand for data rate has been increasing dramatically. According to [2], average monthly data usage was 2-5 GB/month in 2016 and 10x fold increase is expected by 2020. Thus, average monthly usage is expected to be 20-50 GB/month. Moreover, mobile subscriber growth will be 5%-15% for each year in the next decade and one million new mobile broadband subscribers will be added to the wireless networks every day until the end of 2022 [8]. On the other hand, existing wireless telecommunication infrastructure will not be sufficient to meet subscribers' data requirements in the future [4]. From this perspective, network operators may have crucial challenges that have to be solved in upcoming years. Therefore, telecommunications standards development organizations (SDOs) have been working on enhancements and new developments of wireless networks capable of meeting growing capacity demands and other performance requirements of future use cases.

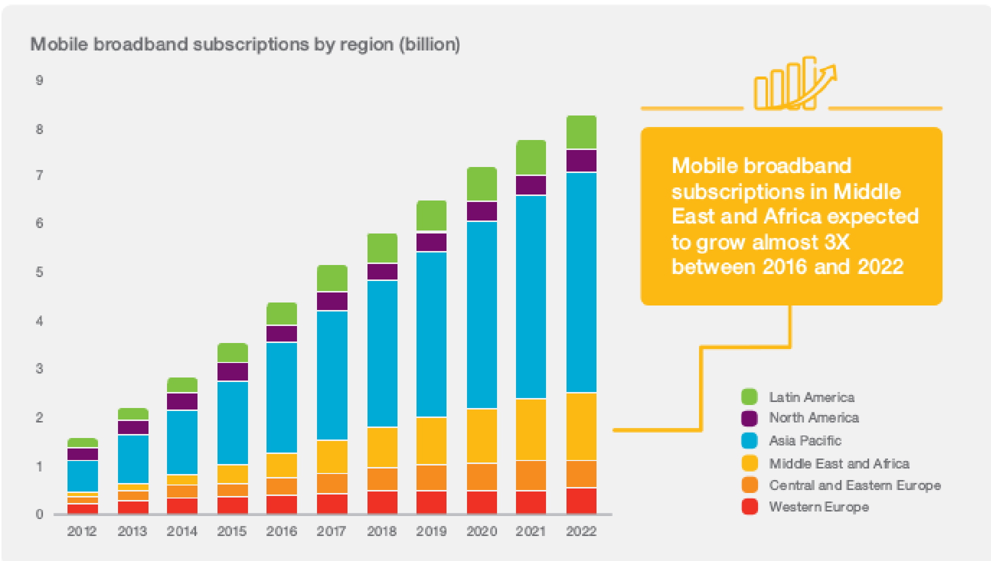


Figure 1: The growth of connected devices [8]

2.1.2 5G Standard

In order to define the next generation of wireless networks, SDOs have been enhancing 4G standards and working on 5G standardization that is also called as "Beyond 2020". Specially, Third Generation Partnership Project (3GPP) is the main association that standardizes the specifications regarding the telecommunication technologies. Starting from 2G, 3GPP has been playing an important role in different standards.

In 2008, LTE was introduced in Release 8 [9]. With LTE standard, IP-based mobile communication technologies were introduced. In order to improve the LTE standard, LTE-A (LTE Advanced) standard was introduced in 2010 in Release 10 [10]. With LTE-A standard, Carrier Aggregation (CA) was enabled to improve wireless capacity. In addition to CA, new technologies were also introduced with LTE-A standard such as Coordinated multipoint (CoMP) transmission and reception and low power consumption in the eNodeB (Evolved Node B). In 2015, LTE-A Pro was introduced in Release 12 [11] and Release 12 was frozen in 2016. With LTE-A Pro, Multi-Radio Access Technologies (Multi-RAT) such as Licensed-Assisted Access (LAA) and LTE-WLAN Aggregation (LWA) were introduced.

In Release 15, first set of the 5G standard was introduced [12]. 5G standardization will consist of different technologies and some of these technologies have been used since first LTE release. According to [13], technologies used in 5G can be given as follows: Distributed Antenna Systems (DAS), Cloud Radio Access Networks (CRAN), Software Defined Network (SDN), Device-to-Device communication (D2D), millimeter wave (mmWave), Massive-MIMO, LWA, and LAA. The purpose of those given technologies is to provide more opportunities to the network operators to serve the subscribers with more seamless and much better services.

Each of given technologies has its own importance for the next wireless telecommunications networks. For example, SDN will be a key player in the device management since it will enable centralized control in the network management. mmWave will enable network operators to use the frequency more aggressively.

In addition to given technologies, sizes of devices such as antennas and base stations will change in order to meet compact design. In this sense, size of base stations should be much smaller as compared to current base stations. Actually, in order to meet these requirements, small cells were invented and offered to the industry.

Small cells have already been considered as key players in Heterogeneous Networks (HetNets) to boost data rate and coverage requirements.

HetNets is a term that represents a network which consists of different base stations with various transmit power levels. HetNets term has been used since the first release of LTE. Moreover, HetNets will be essential in the 5G standard. This thesis focus on UDNs but UDNs are also HetNets with more dense network and UDNs will be introduced in next chapters.

2.2 Motivation for Network Densification

Future wireless networks have to be designed to meet the capacity requirements of data-hungry applications. In order to form more superior wireless connectivity, capacity provided by network operators has to be boosted fiercely.

In literature, there are three techniques to improve the capacity in communication. These techniques can be given as follows: the increased spectrum resources, the increased spectral efficiency, and the increased network densification. In order to understand the differences between those techniques, a brief description for each will be given in this section.

Spectrum is radio frequencies that are allocated for communication between electronic devices. Increased spectrum resources technique provides more spectrum for the wireless communication between devices. Thus, more bandwidth is enabled to improve communication capacity. Carrier Aggregation (CA) is one of the approaches to increase the spectrum resources and it was defined in LTE-A in Release 10/11 [10]. CA provides more than one LTE 8 downlink (DL) and uplink (UL) to User Equipment (UE) in order to transmit and receive more communication signals.

Increased spectrum efficiency is another technique to increase the wireless communication capacity. Spectrum efficiency is the ratio of the data rate that can be transmitted over a bandwidth in a communication channel. Thus, if transmit rate is increased, wireless communication capacity is also increased. In order to stimulate spectrum efficiency technique to improve capacity, downlink MIMO technique was introduced in Release 8 [9]. After downlink MIMO, uplink MIMO was introduced to boost uplink communication capacity. In order to increase the spectrum efficiency, increased modulation can also be taken into account. For example, in Release 12, 3GPP added 256-QAM modulation to improve the spectrum efficiency [11].

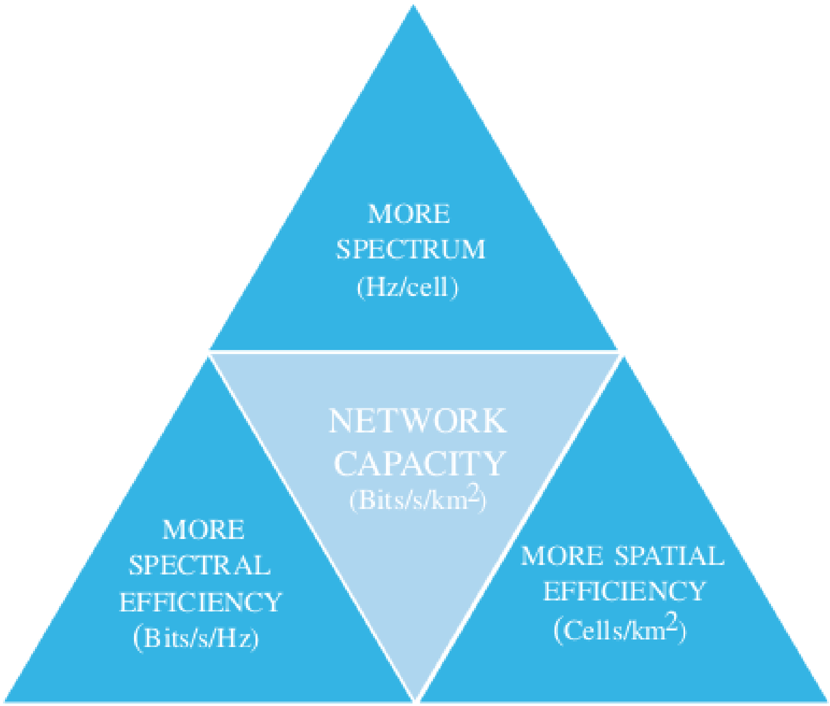


Figure 2: Different techniques to improve the network capacity [14]

These two techniques boost the capacity of wireless communication in a service area. On the other hand, there has been a drastic growth in the number of connected devices as mentioned in the previous chapters. Therefore, device density in a service area will be larger than today's wireless networks. From this perspective, the number of base stations in the service areas can also be increased in order to meet the data demand in a more dense network. Thus, increased network densification technique can play an important role to provide more seamless and superior wireless communication networks. In increased network densification technique, service locations are densified with more base stations. However, network densification may raise the burden of network operators in terms of the cost and effort if network operators use macro base stations for network densification. Fortunately, network densification with small cells is another option for network operators because they can reduce their costs and duration of installation with small cells deployments [15].

Network operators can deploy and operate these techniques in their wireless networks. However, one should note that each technique contributes to the wireless communication networks with different amount of capacity gains. According to [14], the network capacity has been enhanced around 1 million times between 1950 and 2000. When this enhancement is broken down into pieces, it is found that Medium Access Control (MAC) has provided 5x capacity gain, wider spectrum has provided 15x capacity gain, coding techniques provided 5x capacity gain and network densification and smaller cell sizes have provided 2700x capacity gain. Authors in [14] also made a simulation to investigate capacity gain of network densification to the wireless network. In their study, they found that network densification increased cell-edge UE throughput by up to 48x. Moreover, according to [18], network capacity can be increased 3x by increasing the spectrum resources, 6x by increasing the spectrum efficiency and 56x by increasing the network densification. From given data, it can be seen that network densification could play a critical role to meet 1000x fold increase in network capacity.

Network densification is also advantageous in terms of the cell-edge performances and in-building coverage. Building penetration losses cause huge problems for outdoor-to-indoor communication by reducing the received signal strength. Because of that, signal strength may not be strong to maintain the communication between base stations and UEs. Therefore, densifying network by deploying more base stations in the buildings can also solve the coverage problems.

As it can be seen in this chapter, there are different techniques to increase network capacity. Network operators can use any of these techniques by considering their own requirements and regulations. However, if network operators are expected to increase capacity exceedingly, network densification could be the best option.

As a result, network densification had a crucial role in the past and it will be a key solution for the future wireless networks in order to serve the subscribers with better and superior services.

2.3 Small Cells

Communication signals are transferred between the UEs and different base stations. There are various types of base stations with their own features such as design, prices, and installations. Clearly, the UDNs will consist of an enormous number of base stations that will be deployed densely in small areas. In order to meet dense deployment criteria, small cells bring different opportunities to the network operators.

Small cells are low-powered base stations with small coverage distances as compared to macrocells. Small cells differ from macrocells with their transmit power levels, number of resources, size, weight, and prices. Several similarities and differences between small cells and macrocells are given as follows:

- Cell radius of small cells is smaller than cell radius of macrocells,
- Transmit power of small cells is lower than transmit power of macrocells. This may lead to decrease in cell coverage area; however, having small coverage area could be an opportunity for the UDNs,
- Small cells can be deployed on the lamppost, shops, and pay phones by the network operators or they can be deployed by subscribers who want to improve the wireless communication quality in their offices or enterprises,
- Outdoor location of small cells can be 3-6 meters above the street level. Unlike macrocells, small cells should be close to the subscribers to not to lose more power through the path,
- There can be different bandwidth options for small cells. Moreover, similar to macro base stations, small cells can have different radio access technologies,
- Small cells also have plug and play features like Wi-Fi (Wireless Fidelity) routers,
- Small cells are cheaper than macro base stations. Therefore, they can be more attractive to network operators,
- Small cells also have different access types for subscribers. One of the access types is closed access type where only allowed subscribers can connect to small cells. The other access type is open access type where all subscribers of network operator can connect small cells.

Depending on the prices, transmit powers and resources, small cells can be classified into different categories. Generally speaking, there are three different types of small cells in the small cells terminology. These are femtocells, picocells, and microcells. Usually, femtocells are the small cells with the lowest resources and the lowest prices as compared to other small cell types while microcells are the small cells with the highest prices and the highest resources. In terms of the locations, femtocells can achieve better performance inside the buildings while picocells and microcells match the outdoor applications [16].

Deploying small cells into existing networks provides many opportunities to network operators. Network operators can serve their customers with more Quality of Service (QoS) and Quality of Experience (QoE). On the other hand, deployment of new small cells may create new challenges in terms of the wireless communications quality. In wireless communication, interference is one of the challenges that disrupts the signal quality. With small cells deployments, because of the increased number of base stations, interference of existing network will increase. Other challenges of small cell deployments are resources and cell coverage sizes of small cells. In order to cover a large area, network operators may need to deploy a large number of small cells. Thus, this may cause design problems for the network operators because planning the locations and optimization of a large number of small cells may be tough. Small cells have been deployed in the existing network and therefore used the spectrum for small cells and macrocells create different challenges in wireless networks. There are two options for the spectrum and these are in-band where small and macrocells use the same spectrum and out-band where small and macrocells use different spectrum bands. In terms of mobility and continuous traffic, in-band deployment is the better option. However, interference between macro and small cells may reduce capacity. Moreover, the in-band solution is better with low small cell density while the out-band solution is better for high small cell density [17].

As a result, small cells are promising technologies for the future wireless telecommunication networks with their cheap and compact design. There are different types of small cells and they have their own opportunities for the network operators or subscribers. Moreover, small cells can be deployed by subscribers and network operators. Because of different deployment options, deployment strategies gain a huge importance.

2.3.1 Deployment Strategies of the Small Cells

Subscribers use their devices with variable data rates. Because of this, data requirements take place anywhere with variable rates during a day. According to [18], 80% of the total wireless traffic is created by indoor applications since most of the people spend most of their lives inside the buildings. Actually, this situation also creates challenges for the network operators. In order to provide data to the subscribers in the buildings, network operators can use macro base stations. In addition to macrocells, outdoor small cells can also be used to support permanent indoor communication. However, both macrocell and outdoor small cells suffer from penetration losses. Moreover, according to [19], penetration losses create energy consumption and battery usage problems. Therefore, indoor small cell deployment attracts the network operators. In addition to permanent indoor applications, small cells can also be considered for permanent outdoor applications. In order to boost the capacity in the hot-spot areas, small cells can be deployed to complement the macrocell layer for the outdoor applications. In addition to permanent deployments, network operators take advantage of small cells for temporary applications such as football matches and concerts.

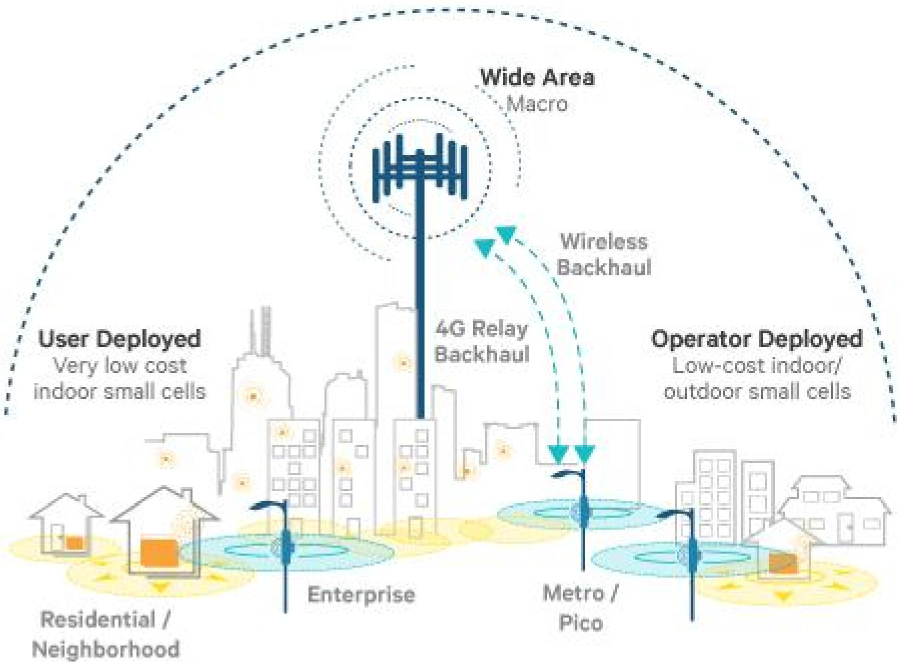


Figure 3: Small cell deployment strategies [20]

Principally, small cells are deployed by the network operators to solve certain capacity and coverage problems and this type of deployment are named *operator-deployed* deployment. In addition, subscribers would be willing to deploy their own small cells in their offices or enterprises for permanent applications because they may not be satisfied with the performance of the operator-deployed wireless network. This type of deployment is named *user-deployed* deployment.

