الجمهورية الجزائرية الديمقراطية الشعبية

People's Democratic Republic of Algeria

وزارة التعليم العالي والبحث العلمي

Ministry of Higher Education and Scientific Research

جامعة غرداية

University of Ghardaia

كلية العلوم والتكنولوجيا

Faculty of Science and Technology

قسم الرياضيات والإعلام الآلي

Department of Mathematics and Computer Science

مخبر الرياضيات والعلوم التطبيقية

Mathematics and Applied Sciences Laboratory

Registration n°:
...../...../...../...../.....

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of

Master

Domain: Mathematics and Computer Science
Field: Computer Science
Specialty: Intelligent Systems for Knowledge Extraction

Topic

Al-Driven Optimization of Cellular Network Coverage and Capacity: Tower Placement and Dynamic Parameter Tuning

---

Presented by:

GUERBOUZ Mohammed Alaa Eddine & *DAOUADI Sliman Abderahim*

Publicly defended on 06 30, 2025

Jury members:

Mr. SAIDI Ahmed	MCA	Univ. Ghardaia	President
Mr. ADJILA Abderrahmane	MAA	Univ. Ghardaia	Examiner
Mr. FEKAIR Mohamed El Amine	MCB	Univ. Ghardaia	Supervisor

Academic Year: 2024/2025

Acknowledgment

First of all, we thank God for giving us the strength of determination to successfully complete this research.

We would like to express our deepest gratitude for our supervisor, Mr. FEKAIR Mohamed El Amine, and for his invaluable guidance, continuous support, and constructive feedback throughout every stage of this thesis. and His expertise and encouragement were essential to the development and completion of our work.

We are thankful to our Department of Mathematics and Computer Science and for the Mathematics and Applied Sciences Laboratory for providing the resources necessary for the completion of this project.

Special thanks go to our families and friends, whose unconditional support, patience, and motivation have been a source of strength throughout our academic journey. finally, we acknowledge all those who near and far who supported contributed to the realization of this work.

Dedication

أعوذ بالله من الشيطان الرجيم

بسم الله الرحمن الرحيم

قال الله تعالى: «**يَرْفَعِ اللَّهُ الَّذِينَ آمَنُوا مِنكُمْ وَالَّذِينَ أُوتُوا الْعِلْمَ دَرَجَاتٍ وَاللَّهُ بِمَا تَعْمَلُونَ خَبِيرٌ**» [المجادلة: 11]. تتجلى في هذه الآية الكريمة مكانة العلم وأهله، حيث يرفع الله درجات العلماء، مما يحثنا على السعي الدؤوب في طلب العلم والمعرفة.

وعن النبي صلى الله عليه وسلم قال: «**من سلك طريقًا يلتمس فيه علمًا، سهل الله له به طريقًا إلى الجنة**» [رواه مسلم]. هذا الحديث الشريف يؤكد فضل طلب العلم، ويجعل منه سبيلاً للفوز برضا الله والجنة، مما يعزز عزيمتنا في مواصلة هذا الجهد العلمي.

أسأل الله العلي القدير أن ينصر إخواننا المسلمين في كل مكان، وأن يرفع عنهم الظلم والبلاء، وأن يجمع كلمتهم على الحق والهدى، «**رَبَّنَا آتِنَا فِي الدُّنْيَا حَسَنَةً وَفِي الْآخِرَةِ حَسَنَةً وَقِنَا عَذَابَ النَّارِ**» [البقرة: 201].

هذا العمل، بفضل الله أولاً وأخيرًا، ثم بفضل توجيهات الأساتذة الكرام الذين أناروا دربي بالعلم والمعرفة، وبذلوا جهودًا جبارة في سبيل إنجاح هذا البحث. فلهم مني جزيل الشكر والتقدير.

أتوجه بالشكر الخالص إلى أمي الحبيبة وأبي العزيز، اللذين كانا سندي وعوني في كل خطوة، فجزاهما الله خير الجزاء. قال الله تعالى: «**وَقَضَىٰ رَبُّكَ أَلَّا تَعْبُدُوا إِلَّا إِيَّاهُ وَبِالْوَالِدَيْنِ إِحْسَانًا**» [الإسراء: 23]. هذه الآية تذكرنا بفضل الوالدين وواجب الإحسان إليهما، وهو ما أسعى لتحقيقه بإذن الله.

كما أتقدم بالشكر إلى إخوتي الأعزاء: عبد الفتاح، طاهر، اسامة، معاذ، و عبد الجليل، الذين كانوا لي عونًا ودعمًا لا ينضب، فلهم كل الحب والامتنان.

وأخيرًا، أهدي هذا العمل إلى صديقي العزيز وأصدقائي الأوفياء، الذين شاركوني لحظات التحدي والنجاح، فكانوا نعم الرفقة في هذا المشوار العلمي.

Dedication

أعوذ بالله من الشيطان الرجيم

بسم الله الرحمن الرحيم

الحمد لله الذي هدانا لهذا، وما كنا لنهتدي لولا أن هدانا الله، حمداً يليق بجلاله وعظمته، على ما أنعم به علينا من التوفيق والسداد، ومنحنا القوة والصبر حتى نبلغ هذا المقام.

قال الله تعالى: «**وَمَا تَوْفِيقِي إِلَّا بِاللَّهِ ۚ عَلَيْهِ تَوَكَّلْتُ وَإِلَيْهِ أُنِيبُ**» [هود: 88]، وقال أيضًا: «**إِنَّمَا يَخْشَى اللَّهَ مِنْ عِبَادِهِ الْعُلَمَاءُ**» [فاطر: 28]، وهي آيات تبين أن التوفيق والعلم نعمتان من الله وحده، لا تُنالان إلا بطاعته والتوكل عليه.

وقال رسول الله ﷺ: «**من خرج في طلب العلم فهو في سبيل الله حتى يرجع**» [رواه الترمذي]، وهذا الحديث الشريف يعزز من قيمة كل لحظة قضيناها في سبيل التحصيل العلمي.

أُهدي هذا العمل المتواضع:

إلى والديَّ الغاليين، الذين قدّما لي كل شيء دون مقابل، وسهرا على راحتي، وسندا ظهري بدعمهما وصبرهما. جزاهما الله عني خير الجزاء، وأطال عمرهما في صحة وسعادة.

إلى إخوتي الأحباء: سيد أحمد، زين الدين، محمد فاروق، ومولاي إدريس، وإلى أختي العزيزة، الذين غمروني بدعائهم، ومساندتهم في كل لحظة.

وإلى ابن اخي الغالي ماحي، الذي كان مصدرًا للفرح والابتسامة، وكان لحضوره الأثر الجميل في تخفيف التعب.

وإلى كل أصدقائي الذين شجّعوني ووقفوا بجانبي، وكل من ساهم من قريب أو بعيد في هذا الإنجاز، أقول لهم: جزاكم الله خيرًا، وبارك فيكم، وجعل ما قدمتم في ميزان حسناتكم.

مــلـخـص

أصبح النمو السريع للاتصالات اللاسلكية حيويًا للمجتمع الحديث، حيث يربط بين الأفراد والأجهزة عبر تطبيقات متنوعة. ومع ذلك، يظل ضمان تغطية قوية وسعة كافية في الشبكات الخلوية، خاصة في المناطق الحضرية المكتظة بالسكان، تحديًا كبيرًا بسبب البيئات المعقدة والطلب المتزايد من المستخدمين. تهدف هذه الدراسة إلى تحسين أداء الشبكة من خلال تحسين الإعدادات التشغيلية الرئيسية وتوسيع البنية التحتية بشكل استراتيجي. نستخدم خوارزميات ذكية لضبط معلمات المحطات الأساسية بدقة باستخدام التحسين البيزي (BO) وتحديد المواقع المثلى للأبراج الجديدة باستخدام الخوارزمية الجينية ،(GA) مع تحقيق توازن بين جودة الإشارة، التداخل، والقيود العملية. تُظهر النتائج أن هذه الأساليب القائمة على البيانات تُحسن التغطية والسعة بشكل كبير، مقدمة نهجًا واعدًا لإدارة الشبكات بكفاءة وتكيف.

كلمات مفتاحية: اتصال لاسلكي، شبكة خلوية، تغطية، سعة، تحسين، تحسين بيزي، خوارزمية جينية.

Abstract

The rapid growth of wireless communication has become vital to modern society, connecting people and devices across diverse applications. However, ensuring robust coverage and sufficient capacity in cellular networks especially in densely populated urban areas remains a significant challenge due to complex environments and increasing user demands. This study aims to enhance network performance by optimizing key operational settings and strategically expanding infrastructure. We employ intelligent algorithms to fine tune base station parameters using Bayesian Optimization (BO) and determine optimal locations for new towers using a Genetic Algorithm (GA), balancing signal quality, interference, and practical constraints. The results demonstrate that these data-driven methods significantly improve coverage and capacity, offering a promising approach for efficient and adaptive network management.

Keywords: Wireless Communication, Cellular Networks, Coverage, Capacity, Optimization, Bayesian Optimization, Genetic Algorithm.

Résumé

La croissance rapide des communications sans fil est devenue essentielle à la société moderne, connectant les individus et les appareils à travers une multitude d'applications. Cependant, garantir une couverture robuste et une capacité suffisante dans les réseaux cellulaires, en particulier dans les zones urbaines densément peuplées, reste un défi majeur en raison des environnements complexes et des demandes croissantes des utilisateurs. Cette étude vise à améliorer les performances du réseau en optimisant les paramètres opérationnels clés et en élargissant stratégiquement l'infrastructure. Nous utilisons des algorithmes intelligents pour ajuster finement les paramètres des stations de base à l'aide de l'optimisation bayésienne (BO) et déterminer les emplacements optimaux pour de nouvelles tours à l'aide de l'algorithme génétique (GA), en équilibrant la qualité du signal, les interférences et les contraintes pratiques. Les résultats montrent que ces méthodes basées sur les données améliorent significativement la couverture et la capacité, offrant une approche prometteuse pour une gestion de réseau efficace et adaptative.

Mots clés : Communication sans fil, Réseaux cellulaires, couverture, capacité, Optimisation, Optimisation bayésienne, Algorithme génétique.

Contents

List of Figures **xi**

List of Tables **xii**

List of Acronyms **xii**

List of Acronyms **xiii**

General Introduction **1**

1 Basic concepts **4**

1.1 Introduction 4

1.2 Overview of Wireless Communication 4

1.3 Mobile Cellular Networks 5

1.3.1 History 5

1.3.2 Architecture 6

1.4 The Impact of Network Configuration on Coverage and Capacity . 7

1.4.1 Static Deployment Parameters 7

1.4.2 Dynamic Configuration Parameters 10

1.5 Mechanism of Antenna Tilt 13

1.5.1 Mechanical Tilt Adjustment 13

1.5.2 Electrical Antenna Tilt 14

1.6 Antenna Tilt Optimization Objectives 14

1.6.1 Coverage and Capacity Optimization 15

1.6.2 Base Station Deployment 16

1.7 Radio Propagation Modeling 17

1.7.1 Empirical Models 17

1.7.2 Path Loss . . . 18
1.7.3 Downtilt Loss Modeling . . . 18
1.7.4 Rationale and Limitations . . . 19
1.8 Problem Formulation . . . 19
1.8.1 Decision Variables . . . 19
1.8.2 Multi-Objective Optimization . . . 20
1.8.3 Evaluation Metrics . . . 22
1.8.4 Regulatory Constraints and Penalty Design . . . 23
1.8.5 Problem Decomposition (Parameter vs Placement) . . . 23
1.9 Conclusion . . . 24

2 Related Work **25**
2.1 Introduction . . . 25
2.2 Related works . . . 25
2.2.1 Traditional Method (Meta-Heuristic) . . . 26
2.2.2 Machine Learning . . . 30
2.2.3 Reinforcement Learning . . . 33
2.3 Conclusion . . . 34

3 Proposed System **35**
3.1 Introduction . . . 35
3.2 System Design and Architecture . . . 35
3.3 Parameter Optimization Using BO . . . 37
3.3.1 First Implementation: Expected Improvement (EI) . . . 38
3.3.2 Second Implementation: q-Expected Hypervolume Improvement (qEHVI) . . . 38
3.3.3 Acquisition Strategy Comparison . . . 39
3.3.4 Problem Setup and Practical Alignment . . . 39
3.3.5 Visualization and Outcomes . . . 40
3.4 Tower Placement Using Genetic Algorithm . . . 40
3.4.1 Motivation and Problem Description . . . 41
3.4.2 GA Encoding and Individual Structure . . . 41
3.4.3 Fitness Function Design . . . 42

3.4.4 Evolutionary Strategy 42
3.5 Conclusion 43

4 Experiments and Results **44**
4.1 Introduction 44
4.2 Simulation Environment 44
4.3 Dataset Description 48
4.3.1 OpenCellID Data and Cleaning 48
4.3.2 Terrain and Regulatory Mapping 49
4.4 Experiments 49
4.4.1 Experiment 1: Overall Optimization 49
4.4.2 Experiment 2: Multi-Objective Optimization 53
4.4.3 Results and Discussion 58
4.5 Conclusion 61

Conclusion and Perspectives **62**

References **64**

List of Figures

1.1 Hierarchy of cells and the connection link between devices and e-UTRAN that is connected to core network . . . 7
1.2 Comparison of frequency: f= f1+f2+f3: larger spectrum per cell means more radio resources per cell. . . . 8
1.3 Higher BS density means larger number of radio Resources per unit area. . . . 9
1.4 Sectorization also increases the available radio resources per unit area. . . . 11
1.5 Azimuth setting helps to avoid radiation in the direction of adjacent neighbor. . . . 11
1.6 Antenna Tilt. . . . 13
1.7 Mechanical Tilt (a) Vs Electrical Tilt (b) . . . 14

2.1 Initial RSRP . . . 31
2.2 Comparison of RF coverage maps shows DDPG outperforms random search by reducing under-coverage from 12% to 9% and over-coverage from 25% to 17%. . . . 32
2.3 Pareto frontier comparison showing DDPG outperforming both BO and random search, with a 10% average gain and a characteristic convex trade-off curve in $\mathbb{R}^2$. . . . 32
2.4 Flowchart of the simplified algorithm for capacity and coverage optimization, utilizing the base station electrical antenna tilt . . . 34

3.1 System workflow for LTE network optimization, integrating BO for parameter tuning and GA for tower placement. . . . 36

4.1 2 km × 2 km Simulation area in Ghardaia, Algeria showing tower locations. . . . 45
4.2 User Grid in the Area . . . 45
4.3 Initial RSRP heatmap of the study area . . . 50
4.4 RSRP heatmap after first optimization . . . 50

4.5 Interference map after first optimization 51
4.6 Coverage improvement after BO optimization 51
4.7 BO convergence over 220 iterations 51
4.8 Pareto frontier for the BO optimization 52
4.9 RSRP heatmap after adding a new tower 52
4.10 Interference map after adding a new tower 53
4.11 RSRP heatmap after first BO run 54
4.12 Improvement after first BO run 54
4.13 BO convergence for the first run 54
4.14 Pareto frontier after first BO run 55
4.15 RSRP heatmap after second BO run 55
4.16 BO convergence for the second run 56
4.17 RSRP heatmap after third BO run 56
4.18 BO convergence for the third run 57
4.19 Pareto frontier after third BO run 57

List of Tables

1.1 Optimization Problem Components 24

2.1 Summary of Metaheuristic approaches 29

4.1 Simulation Parameters for LTE Network Optimization Experiments 47

4.2 Summary of Key Dataset Attributes 49

4.3 Optimized Tower Configuration in Experiment 1 53

4.4 Optimized Tower Configuration in Experiment 2 57

4.5 Comparison of Transmit Power and Downtilt Settings for All Towers in Experiment 1 (EI) and Experiment 2 (qEHVI) 61

List of Acronyms

3GPP	3rd Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
6G	Sixth Generation
ACO	Ant Colony Optimization
AM	Amplitude Modulation
BO	Bayesian Optimization
BS	Base Station
CAEDT	Continuous Adjustable Electrical Downtilt
CDMA	Code Division Multiple Access
COST	European Cooperation in Science and Technology
CRE	Cell Range Extension
DDPG	Deep Deterministic Policy Gradient
EI	Expected Improvement
EHVI	Expected Hypervolume Improvement
FET	Fixed Electrical Tilt
FM	Frequency Modulation
FDMA	Frequency Division Multiple Access
GA	Genetic Algorithm
GSM	Global System for Mobile Communications
GPRS	General Packet Radio Service
HD	High Definition
HetNets	Heterogeneous Networks

HSPA High Speed Packet Access

ICNIRP International Commission on Non-Ionizing Radiation Protection

IoT Internet of Things

JFI Jain's Fairness Index

LS Local Search

LTE Long-Term Evolution

MCC Mobile Country Code

MIMO Multiple-Input Multiple-Output

ML Machine Learning

NFV Network Function Virtualization

QoE Quality of Experience

QoS Quality of Service

RL Reinforcement Learning

RET Remote Electrical Tilt

RSRP Reference Signal Received Power

SA Simulated Annealing

SBS Small Base Station

SINR Signal-to-Interference-plus-Noise Ratio

SMS Short Message Service

SON Self-Organizing Network

TDMA Time Division Multiple Access

TS Tabu Search

UE User Equipment

UMTS Universal Mobile Telecommunications System

VET Variable Electrical Tilt

VoLTE Voice-over-LTE

WCDMA Wideband Code Division Multiple Access

General Introduction

Wireless communication has become an essential part of modern life, connecting people, devices, and services across every sector of society. As mobile technology continues to evolve, the demand for faster speeds, broader coverage, and more reliable connections is growing at an unprecedented rate. In particular, 4G LTE networks play a crucial role in meeting these needs especially in densely populated urban areas, where maintaining both extensive coverage and high capacity is a growing challenge.

The fast increase of mobile data traffic driven by smart devices, multimedia services, and increasing user demands placed unheard-of pressure on cellular networks, especially in high-density urban areas, with its high densities and diverse topographies, making provision of unremitting coverage and sufficient capacity challenging. Conventional rule-based approaches, like those used in Self-Organizing Networks (SON) for 4G LTE, usually depend on static configuration and human involvement and are unable to deal with dynamic radio environments, heterogeneous user requirements, and the complex interdependence of network parameters like antenna tilt, transmit power, and base station placement. These conventional approaches tend to be costly network densification chewing up demand but increasing complexity, inter-cell interference, and operating expense and hence are not scalable to modern demands. With the advent of ample performance and configuration information in cellular networks, gates have been opened to data-driven, intelligent optimization techniques, with artificial intelligence (AI) as the game-changing tool.

Bayesian Optimization and Genetic Algorithms are promising techniques for overcoming these problems and enabling adaptive, automatic, and effective optimization of the most critical performance metrics without extensive and time-consuming manual tuning. A two-component scheme for LTE network optimization in urban macrocells is proposed in this thesis, taking into account two very significant tasks: dynamic parameter tuning of existing base stations and optimal placement of new towers. Using BO, the system adjusts transmit power and antenna downtilt in real time, employing Expected Improvement (EI) for efficient single-objective optimization and q-Expected Hypervolume Improvement (qEHVI) for nuanced multi-objective trade-offs, targeting reduced weak coverage, minimized over-coverage, and controlled interference. When existing infrastructure proves insufficient, a GA determines optimal locations, power settings, and downtilt angles for new towers, incorporating coverage, capacity, interference, and regulatory constraints like zoning restrictions near sensitive areas. The approach is tested within a simulated urban area, leveraging OpenCelliD data for tower coordinates, the COST-231 Hata model for radio propagation, and a synthetic terrain grid to mirror urban complexity. By integrating these AI-driven methods, this study aims to deliver self-optimizing, adaptive networks that perform robustly under real-world variability, surpassing traditional heuristic and rule-based strategies. While rooted in 4G LTE optimization, the principles and methodologies explored here hold relevance for future 5G deployments and beyond, addressing the universal challenge of balancing coverage, capacity, and cost in wireless communications.

This work sets the stage for a comprehensive evaluation of intelligent optimization, offering repeatable insights and a scalable framework to meet the evolving demands of modern cellular networks.

Motivation

The surge in mobile data traffic from smart devices and user demands has strained cellular networks, especially in urban areas with high population density and varied topography. Traditional SON methods for 4G LTE, reliant on static configurations and manual intervention, struggle with dynamic conditions and complex parameter interactions, leading to costly densification and increased interference. AI-driven techniques, such as BO and GA, offer adaptive, automated optimization of key performance metrics, enabling efficient parameter tuning and strategic tower placement to meet modern network demands cost-effectively.

Research Questions

This thesis explores AI-based optimization for LTE networks in urban settings through key questions: How can BO optimize capacity and coverage via dynamic parameter adjustments, balancing weak and over-coverage? What is the impact of real-time tuning in dense urban areas with fluctuating interference and demand? Can GA optimize new tower locations to enhance coverage and capacity while respecting cost, terrain, and regulatory constraints? How do BO and GA compare to traditional methods in performance and scalability? How can these approaches integrate to create adaptive, cost-effective LTE networks? These questions aim to reveal the potential of AI-driven solutions for modern wireless communication challenges.

Objective and Scope

This thesis develops an AI-driven framework for optimizing LTE network coverage and capacity in urban macrocell environments. It has two objectives: (1) real-time optimization of base station parameters using BO to enhance signal quality and reduce interference, and (2) strategic placement of new towers using GA to address coverage gaps while adhering to regulatory constraints. The framework integrates BO for single- and multi-objective optimization with GA for infrastructure planning, tested in a simulated urban setting with a propagation model. Focused on LTE, the findings are scalable to 5G, offering practical solutions for urban network challenges.

Contributions of the Thesis

This thesis pushes wireless communications one step ahead by proposing a new AI-based framework to optimize LTE cellular networks in urban environments, where it is critical to trade off coverage, capacity, and practical constraints. To this end, it first proposes a novel approach that leverages Bayesian Optimization to dynamically adjust base station parameters, i.e., transmit power and antenna downtilt, to enhance signal quality and reduce interference in real time according to single-objective and multi-objective schemes. Second, it proposes a Genetic Algorithm-based model for strategically placing new base stations, optimizing their locations and configurations to address coverage gaps and capacity demands while respecting regulatory restrictions near sensitive areas like schools and hospitals. Third, it integrates these methods into a sequential framework, combining parameter optimization of existing infrastructure with targeted tower placement to deliver an adaptive and cost-effective solution for network enhancement. Fourth, it establishes a reproducible simulation-based testbed, leveraging real-world tower data and a synthetic urban terrain model to create a realistic environment for evaluating optimization results. These contributions elevate LTE network management by providing a flexible and intelligent system that addresses current challenges and lays a foundation for future research into self-optimizing networks for 5G and beyond, offering practical insights for operators aiming to improve service quality, cost-efficiency, and sustainability in complex urban settings.

Thesis Organization

This dissertation systematically explores the development, implementation, and evaluation of an AI-driven framework for optimizing LTE cellular network coverage and capacity, with a focus on urban macrocell environments, guiding readers through its concepts, methods, methods, and outcomes. Chapter 1, "Basic Concepts," provides the theoretical foundation, covering the evolution and structure of mobile cellular networks, the role of network configuration parameters like frequency reuse, base station count, density, and antenna configuration, tilt in enhancing performance, and the application of AI to address these challenges. Chapter 2, "A, "Related Work", reviews existing approaches to network optimization, examining traditional and AI-driven techniques, highlighting their strengths and limitations, and identifying opportunities for intelligent, adaptive solutions addressed by this work. Chapter 3, "Proposed System," outlines the design and architecture of the proposed framework, detailing a sequential process that uses Bayesian optimization to adjust base station parameters and a genetic Algorithm to optimize new tower placement, balancing coverage, capacity, and interference, regulatory constraints in a simulated urban setting. Chapter 4, "Experiments and Results," describes the simulated setting and experiments that evaluate the performance of the framework in terms of measures like signal strength and coverage, interference, and quality of coverage. and finally with Conclusions and Perspectives. This format guarantees a smooth transition, providing an in-depth examination of AI-based optimization for urban LTE networks.

Chapter 1

Basic concepts

1.1 Introduction

The fast-paced development of cellular mobile networks has significantly transformed worldwide communication driven by the surging demand for mass internet access and broadband data services. In this chapter, we provide the foundation for understanding the mechanisms and technologies behind these networks in general, and particularly highlighting 4G Long-Term Evolution (LTE) systems, which form the core objective of this thesis in terms of extending coverage and capacity in cities, The application of artificial intelligence (AI) to network optimization is a promising solution to dealing with interference, resource allocation, and scalability challenges, especially for very dense user contexts. we start with background information on wireless communication, an exploration of its past development and technical foundations, which are the underpinnings of current cellular technology demonstrating that this work can scale to other technologies in that field. It then elaborates on mobile cellular network structure, evolution, and fundamental building blocks and emphasizes their role in facilitating a wide diversity of applications as well as the delivery of public safety. The subsequent parts discuss the effects of network parameter configurations, such as antenna tilt and base station location on coverage and capacity, in addition to radio propagation modeling and structured optimization framework. By combining these elements, this chapter sets the theoretical and practical groundwork for AI-based optimization techniques presented in subsequent chapters, showcasing their relevance in enhancing 4G LTE performance in urban areas.

1.2 Overview of Wireless Communication

The basis on which the global link established by cellular mobile networks based on wireless communication, which refers to transmission without physical wired connections. This expansion was made possible through the work of Guglielmo Marconi on radio waves in the late 19th century. Previous systems utilized analog transmission techniques and simple modulation methods, for example, frequency modulation (FM) and amplitude modulation (AM), which enhanced transmission distance and signal quality via the mid-20th century. This was particularly apparent in their use for military and naval applications. Cellular concepts, created in the 1940s by Bell Laboratories, were a conceptual advancement insofar as they envisioned geographical divides as cells that would be managed by base stations for efficient reuse of frequency. This, together with digital signal processing and multiplexing, evolved into today's sophisticated wireless networks. Understanding these origins is essential to solving present problems, such as maximizing capacity and coverage in densely populated cities, a primary focus of this thesis.

1.3 Mobile Cellular Networks

With the potential to extend internet access and inter-personal communication to billions of people across the globe, mobile cellular networks form a vital part of modern wireless communication networks. inexpensive mobile phones, pervasive internet-based services, and ensuing technology enhancements are the key drivers of their exponential growth. They employ several technologies like satellite communication, Wi-Fi, and cellular radio to maintain persistent connectivity and extensive coverage between locations. This connection is founded on regular communication and QoS-demanding applications that need outstanding network performance, particularly in urban areas. With a top priority on tower positions and dynamic parameter configuration, this thesis addresses these problems with AI-supported optimization techniques for 4G LTE networks.

1.3.1 History

The technology of mobile cellular networks or wireless communication is one of the most revolutionary technologies of the contemporary age, transforming world communication and inter-connectivity in basic ways. Since the time they were introduced for the first time in the mid-20th century, mobile networks have passed through generations, they are characterized by pioneering development in speed, stability, and scalabilty. The initial cell networks established in the 1950s and activated in the late 1970s used analog transmission methods in conjunction with Frequency Division Multiple Access (FDMA) methods. Each cell in the systems had a personal frequency band, providing fundamental voice communication albeit with modest capacity and security.

The second generation (2G) technology innovation in 1980 was a big leap from the analog to digital communication mode. also the fitting of the Global System for Mobile Communications (GSM) in the early 1990 enabled the use of Time Division Multiple Access (TDMA), which allows multiple users to access the same frequency channel by allocating them different time slots.

This generation constitutes the foundation of many new services like Short Message Service (SMS) and General Packet Radio Service (GPRS) establishing a platform for mobile data communication and setting the ground for a trend of mobile internet connectivity. On this basis, third-generation (3G) networks were established in the early 2000 with the introduction of the Universal Mobile Telecommunications System (UMTS). Those networks used Code Division Multiple Access (CDMA), which supported simultaneous voice and data services on broader bandwidths. With higher data transmission rates and remarkably low latency, 3G facilitated the development of multimedia services such as mobile web access, video calls, and email on the move, thereby speeding up the convergence of information technology and telecommunications [50].Fourth generation (4G) Multiple-Input Multiple-Output (MIMO) antennas and the all-IP network architecture, which was standardized by the 3rd Generation Partnership Project (3GPP) in 2008 and commercially launched in 2010, transformed mobile communication. Voice-over-LTE (VoLTE), cloud-based services, and HD video streaming became standard, and data speeds of over 100 Mbps were made possible. 4G ushered in the era of mobile broadband, greatly improving network capacity, spectrum efficiency, and user experience as well. Present fifth generation 5G is the technology which is being deployed in most of the countries, deployed globally from the year 2020, a huge leap and a true game-changer. 5G is intended to meet the varying needs of an ultra-connected world and is envisioned to provide ultra-low latency, gigabit-per-second data rates, massive device connectivity, and network slicing. They are essential for future applications and use cases such as autonomous cars, virtual/augmented reality, IoT, and Industry 4.0 [54]. Furthermore, 5G networks are deploying greater software-defined networking (SDN) and network function virtualization (NFV) in a bid to be more agile, dynamic, and intelligent in the management of the network [50]. In the future, early 6G network research in the 2030s is exploring convergence of artificial intelligence, machine learning, terahertz (THz) communications, and quantum technologies. The networks need to deliver record spectral efficiency, spatial resolution, and context-aware services, and support real-time digital twins, tactile internet, and holographic communications with immersive experiences. Within this overall context, this thesis considers 4G LTE network optimization, which remains the world's connectivity backbone today. Proper configuration of the network parameters, antenna tilt, transmit power, and base station location is crucial in urban areas with dense population to ensure stable coverage and sufficient capacity. While basic principles and optimization problems are the same for every generation, it still stands to gain from maximizing the performance of 4G LTE infrastructure, especially given that these networks will coexist and interoperate with 5G deployments. The techniques and methodologies explored herein are thus relevant not only to existing LTE networks but also provide valuable lessons for next-generation wireless networks.

1.3.2 Architecture

The architecture of mobile cellular networks is designed to connect mobile devices such as smartphones and tablets to radio networks for communication and internet access. It comprises a hierarchical structure of cells (macro-cell, micro-cell, pico-cell, femto-cell), each served by a base station, with 5G networks using gNodeB (gNB) to link devices to the core network in both downlink and uplink directions. The basic network architecture is shown in Figure 1.1 by [11].The core network, or backbone, connects to the public internet via high-capacity links like fiber optic cables or satellite connections, interfacing with Internet Service Providers (ISPs) through the Border Gateway Protocol (BGP) for efficient data routing. This infrastructure supports seamless connectivity, with later 4G enhancements introducing small cells to boost capacity in high-traffic urban zones.

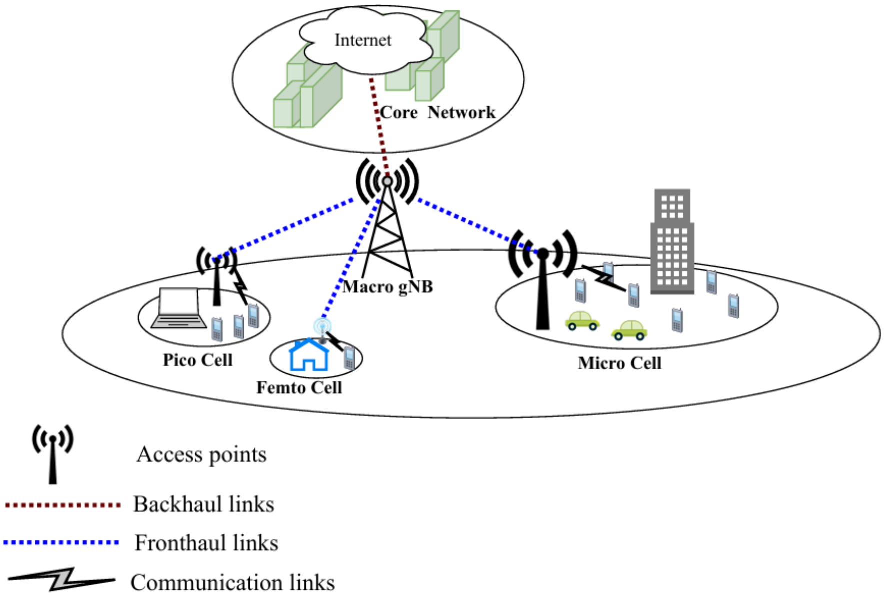

Figure 1.1: Hierarchy of cells and the connection link between devices and e-UTRAN that is connected to core network

The thesis leverages this architecture to explore optimization strategies, such as adjusting antenna tilt and base station placement, to enhance 4G LTE performance.

1.4 The Impact of Network Configuration on Coverage and Capacity

To systematically optimize network coverage and capacity, the most important cellular system parameters must be detected and configured accordingly. It is apparent that a wide variety of network elements can be optimized to satisfy user needs and system constraints. These constraints include things like environmental factors and changes in user needs. Some of the adjustable parameters include base station location, antenna tilt, transmit power, and frequency reuse. In this section, we assess some of these critical parameters, analyze their effects on network behavior, and review the previously defined optimization settings. Our focus is not limited to coverage and capacity alone. We also consider the level of complexity such parameters introduce toward automating self-optimizing systems powered by artificial intelligence. We pay most attention to those that have practically adjustable capabilities as they form the basis of the whole framework constructed using our optimization.

1.4.1 Static Deployment Parameters

We examine key parameters that are established in the early stages of network planning and deployment in this section. Once the infrastructure is deployed, these are typically static and expensive or difficult to change. They are crucial in the context of contemporary cellular technologies like 5G as fundamental design choices have a significant impact on long-term network performance, even though they are frequently disregarded in short-term optimization. Understanding their influence is essential to creating scalable and effective networks.

Frequency Spectrum and Frequency Reuse

The available frequency spectrum plays a pivotal role in determining the capacity of cellular networks. In earlier generations such as GSM (Global System for Mobile Communications), to mitigate co-channel interference, the total spectrum was partitioned and distributed across cells so that adjacent cells operated on different frequency bands. This strategy does not only minimized interference but also enabled dynamic spectrum allocation, allowing cells to adjust frequency usage based on fluctuating traffic demands. As illustrated in Figure 1.2, this traditional approach (left) assigned distinct frequencies (f1, f2, f3) to neighboring cells to reduce interference, whereas modern LTE networks (right) adopt a reuse factor of one, using the full spectrum in each cell to maximize capacity. Modern networks, such as LTE, on the other hand, have a frequency reuse factor of one, which means that each cell uses all of the spectrum. This increases the capacity and spectrum efficiency, but it also increases inter-cell interference, especially in dense areas.[25] Consequently, it is no longer feasible to increase dynamic capacity in LTE and beyond by merely altering spectrum allocation. These networks instead use alternative optimization techniques including power management, antenna tuning, and interference coordination systems to maintain performance in dynamic situations.

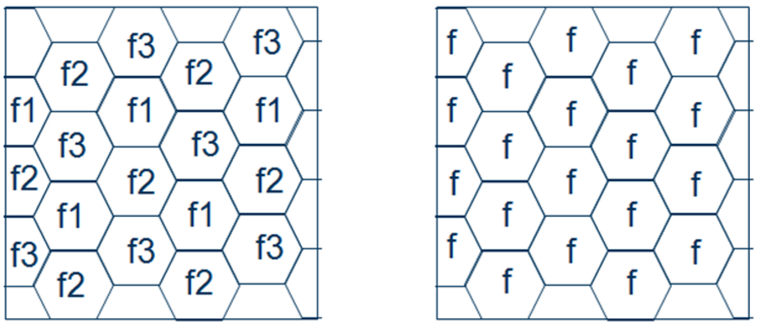

Figure 1.2: Comparison of frequency: f= f1+f2+f3: larger spectrum per cell means more radio resources per cell.