In user-deployed deployment, subscribers buy small cells from their network providers. After that, they deploy those small cells in their buildings or enterprises to improve wireless communication capacity and coverage. In this deployment type, a subscriber can choose anywhere to deploy small cells. Because of this reason, randomness occurs for the wireless network topology and network operators may not have information about the locations of user-deployed small cells. In operator-deployed deployment, locations of the small cells are chosen by the operator in network planning phase [21]. Thus, the network operator can have full information about the small cell locations.

2.3.2 Small Cell Site Requirements

In wireless communication, base stations can be seen as data providers to the subscribers. In order to provide data to the subscribers, base stations should be deployed according to rules and regulations. Small cells provide opportunities to the UDNs; however, there are also requirements for small cell deployments. These requirements can be given as follows: energy efficiency, site acquisition and backhauling.

Many organization and governments have put attention to energy efficiency in different fields [22]. Energy efficiency is also important in the field of wireless communication because the number of connected devices will be larger in the future. According to [14], 50 million small cells, which consume 12 Watts each, could lead to 5.2 TWh/a energy consumption which is half of the power generation of a nuclear plant. Therefore, vendors and manufacturers follow the ways to reduce the energy consumption of devices. In addition, wireless network topologies could be taken into consideration to increase energy efficiency because most of the energy in the wireless system is consumed in the base stations. Thus, network operators can reduce the energy consumption by planning the wireless system by considering the energy efficiency approaches.

Another requirement is the site acquisition for small cells deployment. As stated in the previous chapter, the subscribers or the network operators can deploy small cells. In user-deployed deployment, network operators may not need to rent any places from third parties. On the other hand, in case of operator-deployed deployments, network operators may be expected to rent locations to deploy their small cells. This situation may increase expenditures of the network operators. In addition to expenditures, municipalities and other governmental organizations may prepare different regulations that complicate the deployments for network operators. Furthermore, competition between the network operators in terms of finding good locations may cause troubles for the network operators. [23].

In small cells communication, backhauling can be considered as another requirement. There are two types of backhauling for small cells and these are wired and wireless backhauling. Even though the wired backhauling has advantages for the speed of connection, there may be challenges in terms of the cable infrastructure in the deployment location. If there is no cable infrastructure in a location, network operators should also consider installing the cables before deploying the small cells. On the other hand, wireless backhauling has advantages in terms of the installation. However, having wireless backhauling may cause problems such as communication spectrum which is allocated for backhauling because different frequencies have different effects on the communication channel. Thus, a careful wireless network design is a necessity for a strong backhauling [24].

2.4 Definition of Ultra-Dense Networks

The 5G standard will be the next station in telecommunications systems. Mobile and Wireless Communication Enablers for Twenty-twenty Information Society (METIS) built by the leading telecommunication companies contributes to 5G standardization. The main goal of METIS is to create technologies that provide data to anyone at any time without any geographical restrictions. In order to provide data to anyone anywhere, telecommunication coverage area should be enlarged. Moreover, data rate should be increased drastically to satisfy subscribers. Furthermore, the wireless network should be energy efficient. In order to accomplish these tasks, METIS proposes different concepts such as Moving Networks, D2D communications, Massive Machine Communication (MMC) and the UDNs. The UDNs are one of the milestones for the 5G concept that will shape the future wireless communication. UDNs will be the new concept for the telecommunication networks in the future. UDN term is used to address the network densification; however, precise definition of the UDNs is not revealed.

According to [13], the definition of the UDNs can be given as the networks where the number of cells is higher than the number of users. Moreover, the UDNs can be defined with the density of cells per km^2. In [25], author defined networks as UDNs if cell density is higher than 10^3 cells per km^2. The UDNs can also be defined as the number of users per cell approach by considering the inter-site distance (ISD). According to [2], the UDNs are the networks where the number of active users in one cell is almost 2500 users and inter-site distance (ISD) is 112 m.

	Traditional networks (2014)	Denser networks (2015-2017)	Very dense networks (2017-2020)	Ultra dense networks (beyond 2020)
Site / km2	7 sites	21 sites	26 sites	93 sites
ISD	395m	237m	209m	112m
Traffic volume density	~1 Gb/s/km^2	~5 Gb/s/km^2	~10 Gb/s/km^2	~40 Gb/s/km^2
Active users	250	625	1000	~2500

Figure 4: Site and traffic density evolution towards UDN [2]

In addition to the UDNs, Small Cell Forum (SCF) uses the hyper-dense network to address the network densification. According to SCF, in hyper-dense networks, site density is over 150 sites per km^2 [26]. According to this definition, the network will be extremely densified. In addition to that, Qualcomm claimed that they have tried the world's densest outdoor network which is 1000 site per km^2 [27]. Although there are various terms to address network densification, UDN term will be used to define network densification in this thesis.

The UDNs are different from traditional networks in many ways. The small cells will play a key role in the UDNs and therefore cell sizes will be smaller than traditional networks. Moreover, base stations in the UDNs will be so close to subscribers as compared to traditional networks. This can decrease path losses and increase SINR (Signal to Noise plus Interference Ratio). However, due to the high number of small cells, interference and energy consumption will be challenges of the UDNs. Furthermore, the huge number of small cells in the UDNs will necessitate a larger number of high-capacity backhaul links [13].

2.5 UDN Research and Deployment Trends

2.5.1 UDN Research Trends

The deployment of UDNs opens up a large number of research topics. These include, but is 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.

Channel modeling

As compared to traditional networks, UDNs will be highly dense networks. In order to densify the network, small cells could be deployed on the lamppost or boards. Therefore, base stations will be so close to UEs in the wireless communication environment. This leads to more LOS (Line of Sight) components in the received signal. Therefore, new channel propagation models could be proposed by emphasizing the LOS components. The new channel models are also expected to meet the needs of wide range of applications such as D2D communication. Furthermore, new channel models are expected to be used with different spectrum bands. In terms of channel modeling research, there are studies that are completed by both academia and industry. For example, METIS2020 has proposed different channel models based on the ITU-R M.2135 channel models that can be used for small cells in the urban areas [28]. Besides METIS2020, there are other researches such as ETSI mmWave, COST 2100. In [29], authors proposed a 3D channel model, which can be used by urban micro and macrocells up to 100 GHz. Moreover, they proposed models to account for for building penetration for outdoor-to-indoor propagation (and vice-versa) and the presence of different blockages in the RF signal path.

Operation in mmWave bands

In future wireless communication, higher frequencies will provide opportunities for the UDNs, although propagation losses of high frequencies are larger than propagation losses of low frequencies. High frequencies reduce the cell coverage areas but the decrease in cell coverage area increases the frequency reuse. In [30], researchers studied the UDNs for the indoor environment. In their study, they used multiobjective optimization to find optimal cell locations from a set of candidate locations. According to their results, mmWave bands are very attractive for indoor deployments since mmWave bands create small size coverage areas.

User association

In the UDNs, UE can connect to either macro or small cells. However, transmit power levels of macrocells is higher than transmit power levels of small cells. Therefore, the user may always connect to the macrocells. Because of this reason, Cell Range Expansion (CRE) technique is developed. With CRE, received signal strength (RSS) of a small cell is weighted by a range expansion bias. Therefore, user associates to the small cell with maximum biased signal strength. In addition to CRE, the user can connect to both macro and small cells with Dual Connectivity (DC) approach.

With this approach, macro base stations are used for signaling purposes while small cells are used for data offloading [13].

Interference mitigation

Interference mitigation is critical in all telecommunication systems. In the UDNs, there will be interference between same UDN layer or across different layers for co-channel deployments (e.g. between UDN small cell layer and macro layer). There are different interference mitigation techniques and those can be in time, frequency and spatial domain [31]. According to [13], idle mode capability of small cells is an advantage to mitigate the interference. Inactive small cells can go into sleep mode and therefore they do not cause interference for other small cells.

As mentioned before, small cells could be deployed by both users and network operators. In case of user deployed small cells, users may deploy the small cells so close by. Thus, adjacent small cell interference could cause dominant interferers that could cause challenges for the interference mitigation [32].

Small cells have different access types in terms of availability to the users. If the small cells have the closed access type, only the allowed users could connect to the small cells. In case of closed access type small cell deployments, there cannot be handover between the small cells. Moreover, if there is no coordination between the small cells, interference may become high. In [33], authors propose a method to mitigate the interference from uncoordinated femtocells in the downlink. In this study, the user equipment is allowed to access the femtocell that causes the interference. With this access, a control channel between the user equipment and femtocell is created. According to this study, multiantenna techniques could be used to mitigate the co-channel interference.

Techno-economical aspects

Like all telecommunication systems, techno-economical aspects are extremely important in the UDNs. Techno-economical aspects can consider two main cost expenditures, namely: Capital Expenditure (CAPEX) and Operating Expenses (OPEX). CAPEX is it is related to the cost of infrastructure in a service area. Therefore, wireless network planning is directly related to the CAPEX. Moreover, there is a trade-off between the service quality and CAPEX. In [6], authors propose a framework to address optimum wireless network design to overcome design and optimization challenges in the UDNs by considering the number of small cells. In [34], authors compare the throughput and cell-edge performances of the picocells and relay nodes. From this study, it could be understood that in order to boost the capacity in the cell-edge areas, there may be picocell or relay node deployments. However, the one should consider the relation between the ISD and the cost of the deployments. Moreover, this study emphasizes the importance of heterogeneous deployments over the traditional networks.

In addition to infrastructural costs, there are different costs such as backhaul leasing fees, site rental fees and energy costs (for grid connected small cells). Those can be categorized into OPEX.

Energy efficiency

Energy efficiency can be defined as the ratio of aggregate network throughput to the total consumed energy in the network [13]. Moreover, studies on energy consumption could be motivated by static and dynamic parts of the network [36]. 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% of the energy is consumed in the base stations. Therefore, concentrating on the topology side is crucial to reduce consumed energy because reducing the number of cells can reduce overall energy consumption. In [35], authors propose a cell switch-off framework for cellular networks, which 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 the capacity and coverage; however, it also increases the energy consumption. In [36], 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 nodes which are deployed in a service area on reducing area power consumption which refers to the power consumption of a network. According to the results, both relay nodes and picocells reduce the area power consumption in the uplink. Moreover, picocells reduce the area power consumption in the downlink.

Mobility

Having more base stations in the UDNs may create mobility problems in the wireless networks. In the UDNs, there will be handover between macrocells and small cells, between small cells, between macrocells. Thus, because of the difference between the transmit power levels, handover may be more challenges for UDNs. Besides, coverage areas will get smaller with the densification resulting in more frequent handover operations. Hence, handover for high speed UE presents in even more significant challenges [31].

Radio resource management

Radio resource management has a critical role in both capacity and coverage. According to [14], current scheduling techniques are designed for the lower number of UEs per macrocell. Thus, they may not be optimum anymore and they may be revisited for better communication in the UDNs.

Network planning and optimization

The UDNs will be different from traditional networks in terms of network planning. In traditional networks, there is a basic approach to design the wireless network in a service area. This approach consists of dimensioning, detailed planning and optimization phases. In dimensioning phases, the number of base stations to cover the location with a certain QoS is estimated. After dimensioning phase, the detailed planning phase is started to evaluate the wireless network deployment in the service area in more details. After these two phases, network operators maintain the network optimization according to wireless technology requirements [37]. However, this approach may be more challenging for network operators because of the large number of base stations in the UDNs.

In [38], authors propose an approach to the deployment of the HetNets. In their approach, they firstly, estimate the number of macro base stations and then they divide the service area into the sub-regions with almost equal traffic distribution. After evaluating path losses, spectrum allocations and QoS, they start same procedure for small cell. The number of small cells is estimated first and then they are distributed to location with almost equal traffic distribution. The approach in [38] can also be used in the UDNs. In [39], authors propose a method to analyze the deployment scenarios of the wireless networks and this method can be also considered in the UDN planning. In their methods, they transfer non-uniform physical wireless network map to the conformal domain. In the conformal domain, they calculate the number of base stations. After that, they return to physical map to define the wireless network.

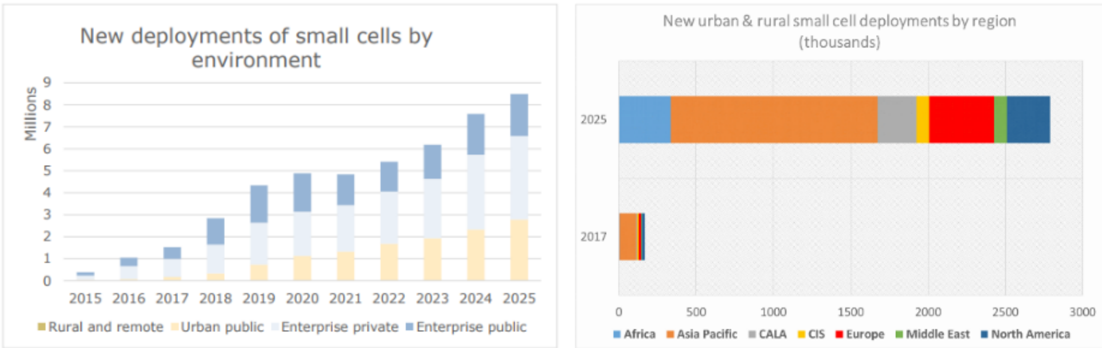
In [6], authors proposed a network framework for planning and optimization of the UDNs by the multiobjective genetic algorithm. According to their proposal, the boundary between planning and optimization will not exist and they will be considered at the same time in network design. These studies show that there is an emerging need for new approaches to future wireless networks 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 situations and different interference levels [40]. In terms of the UDNs, 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.

2.5.2 UDN Deployment Trends

The popularity of small cells has risen with their easy installation and low prices. Due to the fact that, small cells have been used with 4G technologies and they will be largely used in 5G technologies for the network densification.

Figure 5: Deployment scenarios [42]

In order to densify the networks, small cells will be deployed in different areas. Enterprises, which include buildings, shopping malls, hospitals, and hotels, will be the main target for the indoor small cell deployments in 5G. Certainly, indoor network densification will be an excellent solution for the dense population within the busy hours. Small cells in UDNs will be the main player for the hotspot areas in the urban environments. Specially, small cells will be closer to users at the street level as compared to the macrocells because the deployment areas of the small cells will be lampposts, advertisement boards, and other street furniture. In terms of the rural areas, small cells bring opportunities to the small villages with dense population, mines and other rural areas. Obviously, rural areas could be served with macrocells but small cell deployment can be more profitable as compared to macrocells deployment. Moreover, as compared to repeaters, small cells in those areas bring more capacity to the users [42].



(a) (b)

Figure 6: (a) Annual deployments of small cells by environment 2015-2025, (b) New urban and rural small cells deployments by region (thousands) [41]

Because of features of small cells, there is an increasing attention to small cells. Small cell market value was $1.5 billion in 2016 and it will be $2.2 billion in 2021 [41]. The number of LTE small cell sites in Europe, Middle East, and Africa will double itself between 2017 and 2019 and the number of sites will be 260000. Moreover, most of the small cell deployment will be seen in Asia and Africa [42]. The growth for non-residential small cells will be over 30% Compound Annual Growth Rate (CAGR) between 2016 and 2022 [43].

2.6 Planning of UDNs

The UDNs will consist of different type of base stations. Moreover, these base stations can be in different network layers. On the other hand, in this thesis, only small cell layer is used in the simulations.

The purpose of the network operators is to improve the service quality in the locations by deploying, maintaining and optimizing base stations. In order to meet required service quality, network operators need to have some awareness of the mid/long-term subscriber traffic distribution (STD) patterns on service areas. Spatial Traffic Distribution (STD) is a way to represents subscriber traffic distribution. STD can be obtained by using applications based on previous network measurements or even user-installed applications for more up-to-date knowledge of relatively short term fluctuations. Thus, network operators can estimate the number of small cells to cover an area with certain QoS and plan their wireless networks to serve subscribers [18].

Figure 7: Uniform and non-uniform STDs. Pink dots represent UE locations.

On target locations, STD can be classified into different types. Those types are uniform and non-uniform STDs. In uniform STD, subscriber service demand is simply uniformly distributed all over the service area. It means that service demand per m^2 is constant. For this STD type, base stations can be distributed to the target area regularly. In non-uniform STD, subscriber service demand on target location can be higher in some part of the service area because of non-uniform population distribution, presence of hotspots (e.g. transport hubs). Therefore, more base stations have to be deployed in highly populated areas of the service area [44].

As stated, traditional wireless network planning can be divided into three steps: dimensioning, detailed planning and optimization. Each step is analyzed and completed by the network operators. However, because of the increased number of base stations, wireless network planning and optimization can be combined and completed at the same time. Because of this reason, in this thesis, a compact wireless network design is proposed.

In user-deployed deployment, network operators cannot know precise locations of small cells. Because of this reason, wireless network topologies can be random for network operators. These topologies can be called as *random topologies*. On the other hand, in operator-deployed deployment, precise deployment locations of small cells can be identified by network operators. Network operators plan their networks based on obtained STDs, feasibility of site acquisition and so on. These topologies can be called as *optimized topologies*. In addition to these two topology types, both network operators and subscribers can deploy small cells in a real location. Therefore, this situation leads to the *hybrid topologies*. In this thesis, all three topology types are considered with both uniform and non-uniform STDs. The deeper description of these topologies will be given in section 4.

3 Optimization Framework

In mathematics, engineering, and economy, optimization is used to find inputs which maximize or minimize the outputs of functions or methods. In order to design a system with maximum efficiency, optimization provides good intuition. However, the complexity of optimization problems may cause troubles for designers in terms of solving optimization problems. In addition to complexity, optimization should be used to find optimal solutions from a set of solutions. It means that optimization provides possible results which maximize or minimize the output of a function. Depending on results, decisions should be made by designers, engineers or network economists [45].

In this section, I have given system model and performance metrics of simulations. Besides, algorithms that are used to optimize simulations are given in this section.

3.1 System Model

The goal of the study is to plan a UDN that is composed of small cells in a service area $\mathcal{A}$. The service area is divided into the A small area elements which are also known as pixels. The average received power is assumed to be constant within the whole pixel area, hence the pixel resolution provides a trade-off between computation complexity and accuracy of the simulations.

In this study, the wireless system is considered as OFDMA (Orthogonal Frequency Division Multiple Access) downlink with system bandwidth B. The considered service area has a maximum of L predefined candidate small cell locations. Each candidate location represents a possible location for placement of a small cell with maximum transmit power P_{max}.

The RF propagation path loss matrix can be represented by the matrix $\mathcal{L} \in \mathbb{R}^{A \times L}$, 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 maximum received signal power in that pixel. To that end, 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:

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

where the vector $\mathbf{x} \in \{0,1\}^L$ indicates whether a small cell is deployed at the l^{th} candidate location. If the small cell is deployed at the candidate location, then $\mathbf{x}(l) = 1$, otherwise, $\mathbf{x}(l) = 0$. Actually, $\mathbf{x}$ could be considered to refer to the network topology since it represents the actual cellular layout and therefore the main network planning variable.

The average SINR at a^{th} pixel each pixel is given by

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

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 of throughput $\tau(a)$ achievable in the a^{th} pixel is obtained through mapping the SINR results using a modified Shannon formula [46]

$$\tau(a) = \begin{cases} B(a) \cdot B_{eff} \cdot log_2(1 + \frac{\gamma(a)}{SINR_{eff}}), & \text{if } \gamma \geq \gamma_{min}. \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

where $B(a)$ is bandwidth allocated at a^{th} 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 [46].

3.2 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 costs. In order to reduce costs, they use less number of base stations in their service areas. However, more base stations can provide more capacity and coverage. This situation creates a trade-off for network operators. In order to characterize this trade-off in simulations, three different metrics are considered in this thesis. In addition to these three metrics, another metric used for power optimization is created. These metrics and their explanations are given below:

- *Number of base stations (f1):* This metrics represents the number of base stations in the wireless system design. More base stations can provide more capacity and coverage; however, more base stations increase the costs of the network operators.

- *Network capacity (f2):* This metric represents total aggregate throughput in a wireless system.

- *Cell-edge performance (f3):* This metric represents performance in cell-edge areas which are the weakest places of the wireless networks.

- *Pixel SINR* 5^{th} *percentile (f4):* This metric represents the 5^{th} percentile of all pixel SINR values. It is used in order to investigate the power optimization.

(f1), *(f2)* and *(f3)* are used in the simulations in order to investigate the performances of different topologies. *(f4)* is used in simulations in order to investigate the performance of proposed power optimization method.

In addition to those metrics, fairness in achievable throughput is also considered in this study using the Jain's fairness index given.

$$J(t_1, t_2, ..., t_N) = \frac{(\sum\limits_{i=1}^{N} t_i)^2}{n \cdot (\sum\limits_{i=1}^{N} t_i^2)} \tag{4}$$

where t_i represents throughput of the i^{th} user out N users. Jain's fairness index result in ranges of $\frac{1}{N}$ to 1. Fairness of system is maximized when each user has the same data rate.

3.3 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 base stations to maximize capacity and coverage in the service area, network operators investigate service area to find possible base stations locations. However, the large number of base stations locations would complicate investigation for network operators. Thus, optimization algorithms can be used to find optimal locations of base stations.

In this thesis, targets of the network operators are considered as aggregate capacity *(f2)* and cell edge performance *(f3)*. If the target of the network operators is to maximize aggregate capacity *(f2)* of the wireless system, they can select network capacity metric *(f2)* to design their wireless networks. On the other hand, cell edge performance *(f3)* may have priority in wireless system design. Therefore, cell-edge performance metric *(f3)* can be selected to design wireless systems. In this study, two different network optimization problems are considered. Network operators can select one of them depending on their network planning strategy.

Generally speaking, denser wireless networks can provide more capacity because of high-frequency reuse. On the other hand, the large number of base stations increases costs of wireless systems. In this regard, network operators should maximize capacity in their wireless system while minimizing the number of base stations. Therefore, network capacity metric *(f2)* or cell-edge performance metric *(f3)* can be optimized with the number of base stations *(f1)*. As it can be seen, there can be a trade-off between those metrics. This trade-off creates multidimensional optimization and it is called as multiobjective optimization [47]. Actually, this trade-off can be represented by the Pareto front that addresses the possible solutions for the multiobjective optimization. (In figure 8, an example for the Pareto front is given. Objective 1 and objective 2 are two dependent variables. Increase in one of them causes the decrease in the other one.)

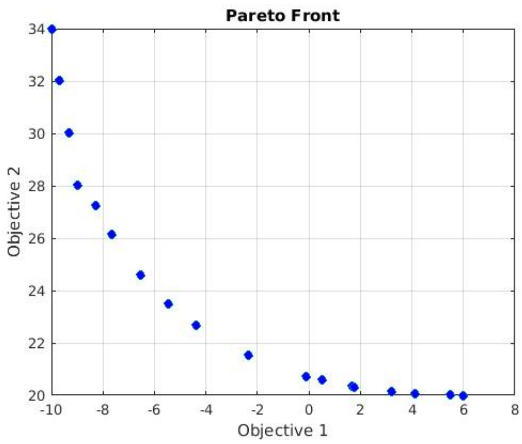


Figure 8: An example for Pareto front

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

$$minimize f = [f1, -f2] \tag{5}$$

For the number of base stations and cell-edge performance, the topologies featuring the best the trade-off between the number of base stations and cell-edge performance can be found by the proposed formulation as follows:

$$minimize f = [f1, -f3], \tag{6}$$

In addition to multiobjective optimization, single objective optimization is also used in order to optimize transmit power levels. The purpose of power optimization is to maximize SINR values of pixels. Thus, it can be formulated as follows:

$$minimize f = [-f4], \tag{7}$$

(6) and (7) are combinatorial problems belonging to NP-Complete class. In this study search space of optimization is a set of $2^C - 1$, where C is the number of candidate locations in the service area. Even for the small number of the set, search space can be huge. For example, if the number of sets is 15, the number of network topologies can be more than $32 * 10^4$. Therefore, it complicates the simulations. Furthermore, because of mathematical structure of (f2) and *(f3)*, search space is highly non-linear and full of discontinuities.

Therefore, Non-dominated Sorting Genetic Algorithm II (NSGA-II) is used in this study in for multiobjective optimization.

3.4 Fast Non-dominated Sorting Genetic Algorithm (NSGA-II)

3.4.1 Background on Genetic Algorithms

Genetic Algorithms (GAs) are optimization algorithms that are used to maximize or minimize functions by mimicking the nature. According to evolution theory and natural selection process, the best creature that has best genes in a population has more chances to survive and to transfer its genes to next generations. Actually, there are different optimization algorithms in literature but GAs are selected in this thesis since GAs are stochastic, efficient and usable with complex problems.

In computer science, there are complex algorithms such as NP-hard problems. These problems can be solved with both traditional optimization algorithms and GAs. However, traditional algorithms such as Enumerative and Random Search algorithms would spend too much time to solve these problems since they check functions at each point in search space. On the other hand, GAs do not check functions at every point and they provide near-optimal solutions. In addition to time complexity, some of the traditional methods such as Hill Climbing obtain a random point at first. Afterward, they start checking maximum or minimum point around initial selected random point since they are based on gradient approach. However, in such problems, there would be local optima as well as global optima. In this regard, this type of traditional algorithms would find local optima and finish the searches and this would cause wrong solutions. Moreover, GAs can solve problems that are stochastic, highly non-linear and discrete. Furthermore, GAs use population selection instead of point selections. It makes the GAs parallel in nature and parallelism property provides an ability to work with different points simultaneously [48, 49].

The procedure of GAs starts with the creation of population in a design space. Processing all design space is not efficient. Thus, the initial population is chosen from a large set of design space in order to reduce computational complexity. Afterward, individuals in the chosen population are assigned fitness values depending on the fitness function. The main consideration here is the computational efficiency of fitness function because fitness function is used every time when the new generation is created. After assigning fitness values, termination test starts. If termination test is not successful, then the algorithm continues to create new generations. After termination test, parent selection is done in order to create the new generation. There are different approaches to select the parents such as Roulette Wheel Selection, Stochastic Universal Sampling and Tournament Selection. After parent selection, main steps of GAs arise, which are *crossover* and *mutation* operations. Crossover matches two individuals and exchanges their genes to create new offspring. There are different crossover techniques such as One Point Crossover, Multi-Point Crossover, and Uniform Crossover. Mutation is a process where genes of individuals are randomly changed. There are different mutation techniques such as Bit Flop Mutation, Swap Mutation, and Scramble Mutation. Crossover and mutation are very important steps to keep variation in the population. After crossover and mutation steps, GAs create the new generation that will be used in next iterations to find the best values [49, 50].

In GA applications, there are different requirements that have to be considered before algorithm starts. One of the requirements is the size of the population because larger sizes would cause computational complexity. Moreover, smaller sizes might not provide optimal solutions. Therefore, size of the population should be considered very carefully. Another requirement is to apply crossover and mutation to keep variation in population to have randomness.

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 details since it may cause extra computational complexity for GA. Another problem is that there is a need for the diverse population because premature convergence is risky for the well-distributed set.

In terms of telecommunication engineering, GAs have been used by researchers for various purposes such as coverage, QoS, and energy efficiency. In [51], 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 in the simulations. In [52], GA is used to optimize the locations of base stations. Authors considered the trade-off between coverage maximization and base station costs. In [53], an energy efficient GA algorithm is proposed for multicast routing problem with QoS in wireless ad hoc networks. There are various GA based algorithms in the literature. Some of these algorithms are Multiobjective 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.

3.4.2 Non-Dominated Genetic Algorithm (NSGA)

NSGA is a type of GAs for multiobjective optimization. NSGA is ancestor of NSGA-II which is used in this thesis. NSGA is different from the other GAs in terms of the selection process.

In the beginning of NSGA, algorithm ranks individuals based on their non-dominations. Afterwards, first group from current population is identified to define first non-dominated front and they are assigned dummy fitness values. It is good to note that dummy fitness values are assigned to all of non-dominated individuals. Efficiency of the NSGA is the usage of dummy fitness value because it does not use the objective functions for each iteration to create new generations.

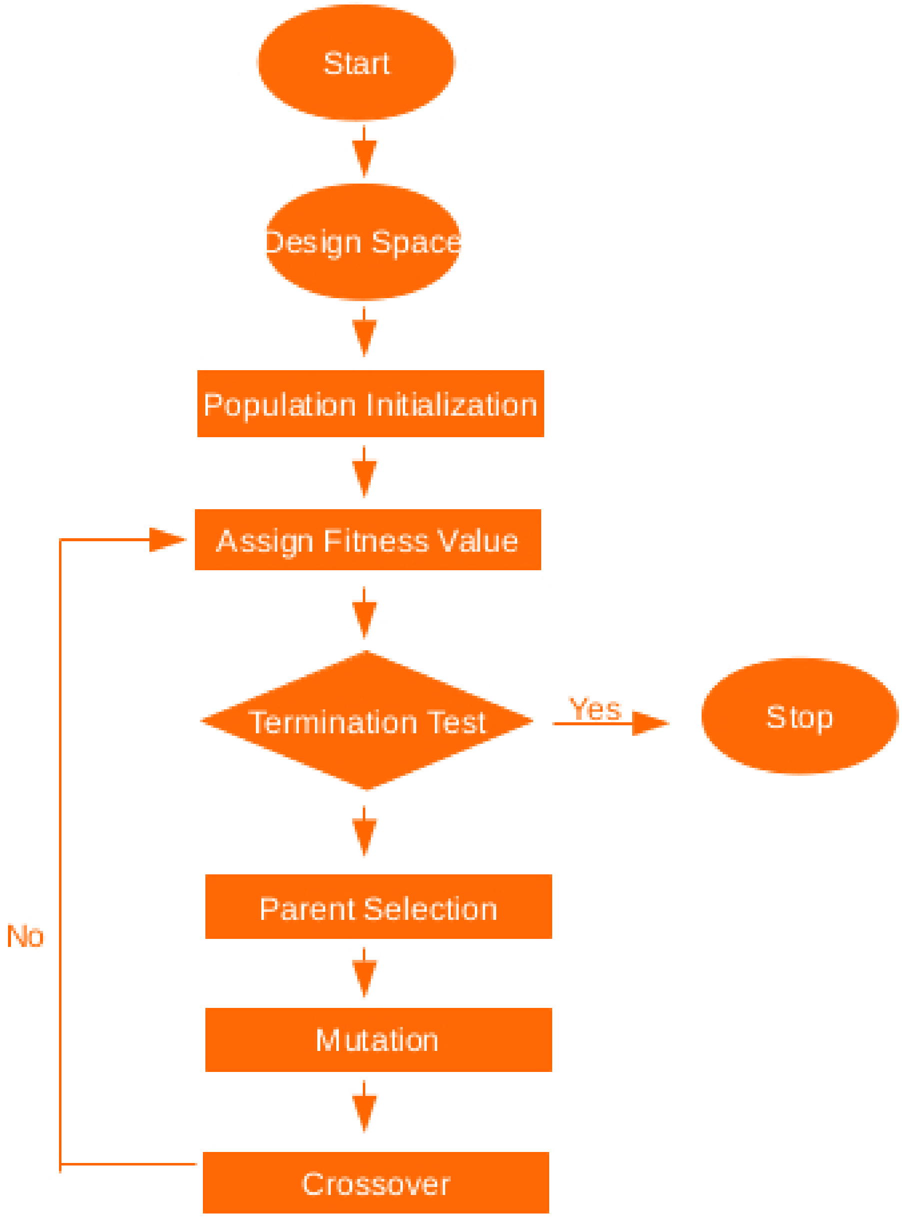


Figure 9: General flow chart of GAs

As mentioned earlier, diversity is an important factor for the 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 same sub-population should share available resources. When number of individuals is in a certain area, fitness value is degraded more. After sharing step, first group of non-dominated individuals is ignored in order to process next non-dominated individuals in 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 in population are classified into different fronts, NSGA reproduces population depending on the dummy fitness values. Then, crossover and mutation is applied to population. Reproduction, crossover and mutation are done until the end of the iterations to find the optimal values [48].

3.4.3 NSGA-II Enhancements

Different algorithms have been developed for many years to improve quality of previous algorithms. Although NSGA is a good algorithm, it has different disadvantages. In [54], authors proposed NSGA-II by improving the NSGA.

NSGA has several disadvantages as an algorithm. First of all, NSGA has high computational demand because of its non-dominated sorting. NSGA has $O(MN^3)$ complexity where M is number of objectives and N is population size. As it can be seen, number of population should be considered in detail since it has a huge impact on complexity of the NSGA. The reason for complexity of the NSGA is that the NSGA sorts non-dominated individuals after every new generation. Secondly, as in evolution theory, survival chance of the best genes is higher than other genes. This situation is protected by elitism that combines new generation with old generation to create better solutions; however, the NSGA is lack of elitism. Thirdly, the NSGA uses sharing approach to maintain the diversity by using the sharing parameter. On the other hand, sharing parameter is not demanded and diversity should not depend on parameters [54].