Base Station Density

The idea of "cells," first proposed by Bell Labs in the late 1940s, is the basis of the infrastructure of today's cellular networks. This model segments a large geographical area into smaller zones, each managed by a dedicated Base Station (BS), allow for efficient frequency reuse and increased network capacity. Due to high data traffic and increasing user demand for improved QoS, Densification, i.e., increasing the number of base stations is a practical way to improve both coverage and throughput[12]. As shown in Figure 1.3, densification is visually represented by comparing a traditional sparse layout of base stations (left) with a denser

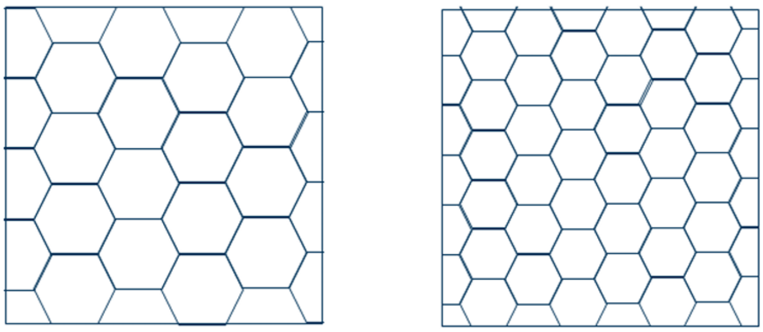

Figure 1.3: Higher BS density means larger number of radio Resources per unit area.

deployment (right), where more BSs per unit area result in improved spectral efficiency and service availability. However, The challenges are critical in this approach. Regulations, environmental concerns, and public health reasons severely restrict the deployment of BSs to designated acceptable sites. Furthermore, rapid or large-scale densification is not feasible for short-term improvements because of the time and expense involved in installing new infrastructure. To achieve short-term performance improvements, densification is therefore usually regarded as a long-term investment and is frequently combined with additional optimization strategies like small cell deployment, antenna parameter modification, and load balancing algorithms [31].

Cell Placement

Optimal cell placement is Crucial for improving network performance in heterogeneous LTE environments, due to the complexity of cell deployment, which involves many complex factors. The locations of base stations (BSs) determine not only the size of their coverage areas but also affect how signals interfere and how resources are allocated throughout the network. This is especially critical in dense networks like LTE heterogeneous networks (HetNets), where both macro and small cells are in use, since poor or uncoordinated placements can lead to overlapping signals and increased interference, ultimately harming the user experience [24]. This work addresses this multi-dimensional challenge an innovative framework designed to carefully select BS locations. There are methods that improve coverage and capacity while keeping interference to a minimum. It does so by using a new technique which has proven to be more effective at solving the BS placement problem in comparison with traditional approaches[18].

Antenna Elevation

The mounting height of a base station (BS) antenna is among the significant parameters that affect wireless signal propagation patterns in a given region. Generally speaking, increasing the height allows signals to cover longer distances by reducing the impact of blocking by buildings and terrain undulation, thus enhancing the overall coverage area. It can be particularly beneficial under rural or semi-urban environments where line-of-sight communications are a primary necessity for crystal clear connectivity. But a higher antenna is not always better.

Too much height can cause greater interference with far-away cells or even signal overshooting, which creates coverage holes on the ground in the immediate area around the BS. It can also decrease signal penetration in urban areas with high population densities, where users can be found indoors at lower elevations. In operational scenarios, antenna height is typically set during the first deployment and network planning stage based on topography, user density, and environmental factors. After installation, it is logistically and economically challenging to modify antenna height, since it can entail civil work or structural modification of rooftops or towers. It is therefore not an appropriate parameter for real-time or adaptive network optimization. In the context of next-generation networks, while smart antennas and beamforming allow for more dynamic control in horizontal and vertical dimensions (via electrical downtilt), the physical height of an antenna remains a comparatively static parameter. Future research may address deployable or variable-height platforms e.g., drone-based BSs or reconfigurable mast systems for temporary events or emergency coverage, though such solutions are not yet mainstream for macrocell deployments.

1.4.2 Dynamic Configuration Parameters

This section focuses on the remotely optimizable and tunable dynamic network parameters over the lifespan of the network. These include parameters such as antenna tilt and transmit power, which can be optimized in real time based on evolving user demand and interference levels. Such parameters are at the heart of contemporary Self-Organizing Networks (SONs) and AI-based optimization suites. Understanding these parameters is crucial to achieving the fulfillment of adaptive, intelligent, and high-capacity cellular networks.

Sectorization

The BS has a fundamental technique called sectorization its used to divide the coverage into different sectors using directional antennas typically three sectors (we use three in our study.). Instead of relying on omni-directional antennas that transmit signals uniformly in all directions, but sometimes more depending on network needs. This targeted transmission approach not only improves signal quality within each sector also helps mitigate interference between neighboring cells by keeping the transmitted power within specific angles. As shown in Figure 1.4, sectorization is visually represented by contrasting a traditional omni-directional layout (left) with a sectorized layout (right), where each cell is divided into smaller directional sectors effectively increasing spatial reuse and improving signal isolation. Due to the financial and logistical burden of physical reconfiguration, which includes site modifications and hardware installation, sector configurations are often decided upon during the original network deployment phase and stay fixed [53]. However, now with the recent developments in smart antenna technologies and beamforming techniques, adaptable and flexible sectorization is possible. Based on user distribution and traffic load, these systems may instantly change the antenna layouts, creating new opportunities for dynamic optimization in next-generation networks like LTE/5G. This adaptability significantly reduces the need for manual intervention and enables self-organizing network (SON) capabilities[22].

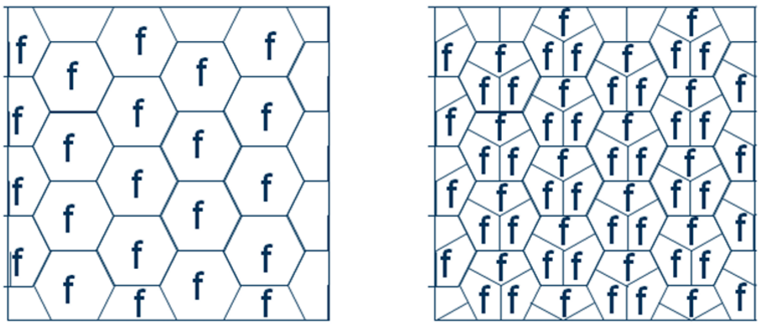

Figure 1.4: Sectorization also increases the available radio resources per unit area.

Antenna Beam Direction (Azimuth Control)

An antenna's azimuth is the horizontal direction of its principal lobe measured from geographic north. This is perhaps the most significant parameter in directing the antenna's coverage footprint to target service zones. With careful adjustment of the azimuth, network planners can concentrate signal strength where it is most needed and reduce off-target radiation into zones that may create interference especially in neighboring cells[48]. Unbalanced alignment, nearby antennas facing each other, increases mutual interference and lead to degradation of performance within the overlap areas. In contrast, meticulous alignment that prevents direct overlap can clean up signals and enhance user experience in high-density deployments[27]. While azimuth adjustment can be a useful tool in the preliminary network design and planning phase, its potential for real-time optimization is somewhat limited. This is because azimuth adjustments typically imply physical re-orientation or complicated mechanical means, not always economically viable or practical for dynamic situations. Additionally, the optimal azimuth direction will likely be determined by static geographic parameters such as user hotspots, base station locations, and terrain profile, and hence updating frequently is not feasible. With the dawn of smart antenna and beamforming technology, however, dynamic beam steering is emerging on the horizon. In its infancy as far as azimuth control is concerned, the technologies hold out the possibility of eventual dynamic realignment to prevailing traffic conditions and interference levels if the seeds are sown for increasingly responsive and adaptive network configurations.

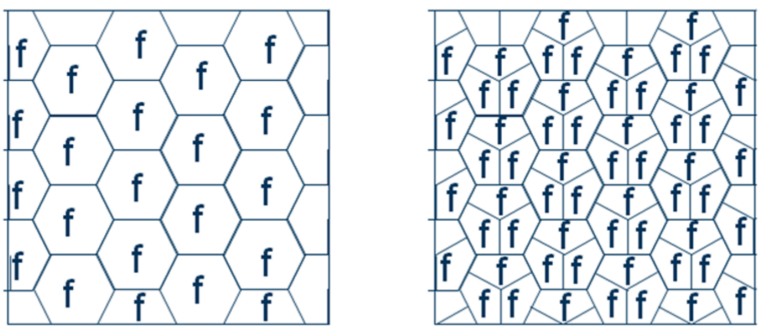

Figure 1.5: Azimuth setting helps to avoid radiation in the direction of adjacent neighbor.

Transmit Power Control

Transmit power is probably the dominant factor on capacity and coverage area in a cellular network. It is one of the most adjustable parameters within the control of network planners that directly impacts signal strength and coverage, particularly at cell edges. Using the assistance of increased transmission power, it is feasible to increase the signal range and improve the quality of service at the edges at the expense of trade-offs. High powers have tendency to overload nearby cells with erroneous signals and generating co-channel interference and network performance in general decline particularly for networks like LTE and 5G where reuses of spectrum among nearby sites. On the other hand, powers that are set too cautiously might not interfere but under service or expose sections of the service area to poor signal conditions, especially indoors or in regions of obstructive terrain [30]. To address this problem, existing mobile networks now largely depend on adaptive power control capabilities integrated into Self-Organizing Network (SON) architecture. These intelligent systems analyze real-time traffic demand, user density, interference levels, and environmental conditions to adjust power outputs dynamically. This enables the network to minimize power consumption, optimize spectrum efficiency, and adapt dynamically to changing load patterns throughout the day. Moreover, with green networks and green architectures, power management passing is even more important not just for greater performance but to reduce cost of energy and carbon footprint[29]. In future deployment, smart power control will be essential in ensuring quality of service (QoS) and eco-friendliness.

Antenna Tilt

Antenna tilt or vertical orientation of a cell antenna's radiation pattern is one of the most significant interference and signal coverage controllable parameters Figure 1.6. It is either downtilt, in which case the direction of the antenna beam is towards the ground, or uptilt, with the beam pointing upward, providing extended coverage. Tilt adjustment alters the manner in which the radio signal interacts with the environment. Greater downtilt concentrates signal power closer to the base station, thereby enhancing signal quality in the vicinity while, simultaneously, limiting interference with neighboring cells. Reducing the downtilt or using uptilt extends coverage over greater distances, which may be advantageous in sparse or rural environments but will also overshoots close-range users and produce inter cell interference[35]. Tilt optimization can yield outstanding gains in LTE and 5G where signal quality (SINR) enables high data rates and spectral efficiency. It is even more useful in urban hotspots where downtilt control allows operators to serve high user density zones like business districts in a controlled manner without signal spillage in less profitable areas. With the recent developments on the base station side, operators can now remotely change antenna tilt due to the introduction of Remote Electrical Tilt (RET), which does not require a site visit for alterations[55]. This is an effective means of responding to real-time traffic patterns, user mobility, and interference dynamics. This responsiveness is all the more critical in 5G where dynamic user clustering and beamforming involve steering direction of signals with precision[21].

Moreover, intelligent tilt optimization can be utilized for load distribution

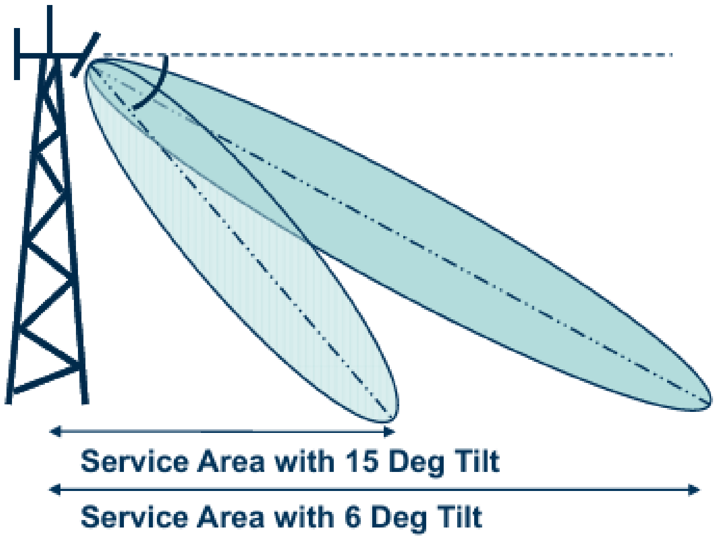

Figure 1.6: Antenna Tilt.

between neighboring cells, offloading over-loaded areas and ensuring end-to-end quality of service results in improved coverage and capacity. Sophisticated optimization platforms can even incorporate tilt control as a part of AI-driven or reinforcement learning algorithms optimizing network parameters continuously for best possible performance.
In our optimization approach, we have chosen to utilize antenna tilt configurations, with a focus on electrical tilt, along with transmit power.

1.5 Mechanism of Antenna Tilt

In essence, antenna tilt offers the ability to control the vertical direction of signal transmission by mechanical or electrical means. In the next section, we provide a concise explanation of how the two mechanisms differ and state which is the subject of research.

1.5.1 Mechanical Tilt Adjustment

Mechanical tilt is the physical adjustment of an antenna's mounting angle so that the main beam is directed downward toward the coverage area. Mechanical tilt is achieved by physically rotating the entire antenna structure to obtain the desired tilt. Although the shape of the antenna radiation pattern is largely preserved, small distortions can result, such as the appearance of a notch at the tip of the main lobe, which can further reduce interference in unintended directions[35]. Although being straightforward, the mechanical tilt suffers from several drawbacks. The rear and side lobes of the radiation pattern are not shifted in the new direction evenly, and in some cases, the rear lobe may even tilt upward, in some cases it may lead to interference. Furthermore, implementing mechanical tilt requires dispatching technicians to the location, making it not only costly but also inconvenient for repetitive or real-time network optimization. Due to this, mechanical tilt is widely used for initial deployment or for long-term static optimizations instead of dynamic network optimization.

1.5.2 Electrical Antenna Tilt

Electrical tilt is the deflection of the direction of a vertical beam of an antenna by electronically changing the phase of the signal between the radiating elements[55]. Unlike mechanical tilt, this technique allows for symmetric coverage angle adjustment in all azimuths without repositioning the antenna hardware. There are several versions in this category. Fixed Electrical Tilt (FET) is deployed fixed and cannot be adjusted except in combination with mechanical techniques or the complete replacement of antennas. Variable Electrical Tilt (VET) extends this further in that it can have a tilt range that can be defined [58], providing flexibility to meet varying coverage demands. As illustrated in Figure 1.7[38], the radiation pattern for mechanical tilt (a) shows asymmetry and a less focused beam direction, while electrical tilt (b) produces a more controlled and symmetric pattern. This distinction highlights the precision advantage of electrical tilt, especially in environments that require dynamic coverage adaptation.

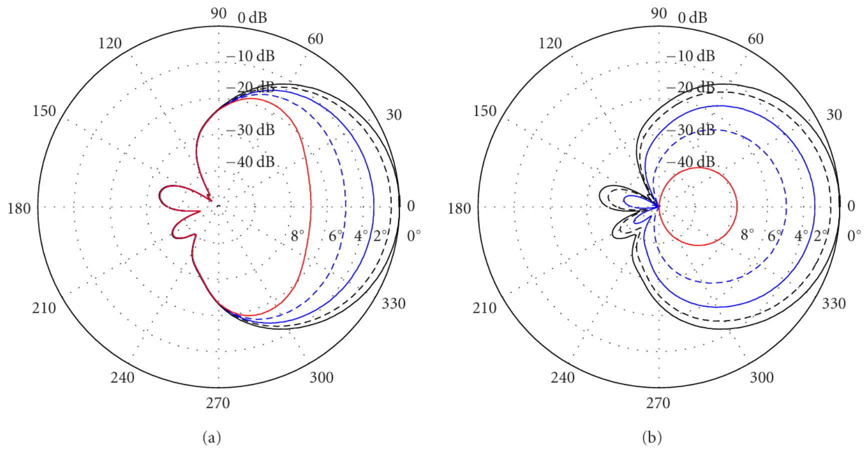

Figure 1.7: Mechanical Tilt (a) Vs Electrical Tilt (b)

A primary innovation is the Remote Electrical Tilt (RET), through which network operators are able to vary antenna angles remotely from central control systems without on-site manual adjustment. Not only does this conserve operational cost but also enhances flexibility in coverage and interference control. Continuous Adjustable Electrical Downtilt (CAEDT), the most advanced one, gives computer-driven beam changes in real time and actively compensates for shifting traffic, atmospheric, and user motion patterns. High-density site deployments and dynamically fluctuating demand levels require a special critical role in LTE/5G launches, where such a high degree of flexibility needs to be preserved in order to guarantee sustainable quality of service.

1.6 Antenna Tilt Optimization Objectives

After we analysis the importance of antenna tilt and the influence that it can offer to optimize cellular networks and its dependence on particular conditions, we propose that it can be optimized more and that's what we will discuss in upcoming subsequent, The upcoming section presents an overview of The studies we focus on that explore how antenna tilt can be adjusted to meet different performance objectives depending on the situation and goals.

1.6.1 Coverage and Capacity Optimization

Antenna tilt optimization is a fundamental approach for ensuring efficient signal coverage in defined areas and improving coverage and capacity to meet user needs. One basic technique involves the use of a uniform tilt for all base stations, which can lead to marginal improvements over unoptimized installations[39]. Yet, actual networks demonstrate a broad variety of topological structures and populations of users, which call for customized tilt adaptations per cell for specific environmental factors, urban population density or terrain variation. Customized optimization has been found to enhance capacity by approximately 15% in UMTS macro cell installations over standard tilt configurations, primarily by reducing inter-cell interference via optimum beam alignment [33]. Power distribution is crucial in UMTS systems, and base stations distribute limited transmission power to data and control channels. Antenna tilt optimization can significantly reduce the power needed for basic control channels such as cell identity broadcast and synchronization signal broadcast. Studies have shown that meticulous tilt tuning can reduce the power of these channels by up to 60%, freeing up vast amounts of resources for data channels [46] [45]. This re balancing optimizes the network's capacity, reduces congestion, and minimizes the occurrence of service disruptions, including dropped calls or call setup failures.

For high-speed data networks, throughput is a key indicator of capacity. Antenna tilt optimization can enhance average user throughput by as much as 30% in advanced HSPA systems, and even greater gains in LTE and 5G systems where frequency reuse across cells enhances the interference risks [2] [48] . In Long-Term Evolution (LTE) networks, finely adjusted tilt configurations enhance signal-to-interference-plus-noise ratio (SINR) characteristics, especially at cell edges, thereby making possible the utilization of advanced modulation techniques and increasing edge throughput by 80% in non-uniform deployments. Such enhancements are essential to maintaining stable service quality and minimizing the digital divide between central cell areas and their edges[41][5]. Apart from coverage and throughput, antenna tilt optimization assists in energy efficiency, a problem of paramount significance in contemporary networks. Optimized tilts, via better concentration of radiated power, reduce overall base station power consumption and facilitate environmentally friendly operation of networks [10]. In heterogeneous networks incorporating macrocells and small cells, adaptive tilt methods maximize load balancing through dynamic redistribution of capacity to areas of high demand during hours of peak usage. These advances underline the sophisticated role of antenna tilt in modern wireless systems, enabling the realization of resilient and user-centric network designs.