NSGA-II starts with the population initialization that has size N. Afterwards, objective functions are used to evaluate fitness values of individuals in population. Depending on fitness values, algorithm sorts individuals. In order to select individuals from population, NSGA-II uses crowding distance selection. Next step is to evaluate objective functions, after crossover and mutation are operated to create 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. Algorithm selects N individuals to continue algorithm. If termination criterion is not met, algorithm continues until termination criterion is matched [55].

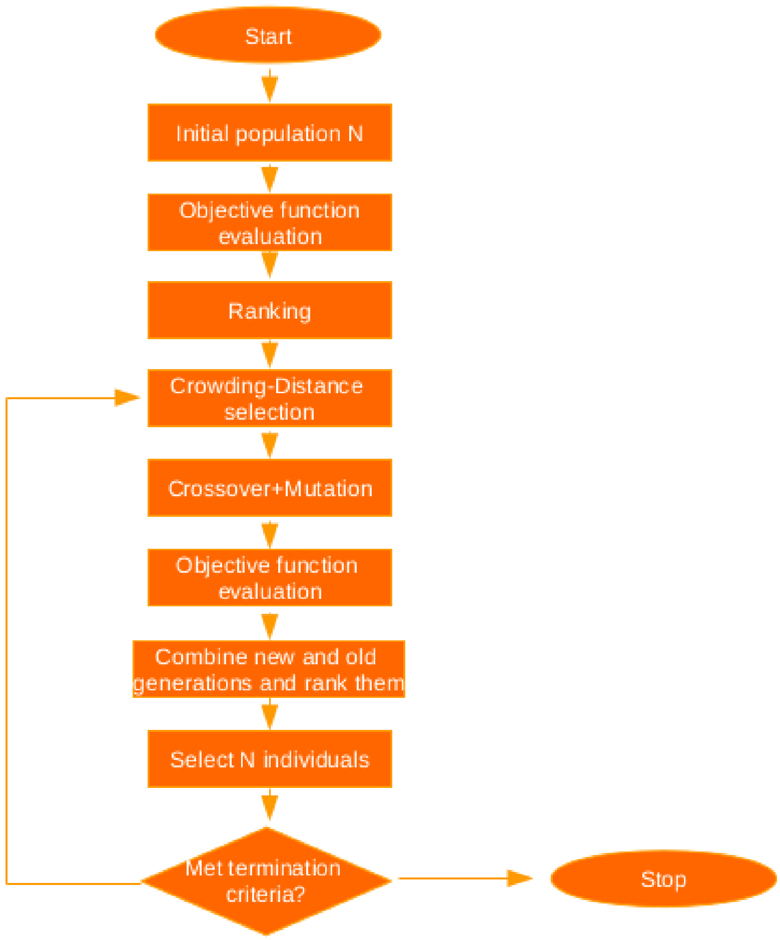


Figure 10: NSGA-II flow chart

NSGA uses sharing function to maintain diversity in the population. In sharing function, a user can define sharing parameter that identifies the extent of sharing between members. Sharing parameter is related to distance metric that is used to find proximity measure between two members. Within distance metric, two solutions share each other's fitness value. However, sharing function has difficulties. Sharing function is depending on 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, 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 particular solution. It is calculated for each solution in the front.

3.5 Transmit Power Optimization

3.5.1 Optimization and Self Organizing Networks

Wireless telecommunication networks are live and dynamic due to changes in spatial traffic distributions, weather situation and etc. Because of dynamic nature of wireless networks, network operators always control their wireless systems for providing the best services. In order to provide best services, network operators optimize their wireless systems based on different metrics.

In traditional wireless networks, employees in the network operators execute tasks to optimize the wireless networks. On the other hand, optimization in future wireless networks will be harder than traditional wireless networks due to a large number of base stations. Furthermore, optimization with a large number of base stations manually could be expensive for the network operators. Thus, network operators could face high expenses in terms of OPEX. In addition to optimization and expenditures, detecting failures in future wireless networks will not be easy. Therefore, Self-Organizing Networks (SONs) could be a way to reduce the network management burden for the network operators.

SONs are networks that can configure, optimize and heal themselves. Therefore, SON provides simplified solutions to network operators. SONs can be used in the cases which are capacity and coverage optimization, energy saving, interference reduction, mobility robustness optimization, random access channel (RACH) optimization and inter-cell interference coordination [56].

SON has different functions and those functions could be executed in different architectures. In terms of architectural perspective, there are three different architectures. Those are centralized architecture, decentralized architecture and hybrid architecture. In centralized architecture, system related configuration parameters and algorithms are executed in Network Management System (NMS). Centralized architecture is useful in terms of finding global optimization of whole network. Moreover, centralized architecture provides more manageable implementation. However, scalability and reaction time could be problems for centralized architecture. In decentralized architecture, each eNB (evolved NodeB) has its own SON entity. Each of eNBs executes SON functions to maximize performance of its own UEs.

This architecture reduces latency and provides more scalable solutions. On the other hand, network operators have less control over SON functions in decentralized architecture. In addition, decentralized architecture may not provide global optimum solutions for whole network since each eNB executes SON optimization functions for its own UEs. Hybrid architecture is combination of centralized and decentralized architectures, where some of SON functions may reside in central entity and others may reside in eNBs. This architecture provides flexibility for the network operators. However, implementation and coordination could be complicated [57].

As it can be seen, there are different optimization objectives and each of them can be considered in their own dimension. In this thesis, power optimization is studied to optimize wireless systems in order to match the best performances.

3.5.2 Transmit Power Optimization in Literature

Power optimization has a key role in coverage and capacity because of interference that is created by neighboring cells. If transmit power levels of neighboring cells are optimally adjusted, interference can be reduced drastically and therefore SINR in UE can increase. In addition to interference, cell transmit power can be optimized to reduce energy consumption.

In literature, there are different power optimization approaches. Generally speaking, some of them are based on either heuristic algorithm or optimization algorithms. In addition, there are researchers in the literature that use game theory in their studies.

In [58], authors proposed Simulated Annealing based algorithm for power optimization and antenna tilting. They assumed that transmit power of each cell is same because using uniform transmit powers can decrease computational complexity. In their approach, depending on the weighting factor, the network can increase cell edge capacity or network total throughput. In [59], authors propose an approach that uses Gibbs Sampling to optimize downlink transmit power of LTE network. According to their proposal, each cell calculates a power value depending on other cells. However, although their algorithm is able to improve cell edge user performance, it reduces total cell throughput. The authors in [60] investigated transmit power optimization and user association by considering CoMP in order to reduce energy consumption. They achieved to reduce total energy consumption. In [61], authors estimates transmit power of small cells by minimizing total transmit power. Their objective function is total transmit power. They also define two different constraints, capacity demand constraint, and power constraint. In [62], same authors of [61] evaluates optimal transmit powers in urban, suburban and rural cases by considering hourly network capacity demand of mobile access networks. Their results show that urban and suburban cases have an increased transmit power comparing to the rural case. Their result also showed that when the number of small cells increases in locations, average transmit power decreases. Power optimization also applied to railway environments. In [63], an adaptive LTE downlink power control scheme is proposed for high-speed train environment.

In real-world heterogeneous network applications, the network consists of macrocells and femtocells layers. Femtocells indeed lower cost of operators. According to [64], offloading traffic to femtocells can reduce costs of network operators up to 70%. However, using more femtocells in the wireless network, where macrocells are already deployed, can increase interference of macrocells. In [65], authors study co-channel deployments of macro and femtocell network downlink interference control scheme. Their results show that femtocell can reduce interference to UEs in macrocell network when eNB in macrocell adjusts its power. In [66], authors proposed the algorithm that can be used with fixed or variable data rates in femtocell and macrocell coverage. In their study, they used Channel Quality Indication (CQI) in order to receive feedback from UEs to increase base station transmit power which is initialized with minimum power. According to their simulation results, variable data rate optimization provides more qualified services.

In macro and femtocell environment, co-channel interference is a factor that can limit achievable capacity. From this perspective, authors in [67] optimized the femtocell transmit power levels by using simulated annealing method. By optimizing femtocell transmit powers, SINR values of macrocell users are improved in their study. In [68], authors address the importance of downlink transmit power optimization and they propose a method to calibrate transmit power with help of the technician. However, their method is not suitable for computer-based simulations.

As a result, there are many transmit power optimization approaches in the literature. However, in terms of complexity and viability, none of those approaches can be applied in this study.

3.5.3 The Method used in Thesis

As stated earlier, simulations are conducted in order to investigate the performances of different types of topologies. In order to conduct simulations, simulation area is divided into pixels and there are 13974 pixels in the simulation area. Each pixel has its own area which is 5x5 m^2 and any users can be dropped in any pixels during simulation time. Simulator description in detail could be found in section 4.

$$maximize f = [f4] \tag{8}$$

The main purpose of power optimization is to find the optimum transmit power levels for different base stations in order to serve users with the best performance. In this sense, in order to serve users with the best performance, SINR values of pixels could be optimized and therefore pixel SINR values could be increased. After increasing pixel SINR values, SINR values of users are expected to increase automatically. In this regards, it is possible to enhance the UE SINR values without evaluating each UE in the transmit power optimization phase. Thus, in this phase, it is assumed that there is no UE in the simulation area.

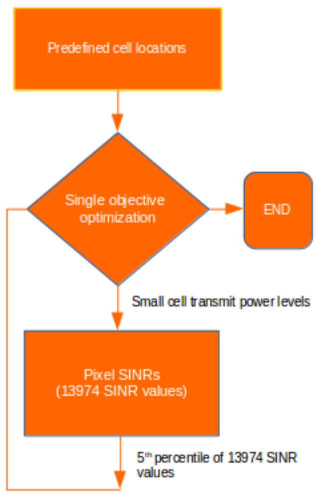


Figure 11: Flow chart of transmit power optimization

Power optimization is investigated by considering the 5^{th} percentile of all pixel values. It means that 5^{th} percentile of all pixel values (13974 Pixel SINR values) is optimized in order to maximize the pixel SINR values. In order to maximize 5^{th} percentile of all pixel values, (f4) metric is used in the single objective optimization.

In figure 11, the flowchart of transmit power optimization is given. To investigate the optimum transmit power levels, small cell locations are predefined. Thus, small cell locations do not change with the single objective optimization but transmit power levels of small cells change. After calculating the SINR values of each pixel, 5^{th} percentile of all SINR values is found. Then, this value is used for the input of single objective optimization. According to this value, the simulation may end or continue.

4 Case Study and Results

Network densification in the future will have several challenges for network operators since network densification will be necessary, particularly for highly densely populated areas. According to [69], 90% of population growth is expected in Asia and Africa by 2050. In addition to that, these areas already have high population density in the range of 40000 – 200000 $people/km^2$. Therefore, these areas would be the main target of the UDNs. On the other hand, these areas will also suffer from limited infrastructure in terms of the energy, backhauling and site acquisition [70].

As stated earlier, small cells in the UDNs can be deployed by network operators or subscribers. Deployment by network operators will be done with information about locations of small cells. It means that network operator will have information about locations of small cells, transmit power and etc. On the other hand, deployment by subscribers cannot be known by network operators since subscribers can deploy their small cells anywhere. Actually, it is possible to detect locations of user-deployed small cells from network operator side; however, network operators still do not know decisions of users. Therefore, this type of deployment will lead to random network topologies where network operators will not have certain decisions about locations of small cells.

In order to study different UDN settlements, static system level simulator is developed. The main purpose of the simulator is to find optimum topologies depending on performance metrics given in section 3. The simulator also investigates performance differences of random, optimized and hybrid topologies. Moreover, transmit power optimization results will be presented in this section. To sum up, simulator and corresponding results will be explained in details.

4.1 Deployment Scenario

In order to contextualize UDN planning and optimization framework, a real case UDN scenario in a highly populated area is considered. In this study, Hanna Nassif ward in Dar es Salaam, Tanzania is assumed as a place where the UDN is deployed. The population density in Hanna Nassif is approximately 40000 $people/km^2$. In $1km^2$ areas of Hanna Nassif includes almost 3000 buildings which their heights are in the range of 3-6 m. Their topographical difference is approximately 19 m. Three-dimensional (3D) representation of UDN deployment scenario is given below.

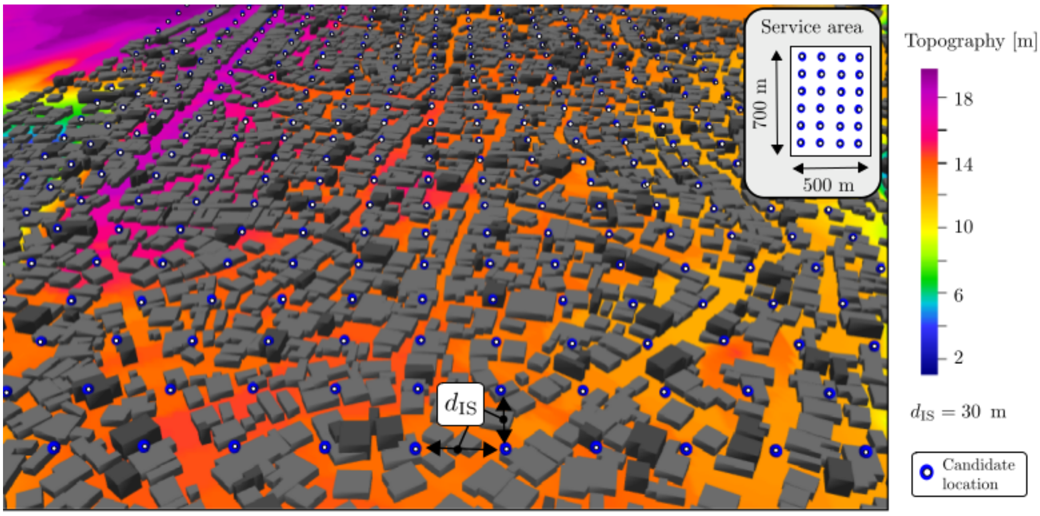


Figure 12: Planning case deployment scenario [6]

There are totally 368 candidate locations for base stations. These candidate locations are represented with white-blue dots in figure 12. They are all located at rooftop level. The reason to choose rooftop base stations is to improve outdoor coverage. Base stations located at rooftop level provides LOS conditions for high-capacity wireless backhauling [71]. Furthermore, the rooftop is a good place for different technologies such as energy harvesting from alternative energy resources such as wind and solar [72].

4.2 Simulation Approaches, Parameters, and Assumptions

In order to investigate different network topologies, a static simulator is developed by considering real wireless networks. In real wireless networks, there are different parameters to consider and parameters used in this thesis are given in table 3.

Algorithms have two distinct features that have key roles in algorithm performance. Simulation time is one of the features that could be shortened by using more cores in the simulations. The other feature is the memory that is a challenge for the computer Random-access memory (RAM). If the memory requirement of the algorithm is large, simulation time becomes a challenge for small RAM.

Simulations could be run in any environment such as local computer and computer clusters. However, to shorten the simulation time, Triton [73] which is Aalto University high performance computing cluster was used. Actually, the local computer could have been considered as a simulator environment but Triton provides more cores and more RAM so that duration of simulations are shortened significantly. Depending on the simulation parameters, Triton speeds up the simulators up to 20 times as compared to the local computer.

4.2.1 Simulator Approaches

As stated earlier, there are three different network topologies in this study. These are optimized topologies, hybrid topologies, and random topologies.

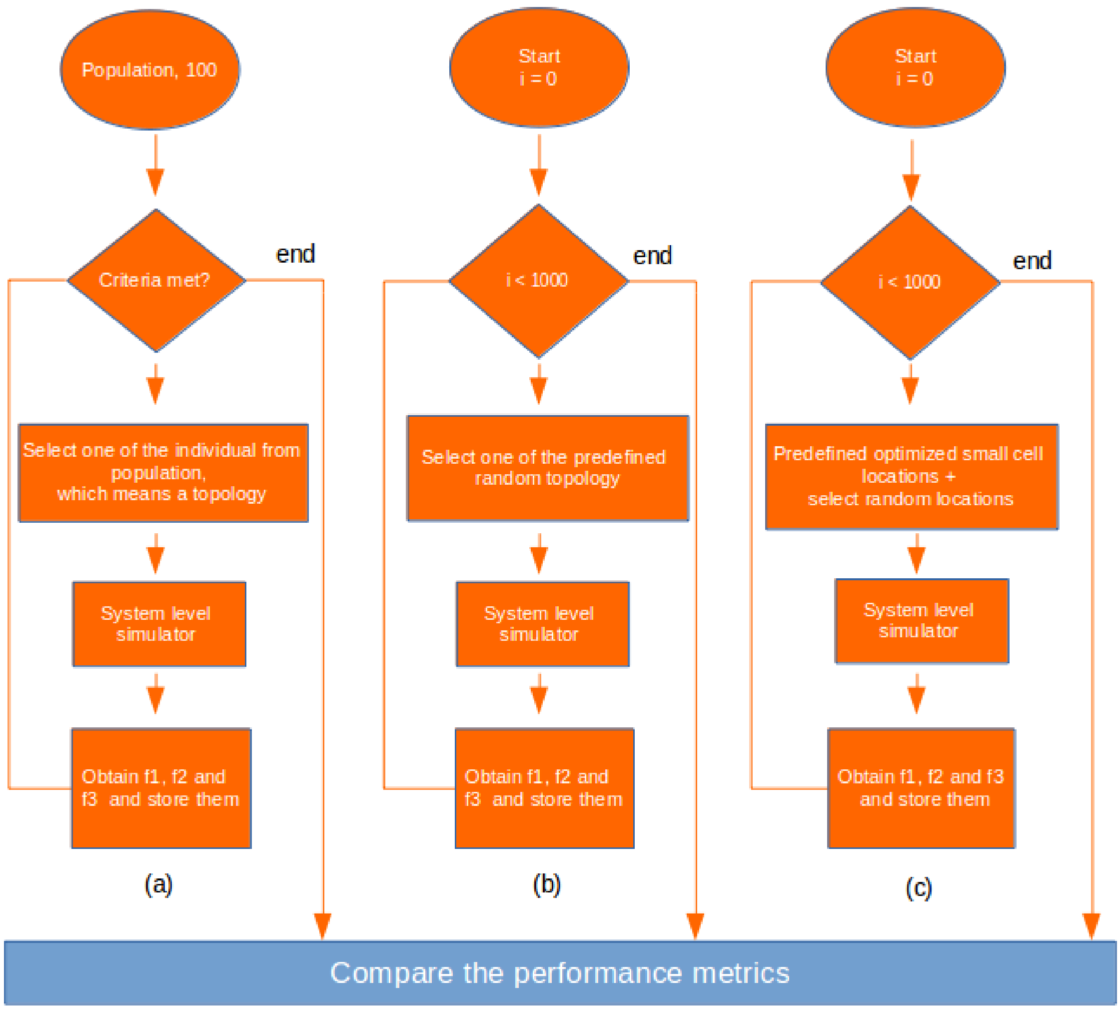


Figure 13: (a) Optimization of small cell locations, (b) Random topologies, (c) Hybrid topologies

In order to obtain optimized topologies, NSGA-II algorithm is used. Actually, NSGA-II algorithm in this thesis optimizes the locations of the small cells. It means that NSGA-II searches for the optimal candidate locations for the certain number of base stations. In this sense, NSGA-II provides the optimal solutions that enhance particular performance metrics.

To investigate the performance of random topologies, 1000 random and different topologies are created. For example, if the purpose is to deploy 140 cells in the service area, 1000 different topologies, which each consists of 140 cells, are created.

Hybrid topologies are combinations of random and optimized topologies. In order to investigate the performance of hybrid topologies, I used the same method that I used for random topologies. 1000 different topologies that consist of both optimized and random topologies are created. Actually, there is the fraction of optimized and random small cell locations for hybrid topologies. For example, if the target is to deploy 140 cells, 60 optimized cell locations and 80 random cell locations can be created. In addition, 100 optimized cell locations and 40 random cell locations can also be chosen. In order to see hybrid topologies used in this thesis, please refer to table 2.

Random	completely random small cell locations for uniform STD/ non-uniform STD
Optimized	optimized small cell locations for uniform STD/ non-uniform STD
Hybrid1	consists of 40 optimized small cell locations and 100 random small cell locations for uniform STD/ non-uniform STD
Hybrid2	consists of 70 optimized small cell locations and 70 random small cell locations for uniform STD/ non-uniform STD
Hybrid3	consists of 100 optimized small cell locations and 40 random small cell locations for uniform STD/ non-uniform STD

Table 2: Topology types

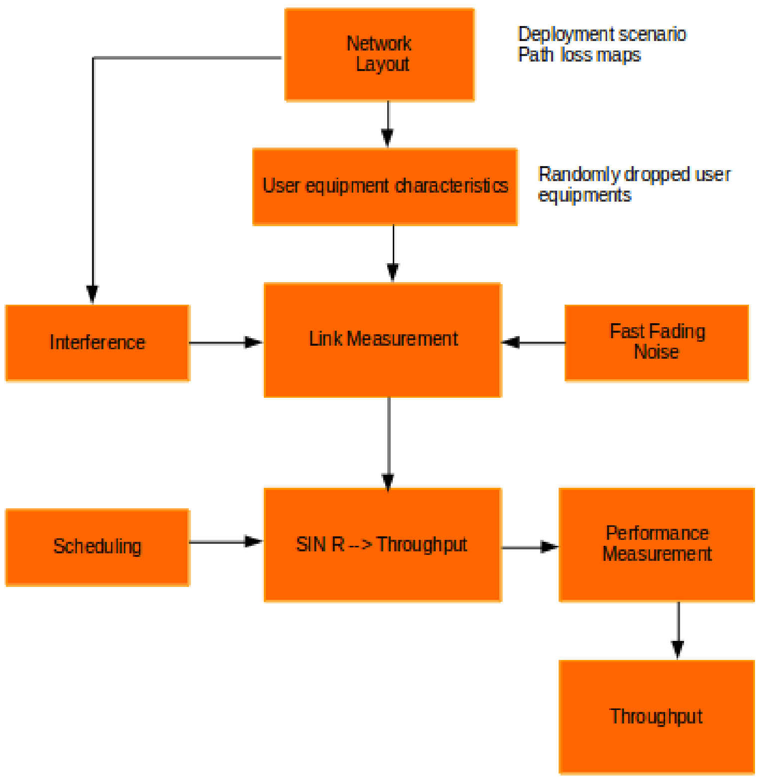


Figure 14: System level simulator block diagram

Two different STD cases are considered in this study and these are uniform STD and non-uniform STD cases. As mentioned in section 2, service demand by users is uniformly distributed over the service area in uniform STD case. Non-uniform STD implies that service demand is more likely to be found in certain areas. Actually, non-uniform STD case could be found in real wireless networks and uniform STD case could be a reference for non-uniform STD case in terms of performance comparisons in this study.

4.2.2 Key Parameters and Assumptions

In order to investigate the performance of different topologies, 400 users are dropped randomly in different 5x5 m^2 pixels the service area following the uniform or non-uniform STD. To increase the statistical quality of the study, the 400 random users are dropped repeatedly for 3000 times. This means that 3000 snapshots are used in static system level simulator.

On the other hand, in terms of transmit power optimizations, only one snapshot is used. It means that there is only one topology and transmit power levels of small cells in this are optimized. Only one optimized topology is obtained by results of optimized topologies. Random topologies are created randomly for only one snapshot. In order to create a hybrid topology, I used different combinations of random and optimized topologies. It should be noted that each topology is same during the simulation time of transmit power optimization. One snapshot is used to reduce the time complexity of the simulations. Moreover, as explained in the section 3.5.3, there is no UE in the transmit power optimization phase. Thus, just working on the pixel SINR values is possible with only one snapshot.

Parameter	**Values/Assumptions**	
Deployment Scenario	Outdoor small cells deployment	
Carrier Freq./ Bandwidths	Carrier Freq : 2600 MHz, BW : 10 MHz	
Simulations	Radio propagation modeling (WinProp) [74], Static system level simulations (Matlab), 5 m resolution	
SINR-throughput mapping	SINRmin (dB)	-10
	BWeff	0.42
	SINReff	1.1
	Smax (b/s/Hz)	7.67
Transmit Power	30 dBm	
Transmiter Gain	0 dBi	
Receiver Gain	0 dBi	
Antenna Height	7 m	
Antenna Patterns	Isotropic	
Number of small cells	368 candidate locations, number of SC changes for topologies	
Location	Deployed on the rooftop	
UE height/location	UEs dropped in whole area (both indoor and outdoor), height is not considered	
Number of UEs	400	
Number of Monte Carlo Iterations	3000	
Fast fading	Rayleigh Fading, number of paths is 10	
Buildings	Heights 3 to 6 m Penetration loss: 20 dB	
Cell association	Cell association: max received signal strength wins. Fast Fading is not considered in the cell association	
Scheduling	Round Robin	
Population	100 for topology optimization, 1000 for power optimization	

Table 3: Simulation parameters

4.3 Simulation Results and Discussions

In this section, simulation results will be introduced. In first two subsections, performance comparisons between different topologies will be presented. In the last subsection, results of power optimization will be presented. In order to compare performances of different topologies, the number of base stations on the network layout is selected as 140.

4.3.1 Results of Random and Optimized Topologies

In this section, random and optimized network topology types are compared. In order to compare those topologies, aggregate capacity (f2) and cell-edge performance (f3) metrics are used.

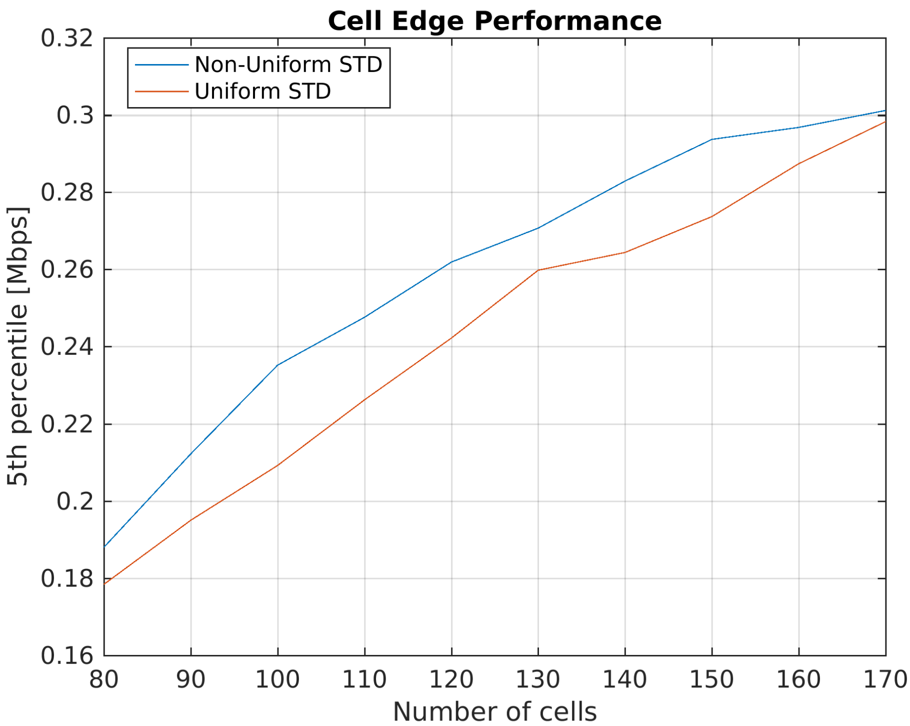


Figure 15: Cell edge performance (f3) of optimized topologies

In figure 15, optimized topologies are compared in terms of cell edge performance (f3). It can be seen that non-uniform STD case has better performance than uniform STD case. This is attributed to the fact in the non-uniform STD case, the higher small cell deployment density closely follows the areas with higher concentration of users, unlike the uniform STD case. Therefore, with the same number of small cells, it is quite possible that non-uniform STD has much better cell edge performance (f3).

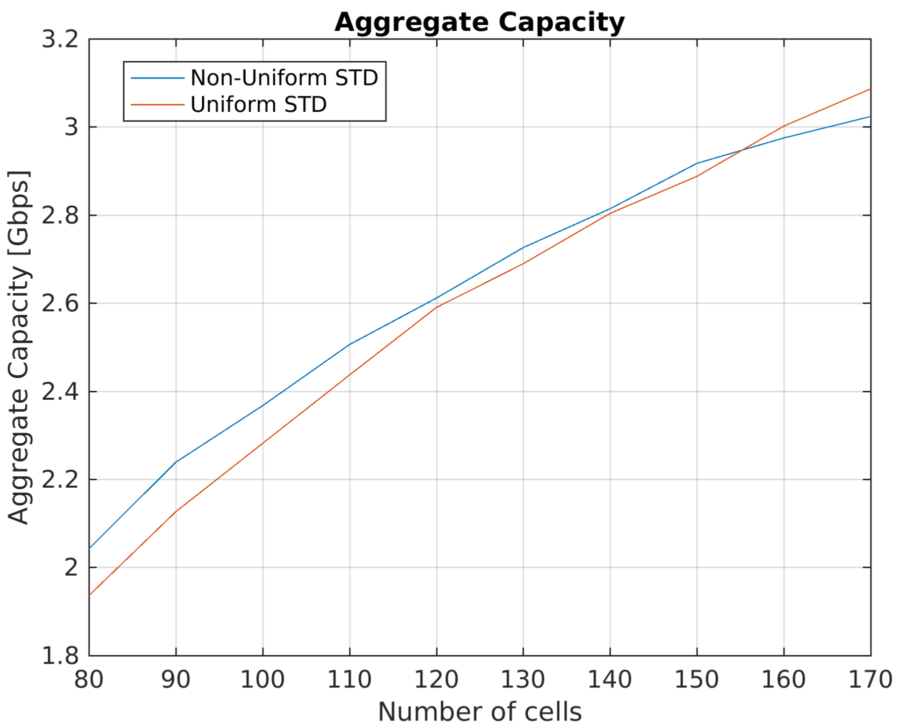


Figure 16: Aggregate capacity (f2) performance of optimized topologies

As mentioned earlier, aggregate capacity (f2) is another metric to compare different spatial traffic distributions. In figure 16, aggregate capacity comparison of non-uniform and uniform STD cases are given. In this figure, it can be seen that non-uniform STD has better performance with the low number of small cells while uniform STD has better performance with the high number of small cells. From this point, it can said that uniform STD case has the almost same characteristic of non-uniform STD case after a certain amount of small cells is exceeded in the same area. In other words it implies that the uniform STD case with the high number of small cells reaches almost same base station/m^2 density of non-uniform STD case and after some points, it becomes better than non-uniform STD case.

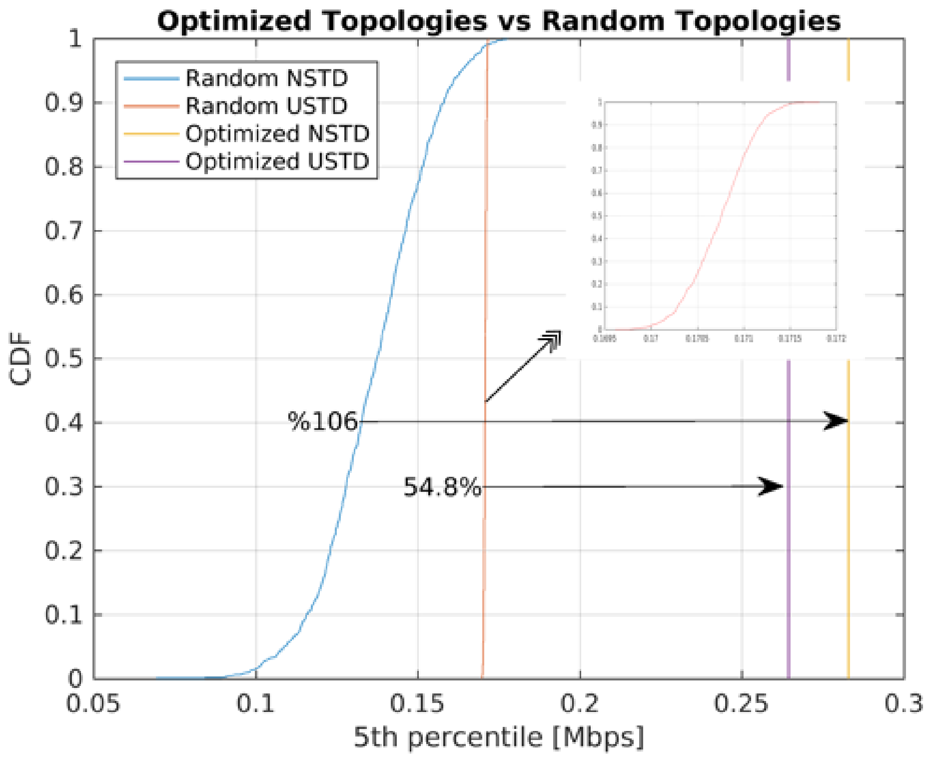


Figure 17: Cell edge performance (f3) comparison of random topologies and optimized topologies

One of the main targets of this study is to investigate the hybrid topologies which are the combination of optimized and random topologies. Therefore, I believe that before presenting the results of hybrid topologies, comparison of random and optimized topologies should be investigated. Random topologies are topologies that are random in nature. It means that locations of 140 small cells are selected randomly. Therefore, there is no optimization procedure for random topologies. From this perspective, random topologies represent user-deployed small cells and optimized small cells represent operator-deployed small cells.