1.6.2 Base Station Deployment

Radio access network planning involves the optimal selection of base station (BS) positions along with their operating modes in order to ensure that the capacity needed is delivered to intended areas of service. It is usually constrained by a variety of real-life situations, including the limited number of sites for deployment, installation expense, target levels of coverage, and user requirement density in each location. Within these limits, the core objective of network planning is to deliver optimum performance at the minimum overall cost of infrastructure deployment. Besides location, the environment for each BS transmit power, antenna tilt, and sector orientation, for example its important in determining its effective service area and overall contribution to network capacity. By optimizing placement and settings simultaneously, operators can reduce the quantity of BSs needed to meet performance requirements. This principle has already been successfully proven in earlier generations like GSM and WCDMA, where the network planners derived tremendous efficiency gains by including configuration-aware deployment techniques [6][7]. With the emergence of LTE and the advent of 5G, this becomes all the more critical. In LTE, with frequency reuse prevalent everywhere, and in 5G, where dense deployments along with higher frequency bands are made, Careful BS planning minimizes interference and improves spectral efficiency. As networks evolve to handle higher traffic volumes, lower latency requirements, and more complex environments, base station deployment must be addressed not just as a matter of coverage, but as an enabling factor of overall capacity and quality of service. Incorporating advanced BS parameters in the planning process continues to be a fundamental way of lowering deployment costs while maximizing performance in current and future wireless systems[5].

Actually, there are more objectives to discuss regarding their importance in cellular networks and Studies conducted for such objective like :

- **Load Balancing** Cellular networks experience non-uniform spatio-temporal traffic variations, causing resource imbalance, where congested cells deteriorate QoS by increased latency and decreased throughput. Dynamic load balancing via antenna tilt manages cell coverage and signal strength, directing traffic towards under-loaded neighbor cells. Real-time tilt adaptation increases capacity by 15% in WCDMA [20] and up to 40% in LTE, with the gains growing in high-imbalance scenarios like event hotspots [34]. In 5G, single frequency reuse maximizes interference, and adaptive tilt is necessary, enhanced by machine learning and Self-Organizing Networks (SONs). In HetNets networks, specialized algorithms optimize macro and small cell traffic for seamless communication and spectral efficiency. Antenna tilt is a low-cost, flexible solution for rapid response to traffic changes without compromising service quality[26].

- **Self-Healing** Cellular networks are susceptible to cell failures caused by hardware or software failures that lead to poor service or total outages with significant impact on user experience. Self-healing capability leverages automation to detect and repair such failures, minimizing downtime and manual intervention[8]. Antenna tilt plays a crucial role in self-healing in the way that it dynamically adjusts coverage to compensate for failed cells so that adjacent cells extend their serving areas and bridge the gap in connectivity. For example, in LTE networks, SON-based tilt optimization can autonomously detect a cell outage and redirect adjacent antennas to cover the gap, minimizing service disruption by up to 80% in simulations[37]. Self-healing based on machine learning, when coupled with tilt optimization, is reported to restore coverage within minutes, increasing the reliability of networks, in recent research on 5G networks. Such enhancements are particularly significant in dense 5G deployment, wherein failure of small cells is ubiquitous due to complex topologies. Through the inclusion of real-time monitoring and adaptative tilt, self-healing brings about fault-resilient network performance, and therefore is highly important to wireless systems in current times[43].

- **Energy Saving** With increasing operational expenditures and environmental awareness, energy efficiency is a top priority in cellular networks. Traffic demands are space and time-heterogeneous and will leave certain cells underutilized during off-peak periods. Dynamically switching off low-traffic cells and using antenna tilt adaptations is one of the most important energy-conserving strategies[8]. In LTE networks where the inter-site distance is 500 meters, simulations are shown to achieve 5% to 13% energy savings through this technique, with even greater savings, (up to 20%) in 5G networks because of denser deployments of small cells. Dynamic tilt optimization focuses radiated power, lowering base station energy consumption in total without compromising coverage continuity[13][56]. Evidence further suggests that the integration of tilt adaptation with SONs and machine learning can predict traffic conditions and cell switching optimization more accurately, with 15%–25% gains in energy efficiency in urban 5G HetNets, without any throughput or latency losses. Not only does this approach reduce operating costs but also supports sustainable network operation, aligning with global green initiatives[44].

1.7 Radio Propagation Modeling

Radio propagation modeling is critical for simulating cellular network performance, because it determines the received signal strength, which influences metrics such as coverage, capacity, and interference. In this thesis, the propagation model is tailored to optimize antenna downtilt and transmit power in an urban macrocell environment, using Bayesian Optimization (BO) and Genetic Algorithms (GA). The model calculates Received Signal Reference Power (RSRP) based on transmit power, path loss, and antenna downtilt effects, following the general structure of the received power equation presented in Section 1.7.2. This section describes the empirical model, path loss calculation, rationale, limitations, and downtilt loss modeling used for the simulation.

1.7.1 Empirical Models

Empirical propagation models estimate path loss from real-world statistical data, offering a balance between accuracy and computational simplicity for urban environments. This thesis adopts the COST 231 Hata model, an extension of the Okumura-Hata model, designed for urban macrocell scenarios at frequencies around 1800 MHz [3]. The model accounts for key parameters such as distance, base station height, mobile height, and carrier frequency, making it suitable for simulating LTE networks in dense urban settings. Unlike deterministic models, which require detailed environmental data, or theoretical models, which may oversimplify complex terrains, the COST 231 Hata model provides robust predictions for the macrocell deployment studied in Chapter 4.

1.7.2 Path Loss

Path loss represents the reduction in signal power as it propagates from the transmitter to the receiver, influenced by distance, frequency, and environmental factors. The COST 231 Hata model is used to compute path loss (PL) in this thesis, expressed as[3]:

$$PL = 46.3 + 33.9\log_{10}(f) - 13.82\log_{10}(h_B) - a(h_M) + \left(44.9 - 6.55\log_{10}(h_B)\right)\log_{10}(d) + C \tag{1.1}$$

where f is the carrier frequency (1800 MHz), h_B is the base station height (30 m), h_M is the mobile height (1.5 m), d is the 3D distance in kilometers, and C is an urban correction factor (3 dB). The mobile correction term is:

$$a(h_M) = \left(1.1\log_{10}(f) - 0.7\right)h_M - \left(1.56\log_{10}(f) - 0.8\right) \tag{1.2}$$

The 3D distance d is calculated using the geodesic 2D distance between the transmitter and receiver, adjusted for the height difference between the base station (30 m) and mobile (1.5 m), ensuring accurate modeling of urban terrain variations. The total path loss includes an additional downtilt loss term, described in Section 1.7.3, to account for antenna orientation effects.

1.7.3 Downtilt Loss Modeling

Antenna downtilt affects signal strength by focusing the radiation pattern toward specific areas, reducing interference and optimizing coverage. The simulation models downtilt loss as:

$$L_{\text{tilt}} = \max\left(0, \frac{\theta_{\text{downtilt}} - \theta}{\text{BW}}\right) \cdot 3 \tag{1.3}$$

where θ_{downtilt} is the antenna downtilt angle (0–10 degrees), $\theta = \arctan\left(\frac{h_B - h_M}{d \cdot 1000}\right)$ is the angle to the user in degrees, d is the distance in kilometers, and BW is the antenna beamwidth (10 degrees). The loss is scaled by 3 dB per beamwidth deviation, a gradual signal loss penalty for misaligned signals. This model is integrated with the COST 231 Hata path loss to compute total loss:

$$L_{\text{total}} = PL + L_{\text{tilt}} \tag{1.4}$$

The downtilt loss enhances the simulation's ability to optimize RSRP by adjusting antenna angles, such as studies like Siomina (2005) [46], where downtilt reduced pilot power by up to 50%. By incorporating downtilt effects, the model supports the BO framework's goal of minimizing weak and over-coverage areas.

1.7.4 Rationale and Limitations

The COST 231 Hata model was selected for its applicability to urban macro-cell environments at 1800 MHz, aligning with the LTE network configuration. Its empirical nature ensures reliable predictions without requiring detailed environmental data, which is often unavailable for large-scale simulations. The model's parameters (30 m base station height, 1.5 m mobile height) match the simulation setup, and its urban correction factor accounts for building density, making it suitable for optimizing coverage and capacity. However, the model has limitations. It assumes homogeneous urban environment, which may not capture specific terrain or building variations. The model is also less accurate for distances below 50 m or above 20 km, though the simulation's grid resolution (50 m) mitigates this issue. Additionally, antenna gains (G_{Ant}, G_{Dir}) are simplified, with directional effects approximated via downtilt loss, which may overlook complex antenna patterns.

1.8 Problem Formulation

To design an effective optimization framework, the problem must be clearly defined in terms of decision variables, objectives, evaluation metrics, and constraints. This section formalizes the optimization problem for both dynamic parameter tuning and cell placement, ensuring alignment with realistic network planning requirements. The formulation draws inspiration from [19], who define coverage and capacity optimization as a multi-objective problem, minimizing under-coverage and over-coverage using RSRP-based metrics.

1.8.1 Decision Variables

The optimization process involves adjusting the following decision variables:

- **Transmit Power ($P_{\mathbf{Tx}}$)**: The power level (in dBm) at which each sector of a base station transmits. For existing towers, the range is 30–50 dBm, reflecting typical macrocell configurations [19][45]. For a new tower, the same range applies to its three sectors.
- **Antenna Downtilt (θ)**: The angle (in degrees) at which the antenna is tilted downward to control coverage and interference. The range is 0–10°, based on standard electrical tilt capabilities [1].
- **Tower Location ($\mathbf{lat}, \mathbf{Lon}$)**: For cell placement, the geographical coordinates (latitude and longitude) of a new base station within the urban area.

These variables directly influence signal strength, coverage patterns, and interference, making their optimization critical for network performance. Similar to

[19], who optimize both transmit power and downtilt to balance signal strength and interference, our approach uses these variables to achieve comparable objectives.

1.8.2 Multi-Objective Optimization

We consider a predefined area of interest that contains multiple base stations, each comprising several sectors, all managed by a centralized controller. Two key issues in cellular coverage are identified:

- **Under-coverage**: Areas where the received signal strength is insufficient to maintain acceptable service quality.
- **Over-coverage**: Areas where excessive signal overlap leads to high interference levels, degrading overall network performance.

To formalize these concepts, we use the Reference Signal Received Power (RSRP), a common LTE performance metric reported by user equipment (UE) to represent signal level and coverage quality. An under-covered location is one where the maximum RSRP from any sector falls below a predefined threshold. Conversely, over-covered locations are those where the difference between the strongest RSRP and the total RSRP received from all other interfering sectors does not exceed a specified threshold[19].

These thresholds are typically chosen based on receiver sensitivity, selectivity, network density, and standard interference management practices. Common values are -110 dBm for under-coverage and 6 dB for over-coverage [19].

A network configuration x defines the transmit power and antenna downtilt for each sector. In our model, the downtilt can take one of eleven discrete values, while the transmit power is treated as a continuous variable within a bounded range. Given N antennas, the search space for all possible configurations is exponential in N, making brute-force search infeasible[19].

Let γ_w and γ_o denote the weak and over-coverage thresholds, respectively. We represent the area as a 2D grid indexed by (i, j). Let $r_{ij}^{(b)}$ denote the RSRP from the serving sector b at grid point (i, j), and $\sum_{b' \neq b} r_{ij}^{(b')}$ the combined interference from all other sectors.

Using these definitions, under-coverage and over-coverage are identified as:

$$\text{Under-coverage: } r_{ij}^{(b)} < \gamma_w \tag{1.5}$$

$$\text{Over-coverage: } r_{ij}^{(b)} - \sum_{b' \neq b} r_{ij}^{(b')} < \gamma_o \tag{1.6}$$

Minimizing both of these conflicting metrics results in a multi-objective optimization problem. Since improving one objective typically worsens the other, we aim to find a set of Pareto-optimal configurations, those in which no objective can be improved without degrading another. These trade-offs allow network operators to choose a configuration that best aligns with operational priorities.

To illustrate this trade-off, we consider a linear combination of the two objectives:

$$x^* = \arg\max_x \sum_{i,j} \left[r_{ij}^{(b)} - (1-\lambda) \cdot \sum_{b' \neq b} r_{ij}^{(b')} \right] \tag{1.7}$$

where $\lambda \in [0,1]$ weights the trade-off between maximizing RSRP (coverage) and minimizing interference. Rewriting in logarithmic terms:

$$x^* = \arg\max_x \sum_{i,j} 10 \log \left(\frac{S_{ij}^{(b)}}{I_{ij}^{(b)\,(1-\lambda)}} \right) \tag{1.8}$$

where $S_{ij}^{(b)}$ and $I_{ij}^{(b)}$ represent the signal and interference power at location (i,j).

To improve optimization performance, we adopt smooth approximations of the objectives using sigmoid functions centered around the thresholds:

$$\text{Under-coverage objective: } \sum_{i,j} \sigma(\gamma_w - r_{ij}^{(b)}) \tag{1.9}$$

$$\text{Over-coverage objective: } \sum_{i,j} \sigma \left(\sum_{b' \neq b} r_{ij}^{(b')} - r_{ij}^{(b)} + \gamma_o \right) \tag{1.10}$$

where σ is the sigmoid function.

This smooth formulation is critical: hard thresholds produce sparse gradients that hinder learning, especially in gradient-based optimization. In contrast, sigmoid functions offer soft, differentiable transitions, enabling denser and more informative gradients. Though our main algorithms (Bayesian Optimization and Genetic Algorithms) use simpler linear formulations for efficiency, these sigmoid-based objectives better align with advanced optimization theory.

In our implementation, we adopt a simplified linear formulation for computational efficiency. Specifically, the objective function minimizes the sum of two terms: (i) the percentage of user locations with RSRP below the weak coverage threshold (-80 dBm), and (ii) the percentage of locations with RSRP above the over-coverage threshold (-60 dBm). Formally, the objective is given by:

$$f(x) = -\left(\frac{1}{N} \sum_{i=1}^{N} \mathbb{1}[r_i < \gamma_w] + \frac{1}{N} \sum_{i=1}^{N} \mathbb{1}[r_i > \gamma_o] \right) \tag{1.11}$$

where r_i is the RSRP at location i, γ_w and γ_o are the weak and over-coverage thresholds respectively, N is the total number of user locations, and $\mathbb{1}[\cdot]$ is the indicator function. This formulation enables rapid evaluation of candidate configurations during optimization, while still aligning with coverage quality goals.

1.8.3 Evaluation Metrics

To evaluate the effectiveness of network configurations, we define the following evaluation metrics based on empirical models and regulatory constraints:

- **RSRP (Reference Signal Received Power)**: RSRP quantifies the signal strength received at each user location. It is computed using the COST-231 Hata path loss model, including additional loss due to antenna downtilt. For sector i, the RSRP at location j is given by:

$$\mathrm{RSRP}_{i,j} = P_{\mathrm{tx},i} - \mathrm{PL}_{i,j} - L_{\mathrm{tilt},i,j} \tag{1.12}$$

  where $P_{\mathrm{tx},i}$ is the transmit power (in dBm), $\mathrm{PL}_{i,j}$ is the path loss between transmitter i and location j, and $L_{\mathrm{tilt},i,j}$ represents downtilt loss, estimated from the vertical angle difference between the antenna and the user. The final RSRP map reflects the highest RSRP received from any sector at each location.

- **Weak Coverage (%)**: This metric represents the percentage of user locations where RSRP falls below a threshold (-80 dBm), indicating insufficient signal strength. It is computed as:

$$\text{Weak Coverage} = \frac{1}{N}\sum_{j=1}^{N} \mathbb{1}\left[\mathrm{RSRP}_j < \gamma_w\right] \times 100\% \tag{1.13}$$

  where $\gamma_w = -80$ dBm is the weak coverage threshold, and N is the total number of user locations.

- **Over-Coverage (%)**: The percentage of user locations where the signal strength is excessively high (RSRP > -60 dBm), increasing the potential for interference. Formally:

$$\text{Over Coverage} = \frac{1}{N}\sum_{j=1}^{N} \mathbb{1}\left[\mathrm{RSRP}_j > \gamma_o\right] \times 100\% \tag{1.14}$$

  where $\gamma_o = -60$ dBm.

- **Interference (%)**: Interference is quantified as the proportion of locations receiving strong signals from multiple sectors the number of user locations that receive strong signals (RSRP > -75 dBm) from multiple sectors simultaneously. A location is considered to experience interference if it receives such signals from more than one sector. This metric is computed as:

$$\text{Interference} = \frac{1}{N}\sum_{j=1}^{N} \mathbb{1}\left[\sum_{i=1}^{M} \mathbb{1}[\mathrm{RSRP}_{i,j} > \gamma_{\mathrm{int}}] > 1\right] \times 100\% \tag{1.15}$$

  where M is the total number of sectors and $\gamma_{\mathrm{int}} = -75$ dBm is the interference threshold.

- **Regulatory Compliance Penalty**: To enforce policy constraints, we penalize tower placements near sensitive land-use areas (educational, healthcare). Each candidate location is evaluated against a neighborhood map, and penalties are accumulated based on proximity to restricted zones. The penalty is integrated into the fitness function to discourage non-compliant solutions. This ensures adherence to urban planning guidelines and real-world deployment feasibility.

These metrics collectively ensure that the optimization framework not only improves user coverage but also mitigates harmful interference and respects regulatory boundaries. This mirrors the multi-objective approach proposed by [19], with additional consideration for spatial constraints and terrain sensitivity.

1.8.4 Regulatory Constraints and Penalty Design

In practical network deployments, regulatory constraints prohibit base station placement near sensitive areas. This study incorporates a **Neighbor penalty** based on proximity to:

- **Educational and Healthcare Areas**: High penalty (weight=15, distance=150m) due to strict radiation regulations.
- **Residential and Civic Areas**: Moderate penalty (weight=2, distance=20m).
- **Commercial and Industrial Areas**: Low penalty (weight=1.2, distance=12m).
- **Open Spaces**: No penalty (weight=0).

The penalty is integrated into the GA fitness function, ensuring compliance with local regulations [28]. Although [19] do not explicitly model regulatory constraints, their focus on practical deployment aligns with our approach, as regulatory compliance is critical for real-world applicability.

1.8.5 Problem Decomposition (Parameter vs Placement)

To manage the complexity of optimizing network coverage under both physical and regulatory constraints, we decompose the problem into two tractable subproblems:

- **Parameter Tuning**: This task involves optimizing the transmit power (P_{tx}) and downtilt angle (θ) of each sector in the existing infrastructure. The goal is to improve signal coverage and reduce interference by fine-tuning these parameters within predefined limits. We use Bayesian Optimization (BO) for this subproblem because of its sample-efficient, model-based approach, which is suited for expensive objective evaluations.
- **Cell Placement**: Here, the objective is to determine the optimal geographic location (latitude, longitude) for a new base station, along with its transmit power and downtilt configuration. Given the combinatorial and spatial nature of this task and the inclusion of terrain and regulatory penalties we apply a Genetic Algorithm (GA), which is well-suited for handling non-convex, mixed-variable search spaces.

This two-level decomposition aligns with standard practices in real-world network engineering: operators typically exhaust parameter tuning before proposing new infrastructure deployments. A similar decomposition appears in [45] and [19], where power control and antenna tilt are optimized independently before infrastructure expansion is considered. Although there are unified joint optimization approaches, they tend to be computationally intensive and less transparent.

To aid in clarity, Table 1.1 summarizes the core components of the optimization framework, including decision variables, objectives, evaluation metrics, and constraints.

Table 1.1: Optimization Problem Components

Component	**Description**
Decision Variables	Transmit Power (P_{tx}), Downtilt (θ), Tower Coordinates (lat, lon)
Objectives	Minimize Weak Coverage and Over-Coverage
Evaluation Metrics	RSRP, Interference Rate, Regulatory Compliance
Constraints	Regulatory Penalties, Power and Downtilt Ranges

1.9 Conclusion

In this chapter, we focus on 4G LTE design and provides a thorough overview of the important factors and parameters involved in cellular network planning and optimization. Before outlining how contemporary networks have developed from basic technologies to intricate data-centric networks, the discussion starts with a summary of past network design advancements in cellular networks. An in-depth evaluation of all elements that make up the LTE network was performed with emphasis on the role that static and dynamic configuration parameters play on frequency reuse, base station density, antenna height, sectorization, azimuth control, transmit power and antenna tilt in capacity and general coverage. Particular attention was given to antenna tilt and its role as a major factor influencing coverage and combating interference. Mechanical and electrical tilts were differentiated and then their respective adjustment mechanisms and implications were discussed. The chapter also discussed radio wave propagation modeling, including empirical path loss models and downtilt loss considerations, thus highlighting their importance from the viewpoint of realistic network planning.We developed a framework for multi-objective optimization for antenna tilt and basestation configuration, considering real-life constraints including regulatory constraints and service level targets, thereby bridging the gap between theoretical concepts and practical applications.

We propose an enabling framework for more intelligent and responsive deployments by separating the challenge of optimization into its constitutive elements that is, parameter adjustment and strategic location of base stations. This framework is quite relevant for next studies on self-optimizing networks, where artificial intelligence and dynamic adaptation will be increasingly critical.

Chapter 2

Related Work

2.1 Introduction

This chapter presents a comprehensive review of the methods and strategies used for optimizing cellular networks, with a particular focus on urban macrocell environments. We begin by exploring traditional optimization methods, particularly metaheuristic approaches, which have historically been applied to antenna tilt and power control problems. Next, we examine the evolution of intelligent techniques, including machine learning and reinforcement learning, which address the limitations of manual and heuristic methods in dynamic network scenarios. Throughout the chapter, we emphasize the relevance of each method to modern network challenges and highlight the justifications for adopting AI-driven solutions such as Bayesian Optimization and Genetic Algorithms. This contextual foundation supports the design choices of our proposed optimization framework.

2.2 Related works

The ideal tilt configuration of a cell is not an isolated decision; it is intrinsically tied to those of adjacent cells. Performance can often be maximized by a balance between user distribution and interference mitigation through optimal cell isolation. Since antenna tilt adjustment is commonly restricted to discrete values (steps of 1 or 2 degrees, say), finding the best set of them is combinatorial in nature. Even in small networks, the number of possible tilt settings grows exponentially with the number of base stations, so exhaustive search approaches are computationally impractical. Thus, determining the best set of tilt values in a network is a highly computationally intensive problem. To correct this, researchers have proposed a variety of intelligent optimization methods capable of producing near-optimal solutions within reasonable computational time. They include heuristic methods, rule-based systems, and more recently Machine Learning and evolution strategies. A short overview of these methods will be presented below, starting from the traditional approaches,Machine Learning-based approaches and finally Reinforcement Learning, which underpins the advanced methods proposed in this work.

2.2.1 Traditional Method (Meta-Heuristic)

Under the direction of certain performance measures, metaheuristic techniques are a class of optimization algorithms that iteratively search the solution space for configurations of high quality. These techniques are good at effectively navigating high-dimensional, complicated areas, but they do not provide a globally optimal result. Due to their balance between performance and computational feasibility, metaheuristic techniques have become widely adopted in antenna tilt optimization, offering practical solutions within reasonable time constraints. These algorithms typically depend on simulation or network planning tools to assess the effectiveness of each candidate configuration based on predefined evaluation criteria.

In [46] Siomina (2005), an LS-based heuristic is proposed for simultaneously optimizing the antenna downtilt settings and the P-CPICH power in UMTS networks. The algorithm begins with an initial valid tilt setting and, in each iteration, investigates neighbor settings by varying the tilt of one base station at a time. The new assignment is only accepted if it leads to a reduction in the uniform pilot power level and coverage restrictions are still maintained. This step is iterated until no further improvements can be made or a convergence condition is met. Although LS is both computationally economical and memory frugal in that it only requires updating local antenna gain matrices rather than bringing in the full set of gains, it is beset by the local optima problem inherently. That is, it may settle on a superior solution to that of nearby configurations but not close to the global optimum. Despite this limitation, the approach was shown to work in practice. In a case study of a real network scenario in Lisbon, the optimal antenna tilt value led to a significant reduction in total pilot power up to 50% compared to a network with no tilt or flat tilt values. Moreover, findings showed improved cell isolation, reduced interference, and better resource utilization, especially when electrical downtilt was used within a given range. The work gives the hope of LS-based methods for optimization of parameters in big radio networks and provides a baseline for comparison with more complex techniques, such as reinforcement learning or metaheuristics, which can dominate the local search by exploring the solution space to a greater extent.

Simulated Annealing (SA) overcomes the local optima problem of Local Search (LS), as described in Siomina (2005)[46], by probabilistically accepting worse neighbor solutions in order to more effectively search the solution space. The acceptance probability of worse solutions decreases with iterations, and hence the optimization becomes more stable, and the chance of finding a global optimum is higher. SA has been successfully used for antenna tilt and power optimization in UMTS and HSDPA networks with tremendous improvements compared to LS-based methods.

In Garcia-Lozano et al. (2004)[23], SA optimized pilot power and antenna tilt for UMTS cell load balancing in the case of inhomogeneous traffic distributions. By more evenly spreading traffic loads, the algorithm enhanced capacity and reduced interference levels by up to 10% using globally adjusted tilts at base stations. According to the study, a well-defined neighborhood for example, gradual tilt changes within a restricted range improves solution quality and lowers computational effort. The starting temperature and cooling schedule are two parameters that the authors noted as being difficult to tune for SA, which could result in sluggish convergence if not properly established.

Siomina et Yuan (2008)[47] applied SA to optimize base station antenna configurations for HSDPA performance. SA was shown to gain 25–30% throughput and reduce inter-cell interference compared to fixed tilt settings. The study showed that SA is susceptible to acceptance probability of sub-optimal solutions, where too aggressive exploration destabilizes the convergence for highly dense networks.

Siomina and Värbrand (2006) [48] studied SA for optimized automated UMTS service coverage and optimization of antenna configuration. They obtained 20–35% pilot power reduction and improved cell isolation but were constrained by increased computational complexity as the network size increased, especially in evaluating several neighbor solutions per iteration. Hybrid solutions were suggested to mitigate this limitation.

Andras Temesváry et al. (2010) [51] used SA for plug-and-play cellular network self-configuration of power and antenna tilt. They achieved a 15–20% reduction in total transmitted power with preserved coverage but cited parameter sensitivity as a limitation, which required tuning for scenario-specific convergence to suboptimal values.

In all these experiments, SA beats LS on average by escaping local optima, as in Siomina (2005)[46]. However, challenges are there in parameter tuning (e.g., temperature and acceptance probability), which affects convergence rate and solution quality, and computational complexity in large networks. These are the weaknesses indicating prudent neighborhood design and potentially using other metaheuristics to enhance SA's efficiency.

Another local Search algorithm is Tabu Search (TS), has been used in several papers to optimize the tilt of the antenna and configuration of the base station in 3G and UMTS networks. This method's primary strength is to escape local optima by having a memory of solutions recently visited so that wider exploration of the search space may be done.

Amaldi et al. (2008) [7] reported up to 20% coverage gain using TS compared to manual configuration. Nevertheless, it was noted that TS becomes computationally demanding with growing network size.

Naseer ul Islam et al. (2010)[52] demonstrated that TS can provide up to 94% user satisfaction in the distributed WCDMA environment very near to the outcomes of global optimization. Aspects like the adaption dynamic and the choice of ideal cluster sizes are still difficult, though. With 15% capacity gains, Siomina et al. (2006) demonstrated the efficacy and adaptability of TS in discrete challenges like tilt adjustment. However, due to memory consumption, its performance was susceptible to resource restrictions and was dependent on the original solution.

Siomina et Yang et al. (2007)[45] reported TS to be effective for small to medium-sized networks, with 10–15% capacity improvement, but with poor scalability for large deployments and with challenges in tuning parameters such as tabu tenure.

In general, despite being promising for antenna tilt optimization due to its capability to avoid local optima, TS is limited in practical use due to high computational complexity, parameter setting sensitivity, and inferior real-time applicability in large scale or dynamic network scenarios.

Genetic Algorithms (GAs) which are meta-heuristic algorithm has been applied by reaserchers to optimize cellular network parameters like base station location, antenna tilt, power control, and performance parameters like SINR and throughput.

Campos and Lovisolo (2019) [14] developed GA strategies for improving mobile positioning in emergency scenarios, where the DcmGaBs+RTT method offered high accuracy and low delay in Line-of-Sight environments. They emphasized the significance of intelligent population initialization and traffic-adaptive fitness functions.

Jamaa et al. (2004) [32] used GA to optimize coverage and capacity in UMTS networks at the same time, achieving significant improvements in SINR and load balancing but noting sensitivity to genetic operator parameters and high computational cost.

Wu et al. (2011) [57] found GA to optimize LTE antenna designs, achieving up to 15% improvement in throughput and better edge performance. However, parameter tuning as well as convergence sluggishness were reported to be main limitations.

Arslan et al. (2017)[9] employed GA in heterogeneous networks to reduce interference and increase spectral efficiency. A dynamic, demand-aware fitness function enhanced the performance, but real-time scalability was a problem due to the processing requirements of GA.

Alam et al. (2024) [4] used in his paper Ant Colony Optimization (ACO), which he designed a Cell Range Extension (CRE) based multi-objective ACO-based scheme for small cell bias tuning. Their method optimized the SBS SINR- and traffic-demand-dependent bias parameters dynamically, and they achieved significant throughput (70.6 Mbps), fairness (JFI = 0.774), and call drop (0.26) reduction. Compared to PSO and other metaheuristics, ACO was better in global search capability and stability in ultra-dense environments. The authors stated that scalability remains a problem as the running time of ACO increased exponentially with user density, suggesting future hybrid approaches that blend ACO with reinforcement learning for real-time learning in 5G/6G networks.

A study in 2015 by Lee, S.,and Kim, Y. H.,[36] proposes a meaningful advancement in the field of radio network planning. The study tackles the challenge of efficiently deploying base stations (BSs) in LTE heterogeneous networks (HetNets), where the growing demand for mobile data has led to a dense use of small cells alongside traditional macro cells.

Table 2.1: Summary of Metaheuristic approaches

References	**Technique**	**Metric**	**Contribution**	**Limitations**
[46]	Local Search (LS)	Pilot Power Reduction, Isolation Index	Achieved up to 50% reduction in pilot power; improved cell isolation in UMTS.	Limited to local optima; lacks robust global search capability.
[23, 47, 48, 51]	Simulated Annealing (SA)	Interference Reduction, Throughput Gain	Reduced interference and pilot power by 10–35%; improved throughput by 25–30% in UMTS/HSDPA.	Sensitive to tuning of temperature and cooling schedule; scalability issues.
[7, 45, 52]	Tabu Search (TS)	Coverage Satisfaction, Capacity Gain	Delivered 10–20% improvements in coverage and capacity; 94% user satisfaction coverage in WCDMA.	High computational and memory requirements; poor scalability.
[9, 14, 32, 36, 57]	Genetic Algorithms (GA)	SINR Improvement, Interference Reduction	Improved SINR and throughput by 15–20%; effectively reduced interference in UMTS/LTE.	Requires extensive parameter tuning; computationally intensive.
[4]	Ant Colony Optimization (ACO)	Throughput, Fairness Index, Call Drop Rate	Achieved 70.6 Mbps throughput, 0.774 fairness index, and 0.26 call drop rate in dense urban settings.	Runtime increases exponentially with user density; limited scalability.

The study points out that randomly and poorly planned deployments can lead to ”interference,” so harming overall network performance. While evolutionary algorithms (EAs) had been applied to this problem before, the team found that these methods often struggled with scalability in large, complex environments. To avoid it, they use a smart correlation-based grouping strategy that clusters BSs according to their interference relationships to improve optimization performance using a refined genetic algorithm (GA). Unlike traditional approaches that group randomly and have bad performance , their method uses interference patterns to lead grouping and to ensure consistent individual sizes during crossover. Their simulations, backed by analytical modeling, showed that the results demonstrated up to 20 % improvement in system throughput over random grouping approaches and that this approach consistently delivered higher system throughput even with fewer BSs compared to existing methods.

2.2.2 Machine Learning

Data-driven methods to improve capacity and coverage are made possible by machine learning (ML), which has become a powerful tool for cellular network optimization. ML enables adaptive changes that are suited to various topologies and user requirements by using algorithms to examine network parameters. Techniques such as optimization and predictive modeling address problems like interference and resource allocation. This part addresses ML techniques that can be used for antenna tilt optimization as a foundation for adaptive network management. These methods complement traditional techniques with greater efficiency and performance.

Dreifuerst et al. (2021)[19] described a comparative evaluation of two state-of-the-art machine learning algorithms Deep Deterministic Policy Gradient (DDPG) and Bayesian Optimization (BO) for the concurrent optimization of antenna down-tilt and transmit power in multi-sector cellular systems. They endeavored to solve the problematic multi-objective task of minimizing both under-coverage and over-coverage by means of a realistic simulation test bed built with the QuaDRiGa MATLAB-based RF channel simulator and an assessment framework developed in Python. The network was a 12×12 km^2 area with 5 base stations, each of 3 sectors, and the space of configurations had 10 discrete tilt values and continuous power values ranging from 30 to 50 dBm which made brute-force search infeasible due to its exponential complexity. For the purpose of measuring system performance, they defined black-box objectives as RSRP thresholds for weak and interfering coverage area identification. These were parameterized using sigmoid functions to enable differentiable optimization and avoid sparse gradient issues at training. the following equations define the dual objectives of network optimization as the minimization of both **under-coverage** and **over-coverage**. These are evaluated over a set of spatial regions and antenna configurations.

The **under-coverage** is defined as:

$$\mathcal{U}_{ij} = \sum_{b} \sigma \left(w - r_{ij}(b) \right) \tag{2.1}$$

The **over-coverage** is defined as:

$$\mathcal{O}_{ij} = \sum_{b} \sigma \left(r_{ij}(b) - o \right) \tag{2.2}$$

where:

- $\sigma(\cdot)$ is the sigmoid function used for soft thresholding.

- $r_{ij}(b)$ is the received signal power (RSRP) at location (i, j) from base station b.
- w is the lower RSRP threshold, below which a region is considered under-covered.
- o is the upper RSRP threshold, above which interference from overlapping coverage becomes problematic.

The following Figure 2.1 is Example of an RSRP map summed over all the sectors. Base stations are marked by a red circle, and all antennas are configured to 5 downtilt and 46dBm transmit power. The upper right base station, circled, has a strong effect on local RSRP due to being placed only 20m above ground as opposed to 25-30m for the other sites.

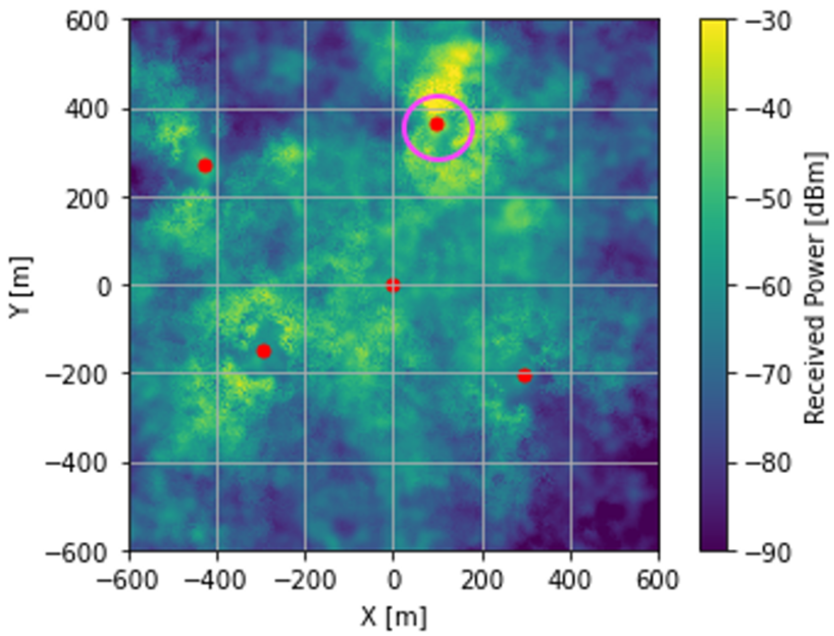

Figure 2.1: Initial RSRP

Bayesian Optimization employed Gaussian Processes with Matern-5/2 kernels and was seeded with a space-filling Sobol sequence, followed by 500 iterations of q-Expected Hypervolume Improvement (qEHVI). DDPG, on the other hand, employed an actor-critic neural architecture to learn continuous actions with exploration via Gaussian noise and convex combinations of under and over-coverage reward metrics the result of this algorithms is shown in Figure 2.2.