In figure 17, cell edge performance (f3) comparison of random and optimized topologies is given. In this figure, it can be seen that optimized topologies have much better performance as compared to random topologies. In the figure, optimization in non-uniform case increases cell edge performance (f3) by 106% while optimization in uniform case increases cell edge performance (f3) by 54.8%. Note that comparison between random and optimized topologies is done by considering the median value of random topologies CDF and cell edge value of optimized topology which has 140 small cells. From these results, it can be seen that non-uniform STD case benefits more from topology optimization. In random topologies, the location of small cells is selected without information of user distribution. As stated, UEs in non-uniform STD case are mostly in the certain areas while UEs in uniform STD case are distributed uniformly. Therefore, it could be expected that performance of random topology non-uniform STD case should be relatively worse compared to random topology uniform STD case. On the other hand, after optimization, performance increase in non-uniform STD case is more than corresponding uniform STD case.

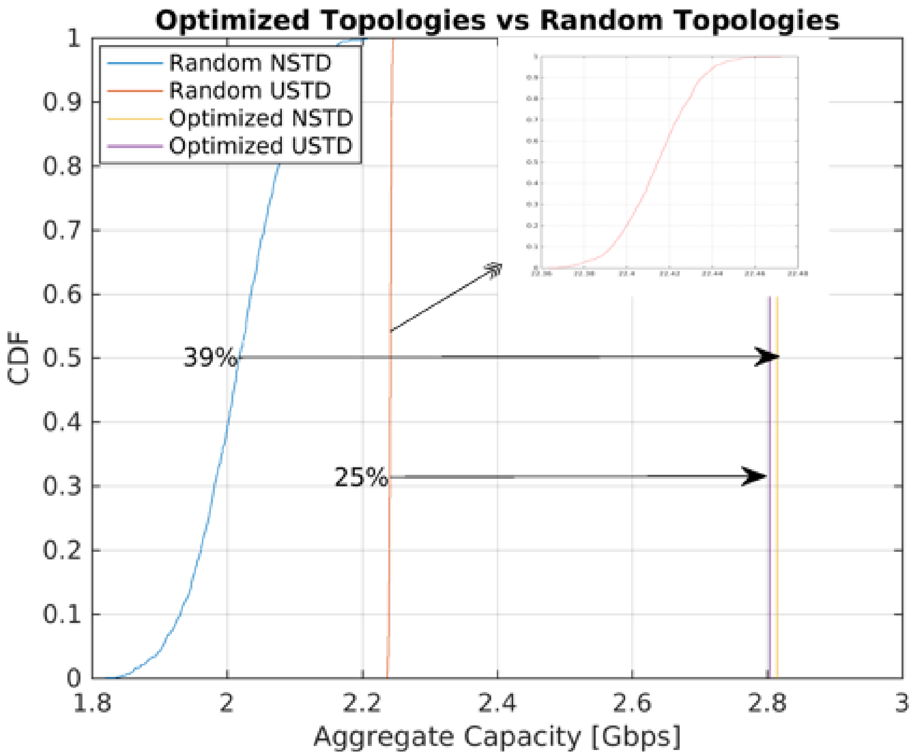


Figure 18: Aggregate capacity (f2) performance comparison of random topologies and optimized topologies

In figure 18, aggregate capacity (f2) performance of random and optimized topologies is shown. As in the previous case of figure 17, optimized topologies have more performance as compared to random topologies. Moreover, similar to figure 17, increase in non-uniform STD case is more than the increase in uniform STD case. It should be noted that optimized topologies in figure 18 are optimized by NSGA-II in terms of aggregate capacity (f2). It means that (f2) performance metric is used for optimization. Therefore, optimized topologies of (f2) and optimized topologies of (f3) could be different from each other.

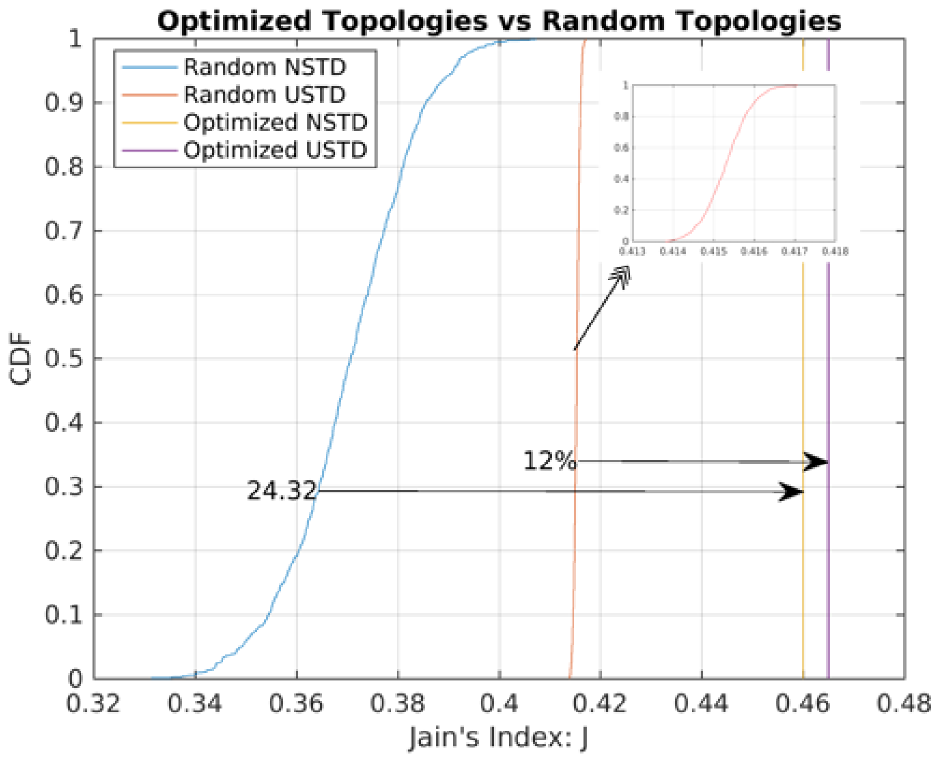


Figure 19: Fairness comparison of random topologies and optimized topologies

Fairness is one of the criteria that has to be taken into consideration. In figure 19, it can be concluded that optimization increases the fairness of the network layout.

After these results and respective interpretations, it can be concluded that operator-led topology optimization. On the other hand, random topologies leveraging user-deployed small cells have result in relatively worse performance than optimized topologies but provide a more feasible way for dense small cell deployments in UDNs. Therefore, there should be other approaches to improve the network performance while leveraging the flexibility of random user-deployed small cells. These approaches could be power optimization, load balancing, etc. The effect of power optimization on topologies will be explained later.

4.3.2 Results of Hybrid Topologies

The results of random and optimized topologies have been given so far. In this subsection, hybrid topologies will also be taken into consideration. As stated, hybrid topologies are combinations of random and optimized topologies. Because of this combination, one may vary the fraction of optimized and random small cell deployments in a hybrid topology, to account for different levels adoption of user-deployed small cells relative to the operator-deployed small cells optimized locations. What it means that the number of optimized small cell locations and the number of random small cell locations could be different for different hybrid topologies. Please note that in figure 20,21 and 22, the comparisons are done by median CDF values of the performance metrics.

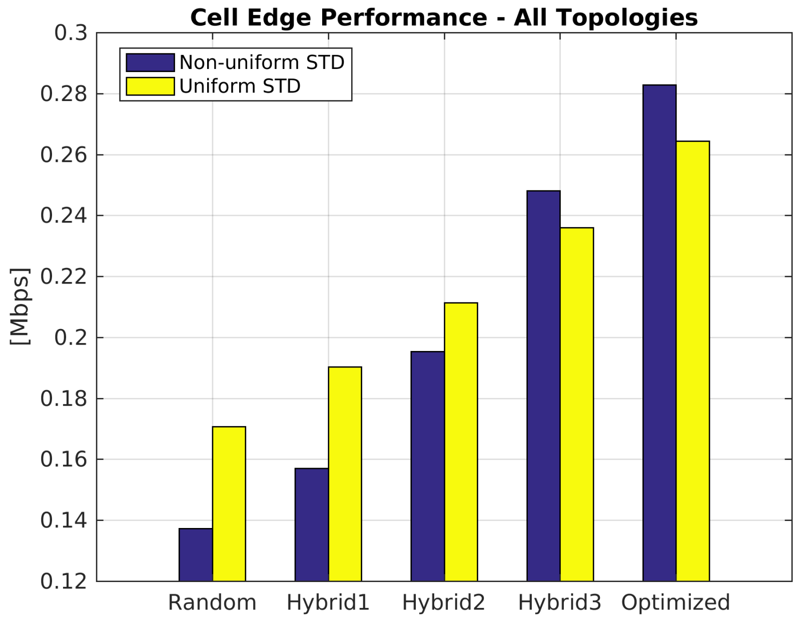


Figure 20: Cell edge performance comparison of all topologies

In figure 20, 21 and 22, performances of all topologies are shown. In terms of performances and fairness, it can be easily seen that random topologies are the worst topologies while optimized topologies are the best topologies. It can be an expected result because optimized topologies are created by considering user traffic distribution. Moreover, random topologies are inherently sub-optimum; therefore, provide relative worse performance and achievable fairness. Furthermore, performances of hybrid topologies are between random and optimized topologies. However, each hybrid topology has different performance depending on the fraction of random versus optimized topologies. Intuitively, one can easily say that the performance improves with the number of optimized small cell deployments in hybrid topologies relative to the number of random small cell deployments.

In figure 20, cell edge performances (f3) of all topologies are given. In terms of hybrid topologies, uniform STD case is better in hybrid1 and hybrid2. On the other hand, hybrid3 has better results for non-uniform STD case. As explained before, non-uniform STD cases consist of UEs that are populated in certain areas. Hence, if there are more random small cell locations in hybrid topology, uniform-STD case provides improved performance. Another important observation from this figure is that the changes in non-uniform STD cases are more than uniform STD cases in terms of the hybrid topologies. For example, increase from hybrid1 to hybrid2 is much larger for non-uniform STD case.

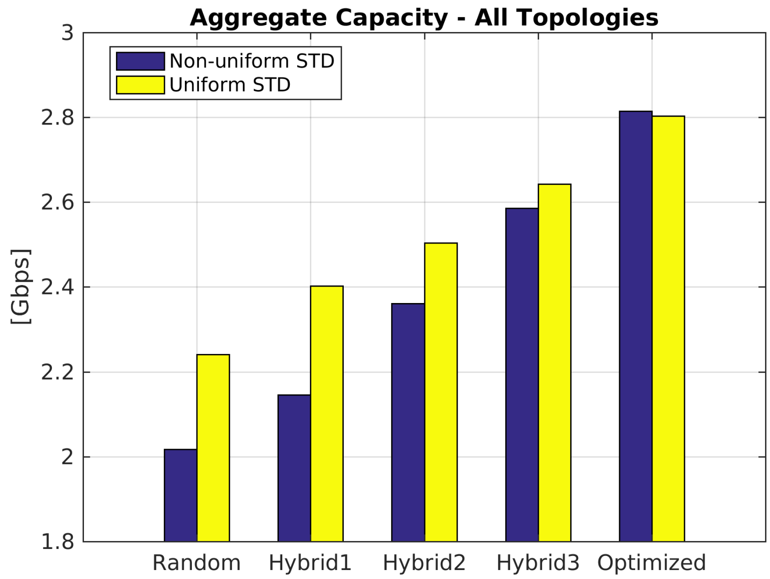


Figure 21: Aggregate capacity performance comparison of all topologies

In figure 21, aggregate capacity (f2) performances of all topologies are given. Actually, in all topologies, uniform STD cases have better performance than non-uniform STD cases. Furthermore, more optimized small cell locations increase aggregate capacity (f2) performances.

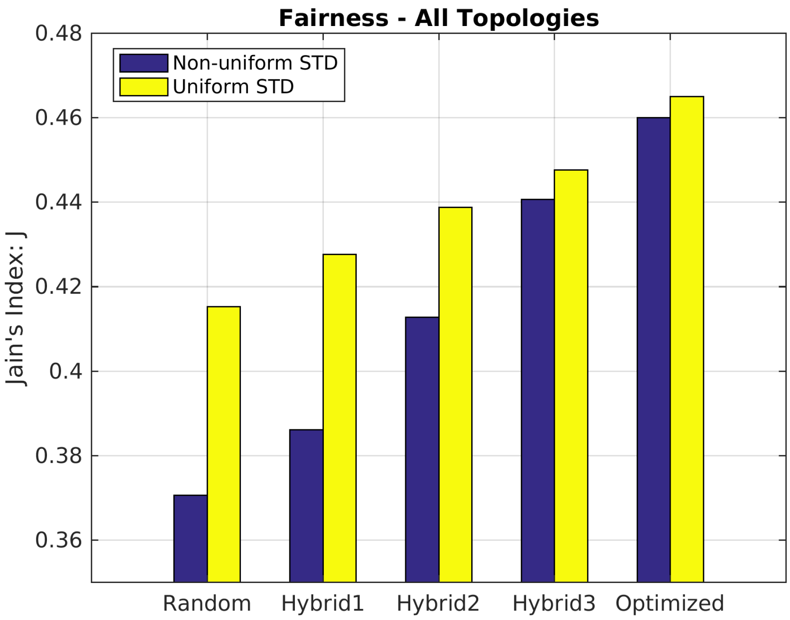


Figure 22: Fairness comparison of all topologies

In terms of fairness, we can see that non-uniform cases are more favorable with the optimized small cell locations. It means that fairness of non-uniform STD cases increases faster than uniform STD cases when the number of optimized small cell locations increases in the hybrid proportionality. This situation can be seen in figure 22.

4.3.3 Results of Power Optimization

Another main target of this thesis is to investigate the impact of post-deployment power optimization on different topologies.

The purpose of power optimization is to serve the subscribers with better performances. As mentioned, power optimization is done by optimizing SINRs of pixels. This improvement will in turn result in the improvements in SINR achievable by UEs.

Power Optimization for Random Topologies

As mentioned before, the benchmark for this study is 140 small cells but it is good to first demonstrate and validate the impact power optimization with a lower number of small cells.

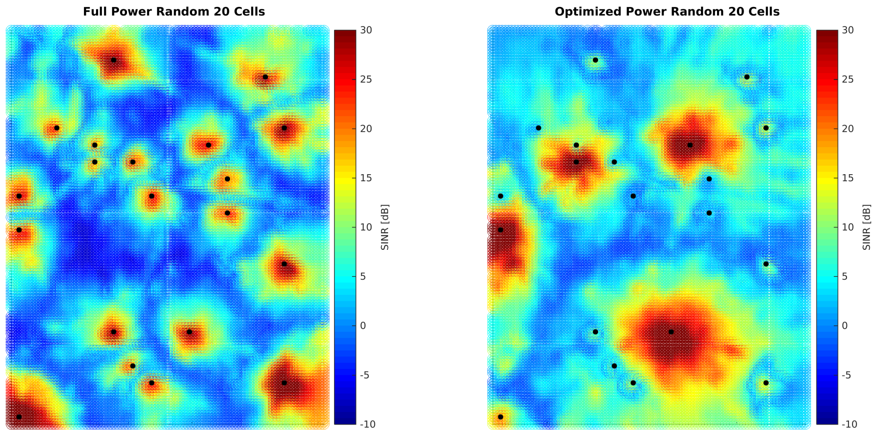


Figure 23: 20 random cells SINR maps

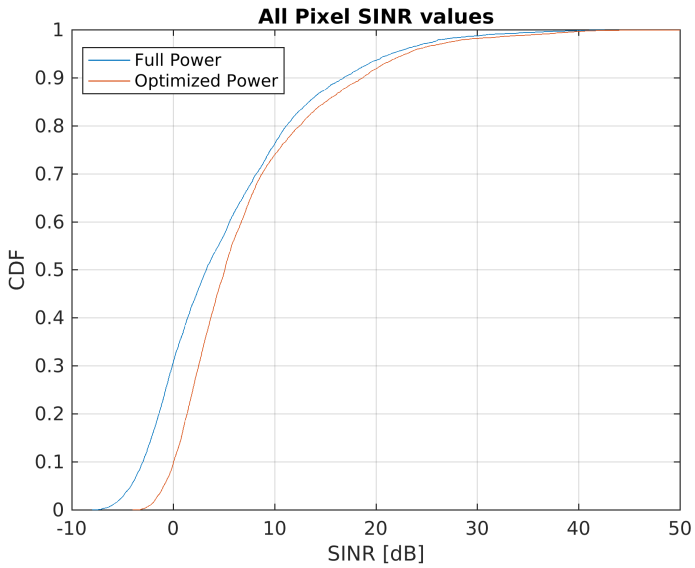


Figure 24: Pixel CDF random 20 cells

In figure 23, there are 20 cells on network layout and locations of small cells are selected randomly. On left picture, each of random 20 cells has full transmit power, 30 dBm. On right picture, each of random 20 cells has its own optimized powers. It can easily be seen that right picture has better SINR values in the simulation area. Moreover, in figure 24, it can be seen that CDF of pixel SINR values is increased. From this point of view, I could say that power optimization approach works correctly.