While both methods far outperformed random search, BO achieved comparable Pareto-optimal solutions using only 1,012 evaluations, whereas DDPG used over 300,000 evaluations,as shown in Figure 2.3.

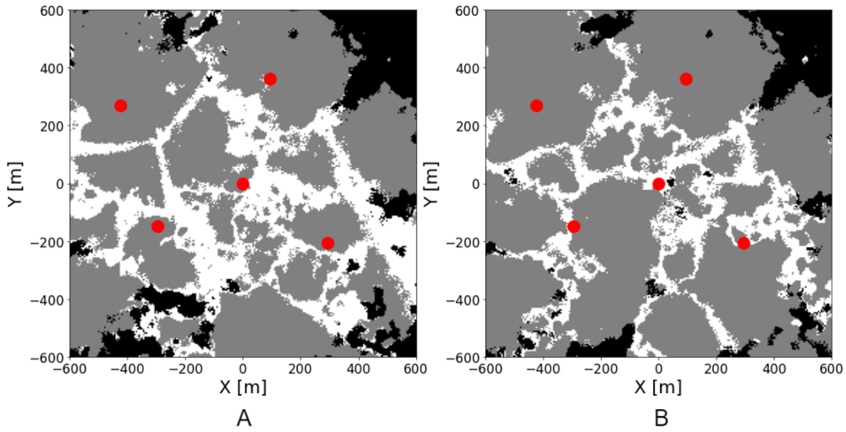

Figure 2.2: Comparison of RF coverage maps shows DDPG outperforms random search by reducing under-coverage from 12% to 9% and over-coverage from 25% to 17%.

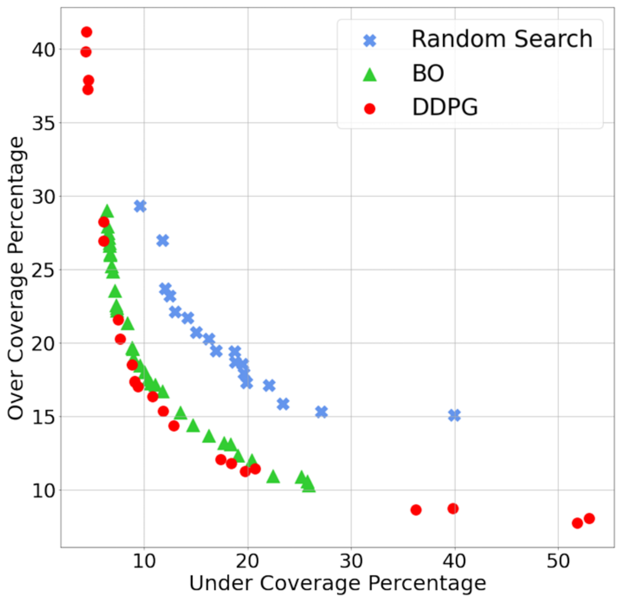

Figure 2.3: Pareto frontier comparison showing DDPG outperforming both BO and random search, with a 10% average gain and a characteristic convex trade-off curve in $\mathbb{R}^2$.

This illustrated a substantial sample efficiency benefit for BO, although slightly better frontier quality was achieved by DDPG. The authors also noted directions for research in the future including scaling the network, risk-averse learning, and combining safe RL or BO techniques in order to avoid configuration that may degrade service quality during live optimization. Their open-source code and simulations provide a reproducible and impactful baseline for future research on ML-based coverage and capacity optimization.

2.2.3 Reinforcement Learning

Under specific performance objectives, reinforcement learning (RL) is a class of optimization techniques where agents learn to make decisions by interacting with their environment and receiving feedback in the form of rewards. RL is particularly well-suited for dynamic and complex problems like antenna tilt optimization, as it enables systems to adapt over time without needing explicit modeling of the environment. Even though RL doesn't always guarantee the perfect solution, it strikes an excellent balance between being flexible and delivering long-term performance. Its ability to learn from real-time experience, continuously adapting and improving, has made it a favorite for network optimization, as it doesn't rely solely on pre-set simulations or planning tools.

A research by Razavi, R., Klein, S., and Claussen, H. (2010)[42], the research introduces a new method for self-adjusting LTE network optimization. This research tackles the challenge of fine-tuning antenna downtilt angles in a fully automatic way, meaning each BS can adjust by itself intelligently without needing any manual setup or human involvement. The study propose a mixed algorithm (hybrid algorithm) that combines fuzzy logic with reinforcement learning called FRL, allowing base stations to self-adjust the parameters in response to network conditions, even in the presence of noisy feedback. Unlike older methods, this approach uses ideas like state and action strength to better guide learning and adapt to changes. It was tested in a realistic LTE setup and compared with the ELF method to show its effectiveness. The results show that the proposed algorithm not only converges to near-optimal solutions but also delivers up to 20% improvement in network performance (in terms of fitness and capacity) and demonstrates superior adaptability, robustness in noisy conditions, and self-healing capabilities when handling network faults. Razavi et al. (2010).

Another paper [16] proposes an RL-based solution to dynamically optimize the electrical tilt angle of base station antennas in mobile networks. The main objective is to improve the trade-off between coverage and capacity in a self-organized manner, reducing manual intervention and operational costs. The authors develop a distributed RL algorithm that uses real-time network metrics such as user distribution, SINR, and throughput to make intelligent tilt adjustments. The approach integrates with Self-Organizing Network (SON) frameworks and models the problem using a Markov Decision Process (MDP). It focuses on the downlink of sectorized, multi-cell urban mobile networks and uses a reward function that balances user satisfaction and overall throughput. Simulation results, carried out in MATLAB, demonstrate up to a 30% improvement in total network data rates. The proposed solution is adaptable to LTE and future 5G networks, enhances user quality of experience (QoE), and minimizes the need for manual network optimization and drive testing.

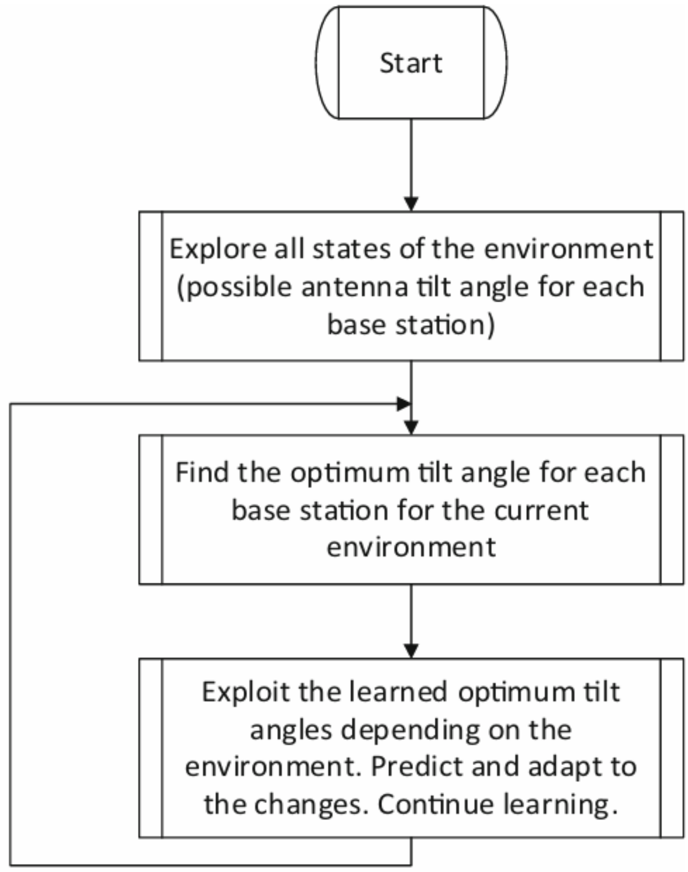

Figure 2.4: Flowchart of the simplified algorithm for capacity and coverage optimization, utilizing the base station electrical antenna tilt

2.3 Conclusion

This chapter has demonstrated the practical applicability of the proposed optimization techniques through a series of controlled simulations. The experimental results validated the capability of machine learning algorithms and reinforcement learning to reduce under-coverage and over-coverage while maintaining regulatory compliance. The findings confirm the advantage of AI-driven methods over traditional strategies in adapting to urban deployment complexities. Overall, the results presented in this chapter provide empirical support for the thesis hypothesis, setting the stage for the coming chapter to introduce the proposed system.

Chapter 3

Proposed System

3.1 Introduction

This chapter outlines the proposed system for optimizing LTE network coverage and capacity using intelligent algorithms. It begins by describing the overall architecture and workflow of the system, including how optimization tasks are carried out in sequence. We then present the two core components of the system: Bayesian Optimization, which tunes the power and downtilt of existing antennas, and the Genetic Algorithm, which assists in the strategic placement of new towers when needed. Each technique is introduced with a focus on its role in improving network performance and adaptability in urban macrocell environments. The chapter concludes by summarizing how these methods work together to provide a scalable and adaptive optimization framework.

3.2 System Design and Architecture

This section outlines the architectural design and operational flow of our LTE cellular network optimization framework. The system operates as a sequential process, depicted in the flowchart Figure 3.1 integrating Bayesian Optimization (BO) for parameter tuning and Genetic Algorithm (GA) for new tower placement, as detailed in Algorithm 1. The system starts with the "Start" phase, loading initial network data (tower coordinates, power, and downtilt values). The first optimization phase, "Parameter Optimization Using BO," adjusts the transmit power (30–50 dBm) and downtilt angles (0–10°) of existing towers, three sectors (azimuths: 0°, 120°, 240°) to minimize weak coverage RSRP below -80 dBm and over-coverage RSRP above -60 dBm. The "Evaluate Coverage/Capacity" decision point assesses the optimized configuration; if coverage gaps persist ("No"), the process transitions to "Run Tower Placement Optimization Using GA" to determine the optimal location, power, and downtilt for a new tower. The suggested new tower is added, and the process reevaluates coverage, looping until satisfactory performance is achieved or no further improvements are possible, concluding with the "End" phase. This iterative approach ensures adaptive network enhancement, aligning with practical deployment strategies in urban environments.

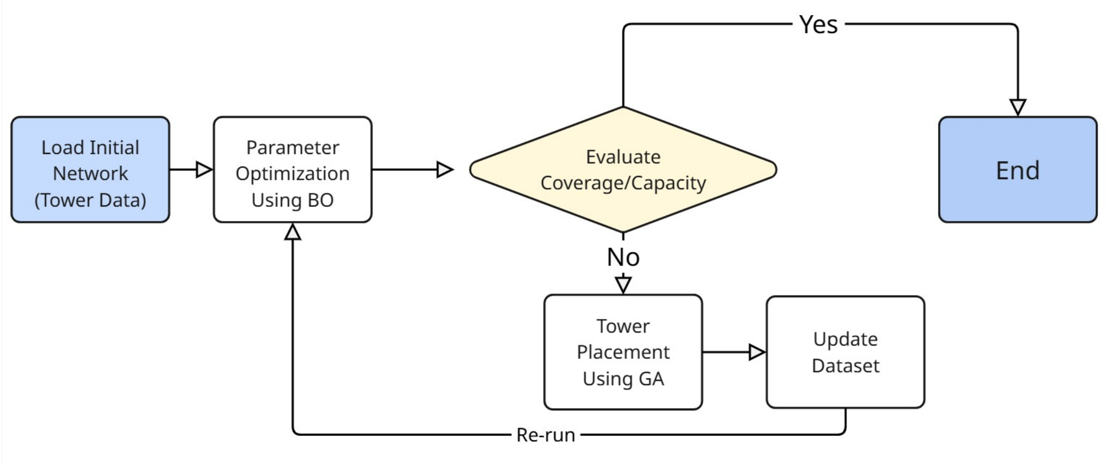

Figure 3.1: System workflow for LTE network optimization, integrating BO for parameter tuning and GA for tower placement.

Algorithm 1 Global LTE Network Optimization System

Input: Network data (tower coordinates, initial powers $P_{\text{tx}} \in [30, 50]$ dBm, downtilts $\theta \in [0, 10°]$), simulation area (2000m × 2000m), user locations grid
Output: Optimized tower parameters, new tower placement (if needed), coverage metrics
Initialize simulation environment: load tower data, generate user locations grid (50m resolution)
Set coverage thresholds: weak coverage (RSRP < -80 dBm), over-coverage (RSRP > -60 dBm)
Phase 1: Parameter Optimization with BO
Run Bayesian Optimization (Algorithm 2) to tune P_{tx} and θ for existing towers
Evaluate coverage: compute RSRP using COST-231 Hata model, assess weak and over-coverage percentages
if coverage goals met (weak coverage ≤ threshold, over-coverage ≤ threshold) **then**
    Save optimized parameters and metrics
    Output: Optimized configuration
    End
else
    Phase 2: New Tower Placement with GA
    Initialize terrain grid with regulatory constraints (e.g., schools, hospitals)
    Run Genetic Algorithm (Algorithm 3) to optimize new tower location, P_{tx}, θ
    Add new tower to network configuration
    Re-evaluate coverage with updated configuration
    if coverage goals met or no further improvement **then**
        Save optimized parameters, new tower details, and metrics
        Output: Final configuration
        End
    else
        Repeat Phase 2 with updated network
    end if
end if

3.3 Parameter Optimization Using BO

Bayesian Optimization (BO) serves as a data-efficient strategy for optimizing black-box functions with high evaluation costs, making it an ideal choice for tuning cellular network parameters where each evaluation is costly in terms of time and computation. In this work, we apply BO to process for tuning antenna parameters is formalized in Algorithm 2, which details both the Expected Improvement (EI) and q-Expected Hypervolume Improvement (qEHVI) implementations to dynamically adjust the transmit power (P_{tx}) and antenna downtilt (θ) of existing base station sectors, aiming to enhance coverage and mitigate interference across an urban macrocell. Two distinct implementations are explored, each employing a different acquisition function to address the optimization problem's evolving complexity.

Algorithm 2 Bayesian Optimization for Parameter Tuning

Input: Tower data (coordinates, initial P_{tx}, θ), user locations, $n_{\text{iter}} = 500$, $n_{\text{init}} = 5$
Output: Optimized $P_{\text{tx}} \in [30, 50]$ dBm, $\theta \in [0, 10°]$, Pareto front
Define search space: $P_{\text{tx},i,j}$, $\theta_{i,j}$ for $i = 1, \ldots, T$, $j = 1, 2, 3$ (3 sectors per tower)
Initialize n_{init} configurations using Sobol sequences
for each initial configuration **do**
    Compute RSRP using COST-231 Hata model
    Evaluate objectives: f_1 (weak coverage, RSRP < -80 dBm), f_2 (over-coverage, RSRP > -60 dBm)
end for
Option 1: Expected Improvement (EI)
for $i = 1$ to n_{iter} **do**
    Fit Gaussian Process (GP) to scalarized objective: $-(f_1 + f_2)$
    Optimize Expected Improvement: $\text{EI}(\mathbf{x}) = \mathbb{E}[\max(f(\mathbf{x}) - f(\mathbf{x}^+), 0)]$
    Evaluate new configuration, update training data
end for
Option 2: q-Expected Hypervolume Improvement (qEHVI)
Set reference point $\mathbf{z}_{\text{ref}} = [-1, -1]$
for $i = 1$ to n_{iter} **do**
    Fit GPs to objectives f_1, f_2 (Matérn 5/2 kernel)
    Compute dominated partitioning of current Pareto front
    Optimize qEHVI with 10 restarts, 100 raw samples
    Evaluate new configuration, update Pareto front and hypervolume
end for
Log Pareto front, hypervolume, and convergence data
Output: Optimal parameters, Pareto front

The BO framework relies on two core components:

- A **surrogate model**, typically a Gaussian Process (GP), which approximates the objective function and provides uncertainty estimates for unexplored configurations.

- An **acquisition function**, which directs the search by balancing exploration (sampling uncertain regions) and exploitation (refining promising solutions).

Both implementations operate over a high-dimensional search space, where each of the $T = 7$ towers contributes three sectors, each with two tunable parameters (P_{tx} and θ), resulting in a 42-dimensional space ($6T$). The parameter bounds are set as $P_{\text{tx}} \in [30, 50]$ dBm and $\theta \in [0°, 10°]$, reflecting practical macro-cell constraints [1, 45]. Coverage performance is evaluated using Reference Signal Received Power (RSRP), computed via the COST-231 Hata model with downtilt loss, as implemented in the provided code.

3.3.1 First Implementation: Expected Improvement (EI)

In the initial implementation, we adopt a scalarized approach to simplify the optimization process. The conflicting objectives of minimizing weak coverage (RSRP < -80 dBm) and over-coverage (RSRP > -60 dBm) are combined into a single objective function:

$$f(\mathbf{x}) = -\left(\text{Weak Coverage}(\mathbf{x}) + \text{Over Coverage}(\mathbf{x})\right) \tag{3.1}$$

where $\mathbf{x} = [P_{\text{tx},1}, \theta_1, \ldots, P_{\text{tx},21}, \theta_{21}]$ represents the decision vector. The BO process starts with a diverse set of configurations (using Sobol sequences), fits a GP to the observed data, and optimizes the Expected Improvement (EI) acquisition function:

$$\text{EI}(\mathbf{x}) = \mathbb{E}[\max(f(\mathbf{x}) - f(\mathbf{x}^+), 0)] \tag{3.2}$$

where $\mathbf{x}^+$ is the current best solution. EI balances exploration and exploitation efficiently, leveraging a single GP model, which ensures faster convergence and lower computational overhead [49]. This approach, inspired by [19], converges rapidly to high-quality configurations suitable for real-time tuning, logging weak and over-coverage percentages to analyze trade-offs post-optimization.

3.3.2 Second Implementation: q-Expected Hypervolume Improvement (qEHVI)

Recognizing the limitations of scalarization in capturing Pareto-optimal trade-offs, we adopt a true multi-objective optimization approach using qEHVI. The problem is formulated with two competing objectives:

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} f_1(\mathbf{x}) = \text{Weak Coverage}(\mathbf{x}) \\ f_2(\mathbf{x}) = \text{Over Coverage}(\mathbf{x}) \end{bmatrix} \tag{3.3}$$

where:

- $f_1(\mathbf{x})$ computes the percentage of user locations with RSRP < -80 dBm (weak coverage)
- $f_2(\mathbf{x})$ computes the percentage with RSRP > -60 dBm (over-coverage)

The qEHVI implementation features three key innovations:

1. **Hypervolume Maximization**: The acquisition function directly optimizes the expected hypervolume improvement (EHVI), measuring the volume of objective space dominated by the Pareto front relative to a reference point $\mathbf{z}_{\text{ref}} = [-1, -1]$.

2. **Batch Parallelism**: Evaluates $q = 1$ candidate per iteration using:
   - 10 random restarts for robustness
   - 100 raw samples for global exploration
   - Dominated partitioning for efficient EHVI computation

3. **Adaptive Modeling**: A Gaussian Process (GP) surrogate with Matérn 5/2 kernel provides uncertainty estimates, updated via exact marginal likelihood maximization.

Advantages over scalarization:

- Preserves the Pareto-optimal trade-off surface without weight tuning
- Automatically balances exploration/exploitation via probabilistic modeling
- It scales efficiently with multiple objectives, which is crucial for future network extensions.

The implementation achieves $\mathcal{O}(n \log n)$ hypervolume computation complexity per iteration through efficient box decomposition [17], with convergence monitored via hypervolume progression.

3.3.3 Acquisition Strategy Comparison

The transition from EI to qEHVI reflects a shift from a single-objective to a multi-objective paradigm. EI's simplicity suits the scalarized first implementation, offering rapid convergence with a single GP and minimal computational cost. In contrast, qEHVI addresses the multi-objective nature of coverage optimization, providing a richer Pareto front by explicitly modeling trade-offs. While qEHVI comes with increased computational overhead (hypervolume computation, multiple GP fits), it outperforms EI in scenarios requiring explicit trade-off exploration, as demonstrated by [19] in cellular network optimization. The choice of acquisition function thus depends on operational priorities: EI for quick tuning, qEHVI for comprehensive trade-off analysis.

3.3.4 Problem Setup and Practical Alignment

Both implementations formulate the tuning problem over the 42-dimensional space, with each sector's P_{tx} and θ independently adjustable. The encoding ensures modularity and scalability, aligning with real-world network management practices where power and tilt adjustments are routine [19, 49]. Physical feasibility is maintained through bound enforcement ensuring practical, deployable configurations. The qEHVI implementation, by preserving multi-objective data, enables operators to select configurations based on specific coverage or interference priorities, offering more flexibility than the EI method.

3.3.5 Visualization and Outcomes

Expected Improvement (EI) and q-Expected Hypervolume Improvement (qEHVI) are both incorporated into the optimization framework as acquisition methods to facilitate exploration-exploitation trade-off during the Bayesian Optimization (BO) process. The two methods yield different insights into how optimization evolves over time and impacts network coverage and capacity performance. Since qEHVI is applied using a multi-objective optimization method, the system addresses weak coverage (RSRP below -80 dBm) and over-coverage (RSRP above -60 dBm) simultaneously. The Pareto front is created through the optimization process, and this Pareto front is illustrated as a scatter plot in which the trade-off between the two goals is highlighted. Every solution point on this chart is a non dominated configuration (no other configuration is more optimal with respect to both objectives), providing network planners with a number of solutions that compromise signal strength distribution against excessive overlap in coverage. Additionally, the hypervolume indicator is a metric that quantifies the volume under the Pareto front was tracked across iterations to monitor convergence. As the BO algorithm progresses, the hypervolume increases, indicating improved trade-off solutions and convergence toward optimal configurations. This evolution is visualized in the hypervolume convergence plots, providing a clear progression toward optimality. To further analyze and compare outcomes, RSRP heatmaps were generated for configurations obtained using both EI and qEHVI. These visualizations provide spatial insights into signal strength across the urban area, highlighting regions of improvement, persistent weak spots, and zones of high interference. The side-by-side comparison reveals how each acquisition strategy influences coverage uniformity, with qEHVI often favoring more balanced solutions across objectives, whereas EI tends to focus more aggressively on minimizing weak coverage, sometimes at the cost of increasing over-coverage. The combination of these visual tools Pareto fronts, convergence plots, and RSRP heatmaps provides comprehensive insight into the optimization dynamics. They not only validate the algorithmic decisions but also empower network operators with actionable intelligence for real-world deployment. Ultimately, this dual-acquisition approach demonstrates the flexibility and robustness of BO in solving both rapid tuning and multi-objective optimization problems in complex, real-world LTE environments.

3.4 Tower Placement Using Genetic Algorithm

For scenarios where BO alone cannot resolve coverage gaps, the Genetic Algorithm (GA) optimizes the placement of a new tower, as described in Algorithm 3. This algorithm initializes a population of 20 candidate tower configurations, each defined by latitude, longitude, and three sector parameters ($P_{\text{tx}} \in [30, 50]$ dBm, $\theta \in [0, 10°]$), evolving over 30 generations. The fitness function balances weak coverage, over coverage, interference (multiple signals > -75 dBm), and regulatory penalties based on proximity to sensitive zones, computed using the Propagation model [3]. Selection retains the top 50% of individuals, with crossover (25% probability) and mutation (1% probability) ensuring diverse exploration, while elitism preserves the best solution [18]. The pseudocode encapsulates this evolutionary strategy, producing optimal tower placements and associated RSRP and interference maps for urban deployment.

Algorithm 3 Genetic Algorithm for Tower Placement

Input: Existing tower data, user locations, terrain grid, $pop_{\text{size}} = 20$, $generations = 30$
Output: New tower location (lat, lon), P_{tx}, θ, coverage metrics
Initialize population: pop_{size} individuals, each with random lat $\in [32.47, 32.50]$, lon $\in [3.65, 3.70]$, $P_{\text{tx},1,2,3} \in [30, 50]$ dBm, $\theta_{1,2,3} \in [0, 10°]$
for $gen = 1$ to $generations$ **do**
    for each individual **do**
        Compute RSRP for existing towers and new tower using COST-231 Hata model
        Evaluate fitness: $-(\text{Weak} + \text{Over} + \text{Interference} + \text{Penalty})$
        Weak: RSRP < -80 dBm, Over: RSRP > -60 dBm
        Interference: Percentage of users with multiple signals > -75 dBm
        Penalty: Weighted sum based on proximity to sensitive zones
    end for
    Select top 50% of individuals by fitness
    Preserve best individual (elitism)
    while population size < pop_{size} **do**
        if random() < 0.25 **then**
            Perform crossover: combine attributes (lat, lon, P_{tx}, θ) from two parents
        else
            Generate new random individual
        end if
    end while
    Mutate individuals: perturb lat, lon ($\pm 0.01°$), P_{tx} (± 1 dBm), θ ($\pm 1°$)
end for
Output: Best tower configuration, RSRP map, interference map

3.4.1 Motivation and Problem Description

Adding new base stations helps resolve coverage gaps and manage increasing traffic load and capacity demands in urban. The placement must consider existing towers, user distribution and regulatory constraints. GA is chosen for its ability to handle multi-objective combinatorial problems where machine learning optimizes complex network layouts.

3.4.2 GA Encoding and Individual Structure

Each individual in the GA population represents a candidate tower configuration:

- **Location**: Latitude (lat $\in [32.47, 32.50]$) and longitude (lon $\in [3.65, 3.70]$).
- **Transmit Powers**: Three values ($P_{\text{tx},1}, P_{\text{tx},2}, P_{\text{tx},3} \in [30, 50]$ dBm) for the tower's three sectors.
- **Downtilts**: Three values ($\theta_1, \theta_2, \theta_3 \in [0, 10]$ degrees) for the sectors.

An individual is represented as a structured data object: $\{\text{lat}, \text{lon}, \text{txpowers}, \text{downtilts}\}$. The population size is 20, ensuring sufficient exploration without excessive computational cost [14, 15].

3.4.3 Fitness Function Design

The fitness of a configuration is calculated via a composite fitness function combining:

- **Weak Coverage Percentage**: Proportion of users experiencing RSRP below -80 dBm.
- **Over-Coverage Percentage**: Proportion of users with RSRP above -60 dBm.
- **Interference Level**: Percentage of users receiving multiple strong signals (above -75 dBm).
- **Regulatory Penalties**: Penalties weighted according to proximity sensitive zones (schools, hospitals, highways) using a spatial terrain grid.

The objective function is defined as:

$$\text{Fitness}(x) = -(\text{WeakCoverage}(x) + \text{OverCoverage}(x) + \text{Interference}(x) + \text{Penalty}(x)) \tag{3.4}$$

This formulation allows the algorithm to favor configurations that balance service quality and regulatory compliance[15].

3.4.4 Evolutionary Strategy

The GA evolves the population over 30 generations using the following mechanisms:

- **Selection**: The top 50% of individuals, ranked by fitness, are retained to preserve high-performing solutions.
- **Crossover**: With 25% probability, two parent individuals are randomly selected, and their attributes (location, powers, downtilts) are combined using a single-point crossover, producing offspring with blended traits.
- **Mutation**: With 1% probability per parameter, values are perturbed by Gaussian noise with a standard deviation of ($\pm$ 0.01° for location, $\pm$ 1 dBm for power), constrained within bounds to maintain feasibility.

- **Elitism**: The best individual is always preserved, ensuring no loss of optimal solutions.

This strategy, is implemented in our GA, balances exploration and exploitation, leveraging the population-based nature of GA to explore diverse placement options, a contrast to BO's sequential sampling[15].

3.5 Conclusion

In this chapter, we presented our proposed optimization system for improving the coverage and capacity of cellular networks. The system consists of two key phases. First, we used Bayesian Optimization to adjust the antenna parameters (transmit power and downtilt) of existing towers. We applied two techniques: Expected Improvement (EI) for fast single-objective optimization and qEHVI for handling multiple objectives like reducing both weak and over-coverage. If these adjustments were not enough to fix the coverage problems, we used a Genetic Algorithm (GA) to find the best locations for adding new towers. This method helps fill the remaining weak coverage areas in a smart and cost-effective way. Overall, the system combines parameter tuning and intelligent tower placement to optimize the network progressively. In the next chapter, we will test this system and show how well it improves the network's performance, and we will evaluate the performance on a simulation environment and extract the results to compare the two methods.

Chapter 4

Experiments and Results

4.1 Introduction

This chapter presents the experimental framework and results derived from the proposed optimization models for enhancing coverage and capacity in LTE cellular networks. The primary objective of this chapter is to evaluate the performance and effectiveness of two distinct strategies: (1) the optimization parameters of existing base stations using Bayesian Optimization (BO), and (2) the strategic placement of a new base station using a Genetic Algorithm (GA). Subsequent sections detail the simulation setup, dataset preparation, and optimization configurations, followed by a discussion of experimental results, including metrics such as Reference Signal Received Power (RSRP), interference levels, and coverage quality.

4.2 Simulation Environment

The simulation environment is designed to replicate an urban macrocell LTE network in Ghardaia, Algeria, covering a 2 km $\times$ 2 km area centered at approximately (32.4806° N, 3.6860° E), derived from the mean coordinates of base stations in the dataset Section 4.3 and Figure 4.1 shows the area of study with the ploting of cell locations. The environment integrates geographical, user distribution, and network parameter assumptions to support two optimization tasks: (1) tuning the transmit power and antenna downtilt of existing towers using BO, and (2) determining the optimal location, power, and downtilt for a new base station using GA, as described in Chapter 3.

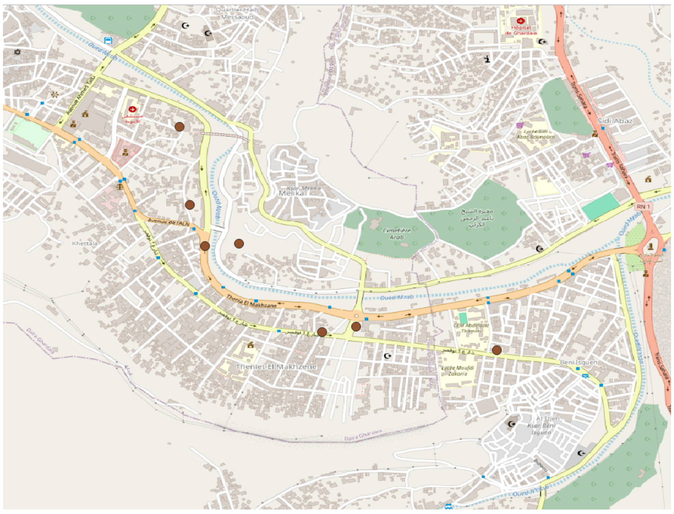

Figure 4.1: 2 km × 2 km Simulation area in Ghardaia, Algeria showing tower locations.

The geographical area is defined based on the tower coordinates, with bounds extending 1 km north, south, east, and west from the center (latitude: 32.4716° to 32.4896°, longitude: 3.67535° to 3.69665°). A grid of potential user locations is generated using a uniform mesh with a resolution of 50 m for the BO based optimization and 100 m for the GA-based new tower placement. The grid is created by discretizing latitude and longitude with steps of 0.000009° and 0.000012°, respectively, corresponding to approximately 1 m in the Ghardaia region. This results in approximately 1500 user locations at 50 m resolution, representing a uniform distribution of potential users across the urban area, which simplifies the modeling of demand in the absence of specific user data Figure 4.2 shows the distribution of this grids over the area.

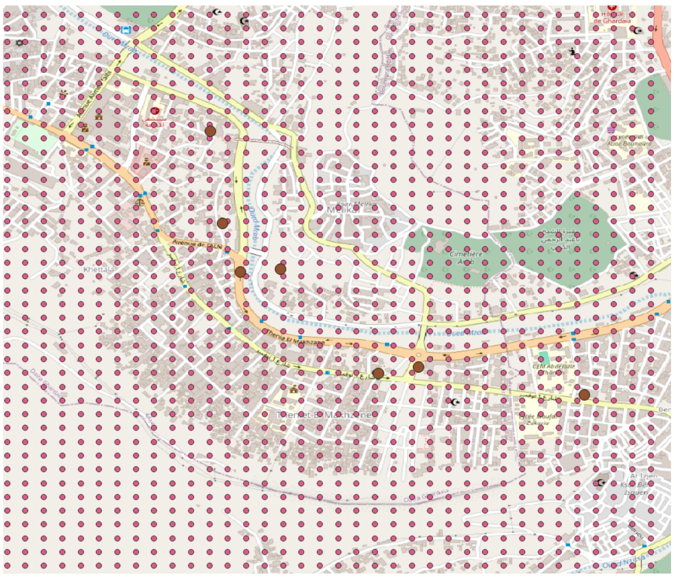

Figure 4.2: User Grid in the Area

The network operates at a carrier frequency of 1800 MHz, typical for LTE urban deployments, with base stations assumed to be 30 m above ground and user devices at 1.5 m, reflecting standard macrocell and mobile heights. The radio propagation model employs the COST 231 Hata model for urban environments, incorporating a 3 dB correction factor, as detailed in Section 1.7.2. Path loss is calculated using a 3D distance metric that combines geodesic 2D distance with height differences, ensuring accurate modeling of signal attenuation. Antenna downtilt effects are modeled with a loss function that applies a 3 dB penalty per 10° beamwidth deviation, as described in Section 1.7.3, enabling precise control of signal directionality to minimize interference and optimize coverage.

The BO simulation optimizes the transmit power and downtilt angles for three sectors per existing tower, with fixed azimuths at, aiming to minimize weak coverage (RSRP < -80 dBm) and over-coverage (RSRP > -60 dBm). The GA simulation places a new tower within the simulation area, optimizing its coordinates, power, and downtilt for three sectors, while considering terrain constraints and regulatory weights for neighboring areas (150 m exclusion zones around educational and health facilities). Terrain is simulated as a grid of urban land types (e.g., residential, commercial, open space), with weights penalizing tower placement near sensitive areas, enhancing the realism of the new tower placement.

Key performance metrics include RSRP, calculated as the maximum signal strength across all sectors and towers at each user location, interference (percentage of locations receiving multiple signals > -75 dBm), and coverage quality. The simulation environment leverages the System Concept we explained earlier, building on prior work such as [46], which demonstrated up to 50% pilot power reduction through downtilt optimization. This setup expected to provides a robust platform for evaluating the proposed BO and GA strategies in a realistic urban LTE context.

The Table 4.1 summarized the simulation parameters define the experimental setup for optimizing LTE network performance using Bayesian Optimization and Genetic Algorithm approaches. The table encapsulates critical aspects of the simulation environment to ensure clarity, reproducibility, and transparency of the study. It includes details such as the simulation area, the configuration of base stations, and coverage thresholds. Additionally, it specifies the frequency, performance metrics, and optimization parameters. The optimization settings outline the Bayesian Optimization configuration, including the qExpectedHypervolumeImprovement and Ei acquisition function and 500 iterations, alongside Genetic Algorithm parameters. This comprehensive summary facilitates understanding and replication of the experimental framework.

Table 4.1: Simulation Parameters for LTE Network Optimization Experiments

Parameter Category	Details
Simulation Area	Approximately 2000 m $\times$ 2000 m Latitude range: 0.0180° (centered at mean tower coordinates) Longitude range: 0.0213° (centered at mean tower coordinates) Grid resolution: 50 m (Bayesian Optimization), 100 m (Genetic Algorithm)
Towers and Antennas	Number of towers: 7 Antennas: 3 sectors per tower (azimuths at 0°, 120°, 240°)
RSRP	Calculated using COST 231 Hata model Range: -250 dBm to -40 dBm
Frequency and Bandwidth	Frequency: 1800 MHz Bandwidth: LTE bandwidth (can be adjusted according to the study)
Simulation Iterations	500 + 5 initial points (BO), 30 generation (GA, adjustable)
Simulation Tools	Tools: Python, NumPy, Pandas, Matplotlib, PyTorch, BoTorch, geopy Environment: Urban macrocell scenario
Performance Metrics	Weak coverage (RSRP < -80 dBm) Over-coverage (RSRP > -60 dBm) Interference (RSRP > -75 dBm from multiple sources)
Parameters to Optimize	Transmission power: 30 to 50 dBm per sector Downtilt angle: 0 to 10 degrees per sector; GA also optimizes tower location (lat, lon)
Bayesian Optimization	Acquisition function: qEHVI And EI Iterations: 500 Initial points: 5 Reference point: [-1.0, -1.0] for hypervolume calculation
Genetic Algorithm	Population size: 20 Mutation rate: 0.01 per parameter Crossover rate: 0.25 Parameters: Transmission power (30–50 dBm), Downtilt (0–10°), Latitude, Longitude

4.3 Dataset Description

The dataset used in this study is derived from OpenCellID, a crowdsourced database of cellular base station locations, providing real-world tower coordinates for the Ghardaia region [40]. The primary dataset contains 7 LTE base stations with key attributes including latitude (`lat`), longitude (`lon`) and sector-specific metadata. Additional attributes, such as power and downtilt, were augmented due to incomplete data in the OpenCellID source and the privacy of the operators, ensuring compatibility with the simulation requirements.