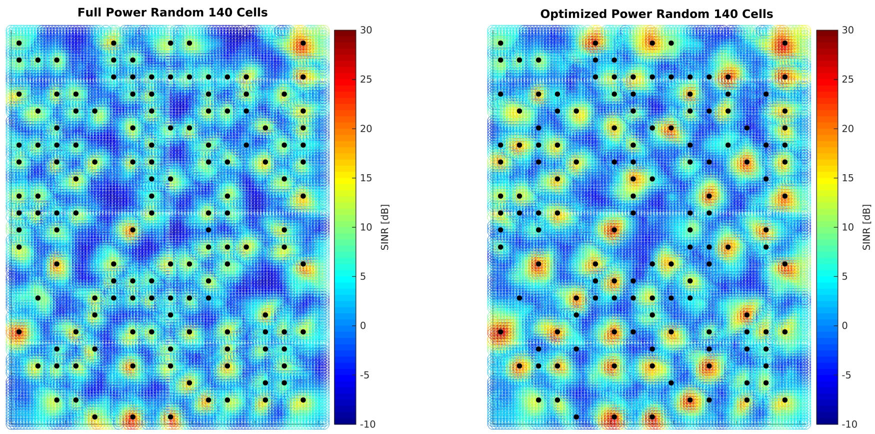


Figure 25: SINR maps for random topologies with 140 small cells

In figure 25, random 140 cells are taken into consideration. On left picture, each of 140 cells has full power 30 dBm while each of 140 cells has its own optimized power on the right picture. On right picture, SINR values are much better since some of the cells are switched off after optimization.

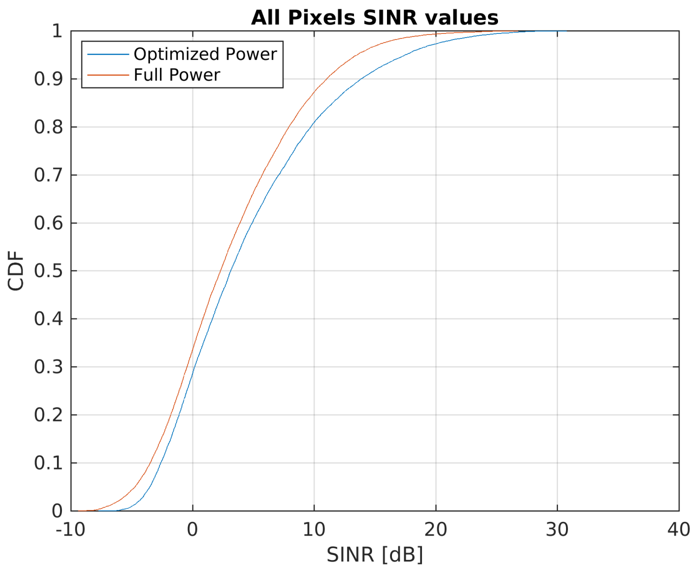


Figure 26: CDF of SINR per pixel for random topologies with 140 small cells

In figure 26, the cumulative distribution function of all pixel SINR values is shown. It is observed that power optimization provides improvement in pixel SINR particularly for random topologies.

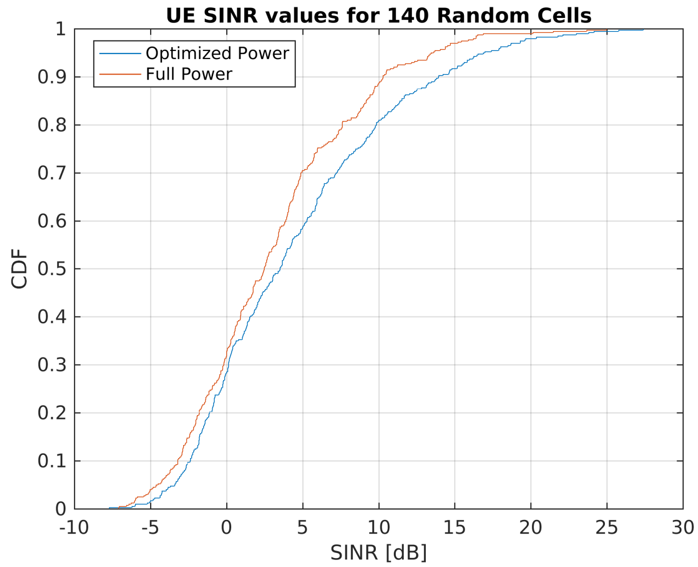


Figure 27: SINR values of UEs for non-uniform STD case-only for one snapshot

So far, we have seen that SINR values can be increased by power optimization. As stated, if pixel SINR values are increased, SINR values of UEs can also be increased. In figure 27, UE SINR values are given. From this figure, we can see that optimized transmit power increases the SINR values of UEs. Thus, we can assume that throughput values of UEs are also increased because of increase in SINR values. On the other hand, if you check figure 25 again, you can see that some of the small cells are switched off after power optimization.

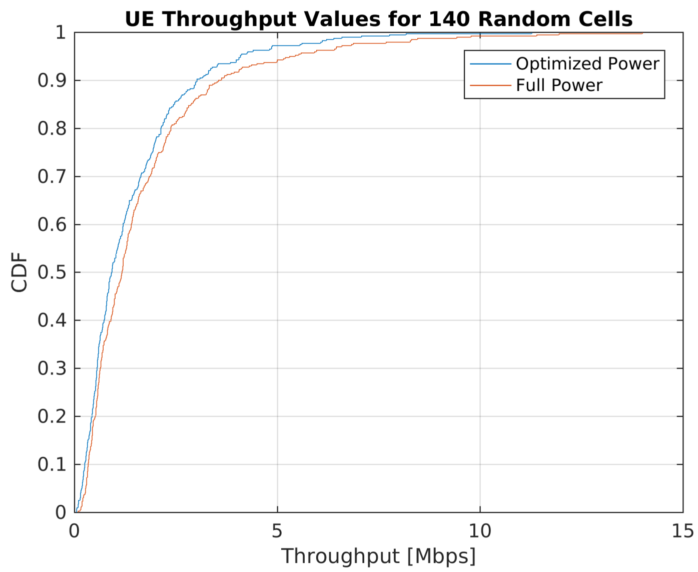


Figure 28: Throughput values of UEs for non-uniform STD case-only for one snapshot

Throughput values of UEs are given in figure 28. According to figure 28, throughput values of UEs are not increased. It means that throughput values of UEs are decreased with power optimization. In wireless telecommunications, bandwidth has a crucial role in terms of data rate. Each cell serves some number of UEs and therefore bandwidth of each cell is shared between its served UEs. Even though SINR values could be increased, the number of resources or bandwidth cannot be shared in the same way after power optimization.

In figure 29, number of UEs for each cell is given by bar plots. (a) represents full power case and (b) represents optimized power case. It can be seen that UEs are distributed more equally in (a) as compared to (b). Since some cells are switched off by power optimization or have their transmit power reduced significantly, their own loads are transferred to other active cells. Therefore, with new optimized transmit power levels, the UE load is shared by a smaller number of cells. Because of that, UEs obtain fewer resources as compared to full power case and this reduces the throughput of UEs. From this perspective, traditional UE association that attaches UE to cell with received signal power actually leads to reduced overall fairness in terms of achievable throughput for all UEs. Thus, load balancing could be considered in a way where estimated available throughput per link is used instead of link quality estimation [75]. In this regard, I can say that load balancing could be studied after power optimization; however, it is not in the content of this thesis.

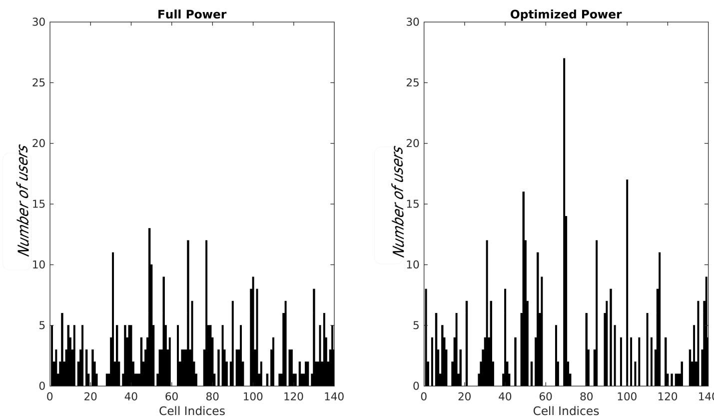


Figure 29: UE association through small cells

Power Optimization for Optimized Topologies

Power optimization is also investigated for optimized topologies. In figure 30, result of power optimization is given for 40 optimized small cell locations. From this figure, we can understand that power optimization increases SINR values of pixels. However, in simulations, power optimization of 140 small cells does not increase SINR values of pixels. Thus, it can be concluded that power optimization has less of an impact for high number of small cells in optimized topologies.

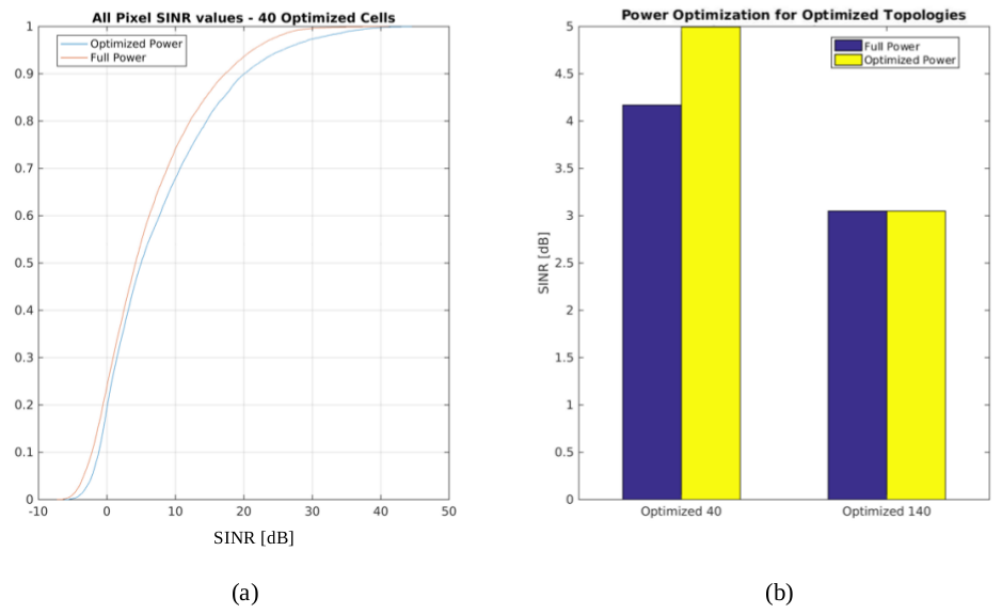


Figure 30: (a) represents CDF of pixel SINR values and (b) represents median SINR values of pixels

Actually, in figure 30, you can see that median of pixel SINR values of optimized 140 cells is less than median of pixel SINR values of optimized 40 cells. It is because in 140 cells case there is more interference in network layout. However, in figure 15, it can be seen that cell edge performance (f3) of 140 cells is better than less number of cells. This situation is created by the resources. 140 cells have more resources as compared to 40 cells. Therefore, cell edge performance of 140 cells is better than 40 cells even though its pixel SINR values are less than 40 cells pixel values.

Power Optimization for Hybrid Topologies

In figure 31, it can be seen that power optimization increases median of pixel SINR values. However, increases for different hybrid topologies are different from each other. For example, hybrid1 has more increase as compared to hybrid2 since there are more random small cell locations in hybrid1. It means that when there are less optimized small cell locations, the impact of power optimization is higher. From this figure, we can also observe that if there are more optimized small cell locations in hybrid topologies, the changes are negligible. Indeed, after power optimization, transmit power levels of hybrid3 is still same as full power.

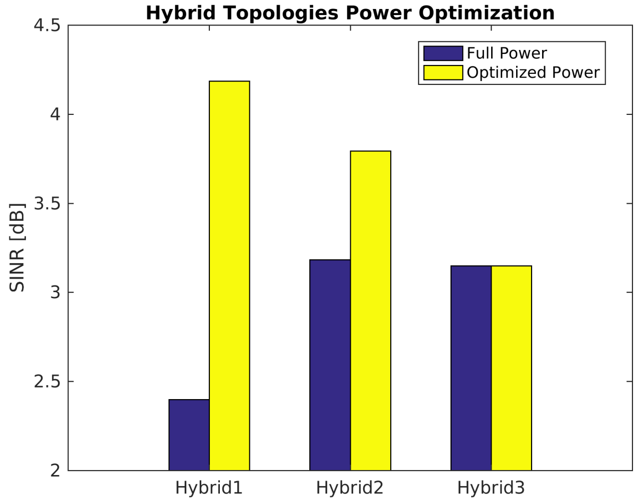


Figure 31: Median SINR values of pixels after hybrid power optimization

In figure 32, it can be seen that throughput of UEs is reduced as expected since some of the small cells are switched off after power optimization. Therefore, although SINR values of pixels are increased with power optimization, throughput values of UEs is reduced because of resource sharing.

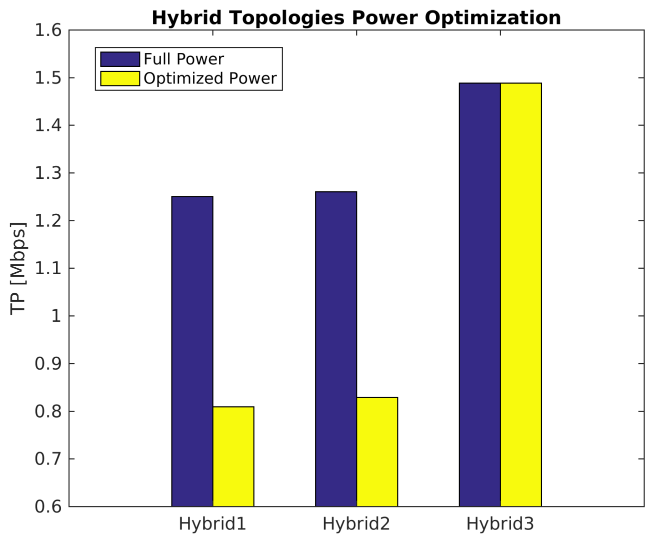


Figure 32: Median throughput values of UEs after hybrid power optimization-only one snapshot

As stated earlier, it should be noted again that power optimization has been done for only one snapshot because of the complexity of power optimization algorithm.

Therefore, those topologies could be optimized with more topologies in order to have better statistical results.

5 Conclusion

In this study, a planning and optimization framework for hybrid UDN topologies is presented. In order to optimize different metrics, NSGA-II algorithm is used in a system level static simulator. The results confirmed that optimized network topologies provided much better performance results compared to both hybrid and random topologies, whereas, the hybrid topologies outperformed the random topologies. Moreover, the performance gap between hybrid and random topologies increased as the fraction of optimized site locations increased in hybrid topologies.

The performance of increasingly dense deployments are interference limited. Therefore, the use of small cell transmit power optimization provides significant performance gains due to SINR improvements. In this study, pixel SINR values are used as an input for transmit power optimization algorithm. According to the results, post-deployment power optimization increases SINR performance for both random and hybrid topologies, with the performance of hybrid topologies approaching that of optimized topologies.

However, power optimization does not increase the throughput values of UEs in the simulations since some of the small cells are switched off in order to have better SINR values in the network layout. Therefore, since the best received signal power case is used in user association, most of UEs connect to a smaller subset of the deployed small cells. This situation reduces bandwidth allocation per user although SINR of UEs is increased. Hence, load balancing can be a good topic for further study in this context.

Also of interest would be comparative performance studies of deployments at different spectrum band, in particular the 5 GHz unlicensed band and the 28 GHz candidate 5G band. The difference in RF propagation characteristics between the 28 GHz and the 2.6 GHz band considered in this study may provide some interesting outcomes in terms for hybrid and optimized topologies. Moreover, the trade-off between the improved propagation at 2.6 GHz versus the larger spectrum resources available at 28 GHz also creates further interesting problems for topology optimization and load balancing with multi-band small cell deployments.

References

[1] Cellular Networks for Massive IoT white paper *Ericsson* 2016. Available: https://www.ericsson.com/assets/local/publications/white-papers/wp_iot.pdf

[2] Ultra dense network (UDN) white paper *Nokia Solutions and Neworks Oy.* 2016, June. Available: https://resources.nokia.com/asset/200295

[3] Successful LTE Strategies: How to use LTE to build a compelling broadband strategy *Informa* 2012. Available: http://telecoms.com/intelligence/successful-lte-strategies-how-to-use-lte-to-build-a-compelling-broadband-strategy/

[4] T. Braud, F. H. Bijarbooneh, D. Chatzopoulos and P. Hui, "Future Networking Challenges: The Case of Mobile Augmented Reality," 2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS), Atlanta, GA, 2017, pp. 1796-1807.

[5] Q. C. Li, H. Niu, A. T. Papathanassiou and G. Wu, "5G Network Capacity: Key Elements and Technologies" in IEEE Vehicular Technology Magazine, vol. 9, no. 1, pp. 71-78, March 2014.

[6] D. G. González, E. Mutafungwa, B. Haile, J. Hämäläinen, H. Poveda, “A Planning and Optimization Framework for Ultra Dense Cellular Deployments”, Mobile Information Systems, March 2017.

[7] ”Neighborhood small cells for hyper-dense deployments: Taking hetnets to the next level”*Qualcomm, Tech. Rep., February 2013.* Available: https://www.qualcomm.com

[8] Ericsson. (2017) Ericsson Mobility Report, Available: https://www.ericsson.com/assets/local/mobility-report/documents/2017/ericsson-mobility-report-june-2017.pdf

[9] 3GPP. (2014, September) Overview of 3GPP Release 8 V0.3.3. Available: http://www.3gpp.org/specifications/releases/72-release-8

[10] 3GPP. (2014, June) Overview of 3GPP Release 10 V0.2.1. Available: http://www.3gpp.org/specifications/releases/70-release-10

[11] 3GPP. (2015, September) Overview of 3GPP Release 12 V0.2.0. Available: http://www.3gpp.org/specifications/releases/68-release-12

[12] 3GPP. (2017, March) Overview of 3GPP Release 15 http://www.3gpp.org/release-15

[13] M. Kamel, W. Hamouda and A. Youssef, "Ultra-Dense Networks: A Survey", in IEEE Communications Surveys & Tutorials, vol. 18, no. 4, pp. 2522-2545, Fourthquarter 2016.

[14] D. López-Pérez, M. Ding, H. Claussen and A. H. Jafari, "Towards 1 Gbps/UE in Cellular Systems: Understanding Ultra-Dense Small Cell Deployments", in IEEE Communications Surveys & Tutorials, vol. 17, no. 4, pp. 2078-2101, Fourthquarter 2015.

[15] Huawei. (2014, February) Small Cells Big Opportunities white paper. Available: www.huawei.com/ilink/en/download/HW_330984

[16] Fujitsu Network Communications Inc. (2013) High-Capacity Indoor Wireless Solutions: Picocell or Femtocell white paper. Available: https://www.fujitsu.com/us/Images/High-Capacity-Indoor-Wireless.pdf

[17] Nokia. (2015) Deployment Strategies for Heterogeneous Networks white paper. Available: https://resources.nokia.com/asset/200070

[18] Viavi. (2015) Optimizing Small Cells and the Heterogeneous Network (HetNet) white paper. https://www.viavisolutions.com/es-mx/literature/optimizing-small-cells-and-heterogeneous-network-hetnet-white-paper-en.pdf

[19] Nokia. (2016) Indoor Deployment Strategies white paper. Available:https://resources.nokia.com/asset/200118

[20] Qualcomm. Online resource. Available: https://www.qualcomm.com/products/small-cells/technology

[21] Cambridge Broadband Networks. (2012) Small Cell Deployment Strategies and Best Practice Backhaul white paper. Available: http://cbnl.com/resources/small-cell-strategies

[22] International Energy Agency. (2017) Energy efficiency 2017 report. Available: http://www.iea.org/publications/freepublications/publication/Energy_Efficiency_2017.pdf

[23] Nokia. (2016) Small cell deployments: you don't have to learn the hard way discussion paper. Available: https://resources.nokia.com/asset/200248

[24] NGMN Alliance. (2012) Small Cell Backhaul Requirements white paper. Available: https://pdfs.semanticscholar.org/0e84/34b16bf0a3a83d03ae8f475c85ccdad0f5ab.pdf?_ga=2.199780070.912464291.1515632356-44052259.1515632356

[25] M. Ding, D. Lopez-Perez, G. Mao, P. Wang and Z. Lin, "Will the Area Spectral Efficiency Monotonically Grow as Small Cells Go Dense?" 2015 IEEE Global Communications Conference (GLOBECOM), San Diego, CA, 2015, pp. 1-7.

[26] SCF. (2017) "Hyperdense HetNets: Definition, drivers and barriers" SCF Report version 180.09.01. Available: http://scf.io/en/documents/180_Hyperdense_HetNets_Definition_drivers_and_barriers.php

[27] Qualcomm. (2014) Hyper-Dense Small Cell Deployment Trial in NASCAR Environment. Available: https://pdfs.semanticscholar.org/ad2d/80f81a867041255728eaa7aa3a68f4e4b86e.pdf

[28] Mobile and wireless communications Enablers for the Twenty-twenty Information Society (METIS), Channel Models, February 2015. Available: https://www.metis2020.com/wp-content/uploads/METIS_D1.4_v3.pdf

[29] K. Haneda et al., "5G 3GPP-Like Channel Models for Outdoor Urban Microcellular and Macrocellular Environments", 2016 IEEE 83rd Vehicular Technology Conference (VTC Spring), Nanjing, 2016, pp. 1-7.

[30] S. R. Lamas, D. Gonzalez G and J. Hamalainen,"Indoor planning optimization of ultra-dense cellular networks at high carrier frequencies", 2015 IEEE Wireless Communications and Networking Conference Workshops (WCNCW), New Orleans, LA, 2015, pp. 23-28.

[31] W. Yu, H. Xu, H. Zhang, D. Griffith and N. Golmie,"Ultra-Dense Networks: Survey of State of the Art and Future Directions", 2016 25th International

Conference on Computer Communication and Networks (ICCCN), Waikoloa, HI, 2016, pp. 1-10.

[32] M. Husso, Z. Zheng, J. Hämäläinen and E. Mutafungwa, "Dominant interferer mitigation in closed femtocell deployment," 2010 IEEE 21st International Symposium on Personal, Indoor and Mobile Radio Communications Workshops, Instanbul, 2010, pp. 169-174.

[33] Husso, Mika , Hämäläinen, Jyri , Jäntti, Riku , Li, Juan , Mutafungwa, Edward , Wichman, Risto , Zheng, Zhong , Wyglinski, Alexander M. (2010). Interference Mitigation by Practical Transmit Beamforming Methods in Closed Femtocells. EURASIP Journal On Wireless Communications And Networking, 2010.

[34] A. Bou Saleh, S. Redana, B. Raaf and J. Hamalainen, "Comparison of Relay and Pico eNB Deployments in LTE-Advanced," 2009 IEEE 70th Vehicular Technology Conference Fall, Anchorage, AK, 2009, pp. 1-5.

[35] D. González G., J. Hämäläinen, H. Yanikomeroglu, M. García-Lozano and G. Senarath, "A Novel Multiobjective Cell Switch-Off Framework for Cellular Networks", in IEEE Access, vol. 4, no. , pp. 7883-7898, 2016.

[36] A. B. Saleh, Ö. Bulakci, S. Redana, B. Raaf and J. Hämäläinen, "Evaluating the energy efficiency of LTE-Advanced relay and Picocell deployments," 2012 IEEE Wireless Communications and Networking Conference (WCNC), Shanghai, 2012, pp. 2335-2340.

[37] A.Syed, "Dimensioning of LTE Network", M.S. thesis, Department of Electrical and Communications Engineering, Helsinki University of Technology, Helsinki, Finland, 2009.

[38] S. Wang and C. Ran, "Rethinking cellular network planning and optimization", in IEEE Wireless Communications, vol. 23, no. 2, pp. 118-125, April 2016.

[39] D. González G. and J. Hämäläinen, "Looking at Cellular Networks Through Canonical Domains and Conformal Mapping", in IEEE Transactions on Wireless Communications, vol. 15, no. 5, pp. 3703-3717, May 2016.

[40] M. Jaber, Z. Dawy, N. Akl and E. Yaacoub, "Tutorial on LTE/LTE-A Cellular Network Dimensioning Using Iterative Statistical Analysis" in IEEE Communications Surveys & Tutorials, vol. 18, no. 2, pp. 1355-1383, Secondquarter 2016.

[41] SCF. (2017) Small cells market status report, SCF report version 050.10.01. Available: https://scf.io/en/documents/050_-_Small_cells_market_status_report_December_2017.php

[42] Global5G. (2017) Global vision, standardisation stakeholder engagement in 5G. Available: http://www.global5g.org/

[43] Mobile Experts. (2017) Available: https://www.prnewswire.com/news-releases/small-cell-market-will-rise-relentlessly-through-2017-300434914.html

[44] I. Hwang, B. Song and S. S. Soliman, ”A holistic view on hyper-dense heterogeneous and small cell networks” in IEEE Communications Magazine, vol. 51, no. 6, pp. 20-27, June 2013.

[45] K. Amouzgar, ”Multi-Objective Optimization using Genetic Algorithms”, M.S. thesis, Product Development and Materials Engineering, Tekniska Högskolan, Jönköping, Sweden, 2012

[46] P. Mogensen, W. Na, I. Z. Kovacs, F. Frederiksen, A. Pokhariyal, K. I. Pedersen, T. Kolding, K. Hugl and M. Kuusela, ”LTE Capacity Compared to the Shannon Bound”, *in Proc. 2007 IEEE 65th Vehicular Technology Conference - VTC2007-Spring*, April 2007, pp. 1234–1238.

[47] Y. Sawaragi, I. Hirotaka, and T. Tanino, Theory of Multiobjective Optimization, 1st ed. Academic Press., 1985.

[48] K. Deb, (September 2011). Multi-Objective Optimization Using Evolutionary Algorithms: An Introduction. Multi-objective Evolutionary Optimization for Product Design and Manufacturing (pp.3-34), Springer London

[49] M. Usama, Q. Junaid, A. Salman and A. Vasilakos, ”Genetic Algorithms in Wireless Networking: Techniques, Applications, and Issues”, Soft Computing, vol.20, no. 6, pp. 2467-2501,2016

[50] D.Gjylapi, V. Kasemi, ”The Genetic Algorithm for finding the maxima of single-variable functions”, International Journal Of Engineering And Science, vol. 4, issue 3, pp.46-54, March 2014

[51] L. Chiaraviglio, D. Ciullo, G. Koutitas, M. Meo and L. Tassiulas, ”Energy-efficient planning and management of cellular networks”, 2012 9th Annual

Conference on Wireless On-Demand Network Systems and Services (WONS), Courmayeur, 2012, pp. 159-166.

[52] K. Lieska, E. Laitinen and J. Lahteenmaki, "Radio coverage optimization with genetic algorithms", Ninth IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, Boston, MA, 1998, pp. 318-322 vol.1.

[53] T. Lu and J. Zhu, "Genetic Algorithm for Energy-Efficient QoS Multicast Routing" in IEEE Communications Letters, vol. 17, no. 1, pp. 31-34, January 2013.

[54] K. Deb, A. Pratap, S. Agarwal and T. Meyarivan, "A fast and elitist multi-objective genetic algorithm: NSGA-II" in IEEE Transactions on Evolutionary Computation, vol. 6, no. 2, pp. 182-197, Apr 2002.

[55] R. G. L. D. Souza, K. C. Sekaran, A. Kandasamy, "Improved NSGA-II Based on a Novel Ranking Scheme", Journal of Computing, vol. 2, issue 2, February 2010.

[56] O. G. Aliu, A. Imran, M. A. Imran and B. Evans, "A Survey of Self Organisation in Future Cellular Networks" in IEEE Communications Surveys & Tutorials, vol. 15, no. 1, pp. 336-361, First Quarter 2013.

[57] Urban SON use cases, Small Cell Forum. Available: https://scf.io/en/documents/077_-_Urban_SON_use_cases.php

[58] N. M. Balasubramanya and L. Lampe, "Simulated annealing based joint coverage and capacity optimization in LTE", 2016 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), Vancouver, BC, 2016, pp. 1-5.

[59] T. Cai, G. P. Koudouridis, C. Qvarfordt, J. Johansson and P. Legg, "Coverage and Capacity Optimization in E-UTRAN Based on Central Coordination and Distributed Gibbs Sampling", 2010 IEEE 71st Vehicular Technology Conference, Taipei, 2010, pp. 1-5.

[60] L. You, L. Lei and D. Yuan, "Optimizing power and user association for energy saving in load-coupled cooperative LTE," 2016 IEEE International Conference on Communications (ICC), Kuala Lumpur, 2016, pp. 1-6.

[61] S. Abeywickrama and E. Wong, "Estimation of transmit power for small cell networks", 2014 OptoElectronics and Communication Conference and Australian Conference on Optical Fibre Technology, Melbourne, VIC, 2014, pp. 419-421.

[62] S. Abeywickrama and E. Wong, "Transmit power control for small cell networks in urban, suburban, and rural environments", 2014 12th International Conference on Optical Internet 2014 (COIN), Jeju, 2014, pp. 1-2.

[63] C. Park and H. S. Choi, "Optimization of downlink power control based on LTE", 2012 International Conference on ICT Convergence (ICTC), Jeju Island, 2012, pp. 536-539.

[64] H. Claussen, L. T. W. Ho and L. G. Samuel, "Financial Analysis of a Pico-Cellular Home Network Deployment", 2007 IEEE International Conference on Communications, Glasgow, 2007, pp. 5604-5609.

[65] Z. Wang, W. Xiong, C. Dong, J. Wang and S. Li, "A novel downlink power control scheme in LTE heterogeneous network", 2011 International Conference on Computational Problem-Solving (ICCP), Chengdu, 2011, pp. 241-245

[66] X. Xu, G. Kutrolli and R. Mathar, "Dynamic Downlink Power Control Strategies for LTE Femtocells", 2013 Seventh International Conference on Next Generation Mobile Apps, Services and Technologies, Prague, 2013, pp. 181-186.

[67] Kalaycıoğlu, Aykut & Akbulut, Ahmet. (2017). Simulated Annealing Based Femtocell Power Control in Heterogeneous LTE Networks. International Journal of Communications. 11. 27-33.

[68] S. Nagaraja et al., "Downlink Transmit Power Calibration for Enterprise Femtocells", 2011 IEEE Vehicular Technology Conference (VTC Fall), San Francisco, CA, 2011, pp. 1-5.

[69] UN, "World urbanization prospects: The 2014 revision, highlights," United Nations, Department of Economic and Social Affairs, Population Division, UN Report ST/ESA/SER.A/352, 2014. Available: https://esa.un.org/unpd/wup/Publications/Files/WUP2014-Highlights.pdf

[70] GSMA, "The mobile economy Africa 2016", 2016. [Online]. Available: http://www.gsma.com/mobileeconomy/africa/

[71] P. Amin, N. S. Kibret, E. Mutafungwa, B. B. Haile, J. Hämäläinen, and J. K. Nurminen, "Performance study for off-grid self-backhauled small cells in dense informal settlements," in Proc. 2014 IEEE 25 th Annual International Symposium on Personal, Indoor, and Mobile Radio Communication (PIMRC), Sept 2014, pp. 1652–1657.

[72] Y. Mao, Y. Luo, J. Zhang, and K. B. Letaief, "Energy harvesting small cell networks: feasibility, deployment, and operation," IEEE Communications Magazine, vol. 53, no. 6, pp. 94–101, June 2015.

[73] Aalto Triton. Online resource. http://science-it.aalto.fi/for-triton-users/

[74] Altair.Winprop overview. Online resource. http://www.altairhyperworks.com/product/FEKO/WinProp

[75] Nokia. (2016) Ten key rules of 5G deployment white paper. Available: www.nokia.com