4.3.1 OpenCellID Data and Cleaning

The OpenCellID dataset includes 7 towers with coordinates ranging from 32.4771° to 32.4857° N and 3.6819° to 3.6941° E, defining the simulation area. Each tower entry contains metadata such as `radio` (LTE), `mcc` (603, Algeria), `range`, `samples`, `created`, `updated`, `averageSignal`, and `elevation` (487–496 m). However, critical parameters for radio propagation modeling, namely transmit power (`power_1`, `power_2`, `power_3`) and downtilt angles (`angle_1`, `angle_2`, `angle_3`), were incomplete or missing (downtilt values set to 0°, some power values at 0 dBm). To address this, the dataset was cleaned by focusing on `lat` and `lon` as the primary spatial inputs, with power and downtilt values randomly assigned within realistic ranges: 30–50 dBm for power and 0–10° for downtilt, reflecting typical LTE macrocell configurations.

Data cleaning involved validating the dataset for completeness and consistency. Entries with missing or invalid `lat` or `lon` values were discarded. Power values outside the range were replaced with random values within the range that we selected, and all downtilt angles, initially set to 0°, were similarly reassigned. Validation checks in the GA-based simulation ensured that power and downtilt values adhered to these constraints, reverting to a simulated dataset if violations were detected. This process ensured that the dataset was suitable for modeling RSRP and interference across the simulation area.

Each tower is configured with three sectors, corresponding to azimuth angles of 0°, 120°, and 240°, standard for tri-sector macrocell deployments. The `power_1`, `power_2`, and `power_3` fields represent the transmit power for each sector, while `angle_1`, `angle_2`, and `angle_3` denote the downtilt angles. These parameters were optimized in the BO simulation to adjust existing tower performance and in the GA simulation to configure the new tower. The fixed azimuths ensure consistent sector coverage, while the variable power and downtilt allow the algorithms to balance coverage and interference, as discussed in Chapter 1. a summuray of the dataset attribute is shown in Table 4.2

Table 4.2: Summary of Key Dataset Attributes

Attribute	Type	Description
lat, lon	Float	Geographic coordinates (latitude and longitude) of each tower
radio	String	Technology type (LTE)
mcc	Integer	Mobile Country Code (603 for Algeria)
cell	Integer	Cell international id
power_1,2,3	Float	Transmit power (in dBm) for each of the three sectors
angle_1,2,3	Float	Electrical downtilt angle (in degrees) for each sector

4.3.2 Terrain and Regulatory Mapping

To enhance the realism of the new tower placement, the GA simulation incorporates a simulated terrain model, dividing the simulation area into a grid of urban land types (residential, commercial, educational, health, open space). Each cell in the grid is randomly assigned a type, with the probability 20% of a non-open space designation, reflecting the urban diversity of Ghardaia. Regulatory constraints impose minimum distance requirements and penalty weights for tower placement near sensitive areas: 150 m and 15 weight for educational and health facilities, 20 m and 2 weight for residential areas, and 50 m and 5 weight for highways. These constraints penalize placements that violate zoning regulations, ensuring practical deployment feasibility. The terrain model is integrated into the GA's fitness function, balancing coverage, interference, and regulatory compliance.

4.4 Experiments

This section presents and analyzes the experimental results of the proposed optimization framework. Two main experiments were conducted to evaluate the performance of the system: (1) overall network optimization using a sequential Bayesian Optimization (BO) and Genetic Algorithm (GA) approach, and (2) multi-objective optimization using a qEHVI-based BO strategy. All experiments were performed on a system equipped with an Intel i7 processor, 32GB RAM, and an NVIDIA RTX 4060 GPU with 8GB of memory, running Ubuntu 24.04.1 LTS.

4.4.1 Experiment 1: Overall Optimization

This experiment evaluates the first implementation discussed in Section 3.3.1, which combines Bayesian Optimization using the Expected Improvement (EI) acquisition function with a Genetic Algorithm executed sequentially. The objective was to extract optimal transmit power and downtilt settings per sector and identify potential new cell locations to improve network performance.

For evaluation, we defined weak coverage as the percentage of the area with an RSRP below -80 dBm and over covergae with an RSRP more than -60 dbm. The target was to reduce weak coverage to below 20% and over-coverage to below 15%. These thresholds are configurable and can be adjusted based on the operator's strategic goals. Additionally, the number of newly placed towers was treated as a soft constraint, subject to optimization and cost considerations.

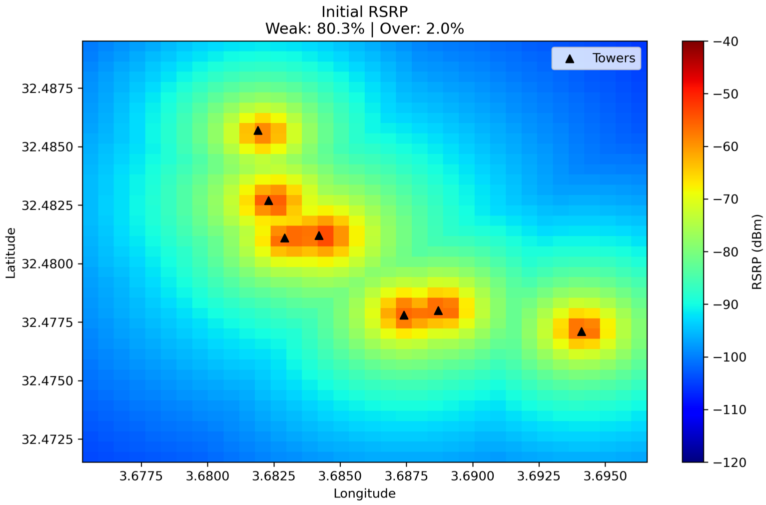

Figure 4.3: Initial RSRP heatmap of the study area

Figure 4.3 shows the initial RSRP distribution across the study area. At this stage, the network exhibited approximately 80.3% weak coverage and 2.0% over-coverage. Each grid cell's RSRP was computed using a path loss model, and the highest received power from all available towers was considered. Signal strengths between -60 and -80 dBm were considered acceptable to excellent.

After running BO for 220 iterations, the optimization resulted in 39.8% weak coverage and 8.6% over-coverage, as shown in Figure 4.4. The signal strength distribution improved considerably, extending beyond the immediate vicinity of towers. However, over-coverage increased due to overlapping strong signal areas, as further illustrated in the interference map in Figure 4.5. A summary of the performance improvement is presented in Figure 4.6.

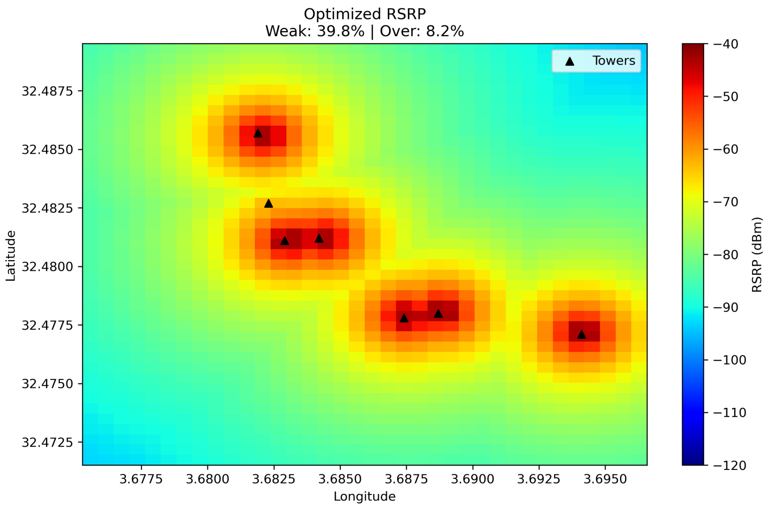

Figure 4.4: RSRP heatmap after first optimization

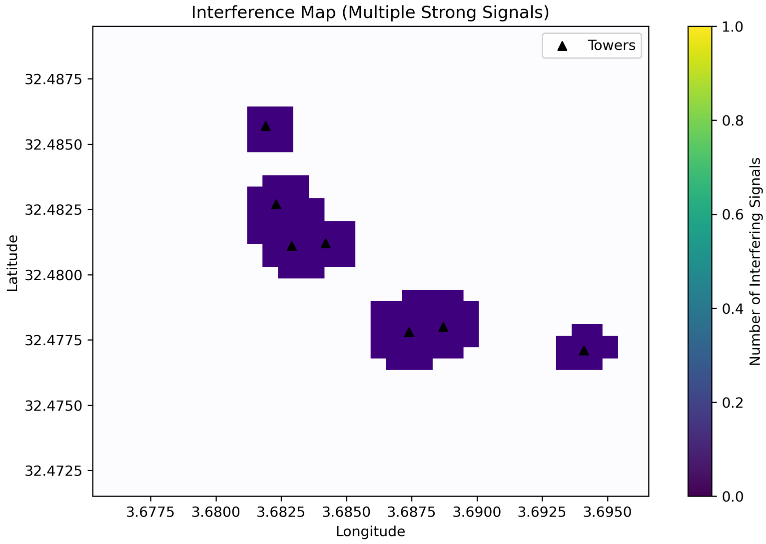

Figure 4.5: Interference map after first optimization

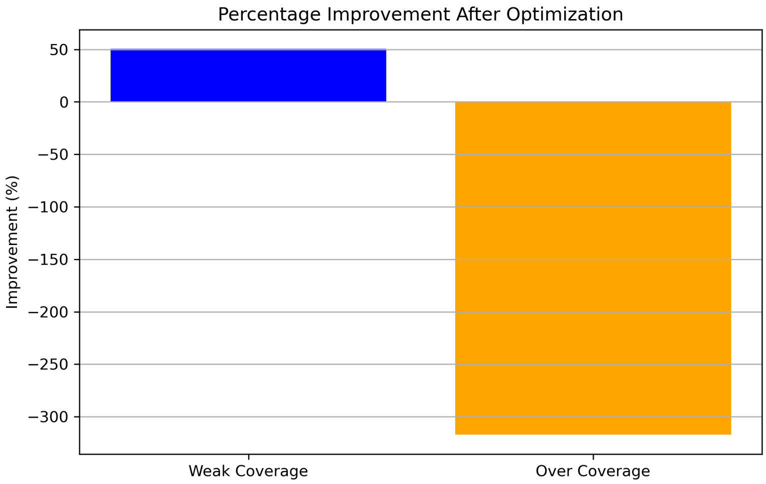

Figure 4.6: Coverage improvement after BO optimization

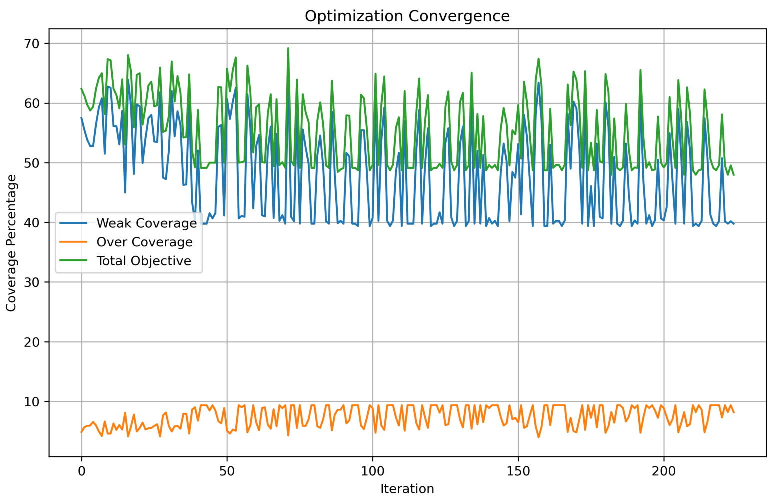

Figure 4.7: BO convergence over 220 iterations

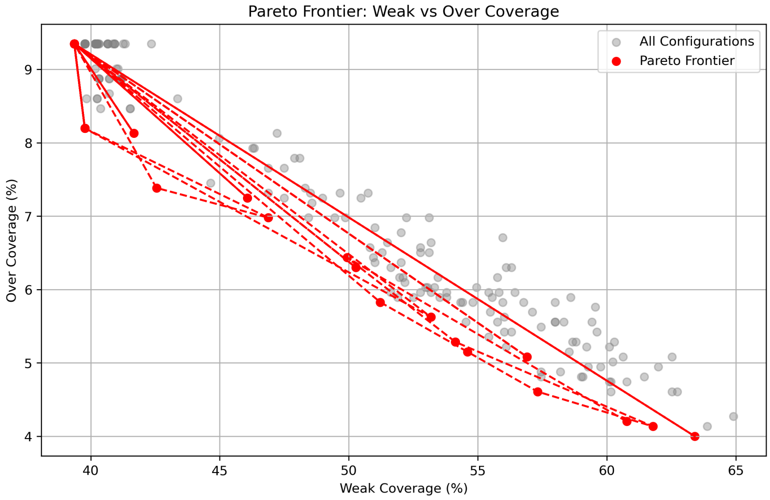

Figure 4.8: Pareto frontier for the BO optimization

As shown in Figure 4.13, the BO algorithm converged after approximately 40 iterations. Although the optimization improved network performance, the weak and over-coverage values did not meet the predefined thresholds. Therefore, a new tower was added using the GA module with a population size of 20 and 30 generations. Table 4.3 details the optimized configuration of the 8 towers, including the new tower (ID 7) at latitude 32.4865 and longitude 3.6936. The table lists the transmit power (in dBm) and downtilt angles (in degrees) for each sector. Notably, the new tower's sectors are configured with high power (50 dBm) and a mix of downtilt angles (0° and 10°), enhancing coverage in previously weak areas. Figure 4.9 and Figure 4.10 (interference map) show the updated RSRP distribution and interference patterns after placing the new tower, achieving a final weak coverage of 13.1% and over-coverage of 12.3%.

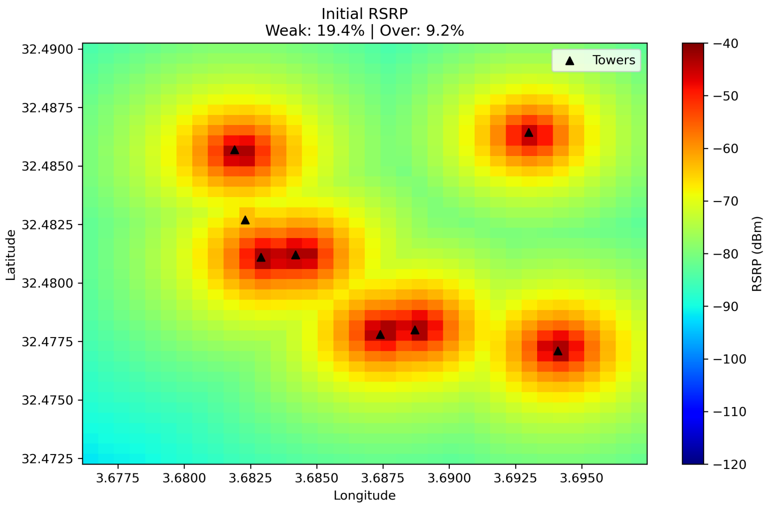

Figure 4.9: RSRP heatmap after adding a new tower

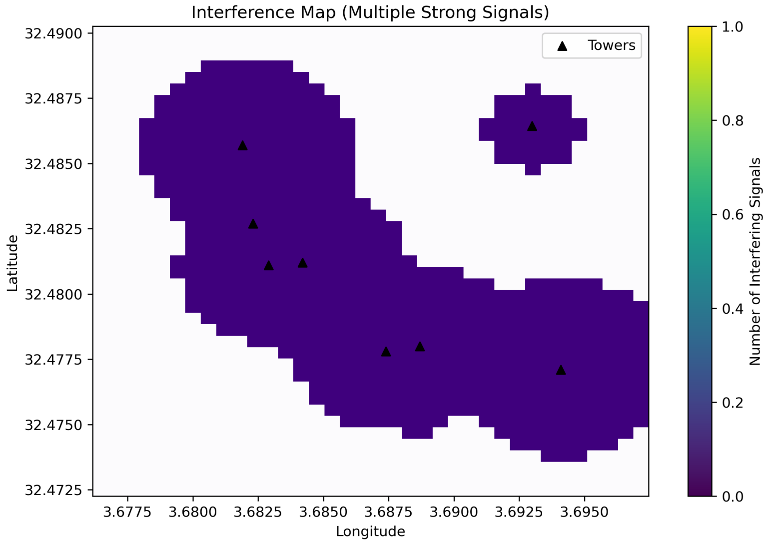

Figure 4.10: Interference map after adding a new tower

Table 4.3: Optimized Tower Configuration in Experiment 1

Tower ID	Latitude	Longitude	Power 1	Angle 1	Power 2	Angle 2	Power 3	Angle 3
0	32.4780	3.6887	46.94	10.00	48.54	10.00	36.26	0.00
1	32.4778	3.6874	50.00	0.00	50.00	0.00	50.00	6.55
2	32.4771	3.6941	42.96	10.00	50.00	1.91	38.17	10.00
3	32.4827	3.6823	30.00	10.00	36.14	0.00	35.54	0.00
4	32.4857	3.6819	40.61	10.00	50.00	10.00	50.00	1.66
5	32.4812	3.6842	30.00	0.00	44.97	10.00	50.00	0.00
6	32.4811	3.6829	50.00	0.00	36.34	0.00	40.20	0.00
7	**32.4865**	**3.6936**	**50.00**	**0.00**	**50.00**	**10.00**	**50.00**	**0.00**

4.4.2 Experiment 2: Multi-Objective Optimization

In this experiment, we evaluated the performance of the second implementation discussed in Section 3.3.2, which leverages qEHVI-based Bayesian Optimization for true multi-objective optimization. The same simulation environment and initial dataset were used as in Experiment 1. The optimization again aimed to reduce weak coverage below 20% and over-coverage below 10%.

Initially, the network exhibited 80.3% weak coverage and 2.0% over-coverage, as shown in Figure 4.3. After the first run of BO over 500 iterations, the system achieved 41.7% weak coverage and 8.3% over-coverage (Figure 4.11). Although performance improved, the values were still above the desired thresholds.

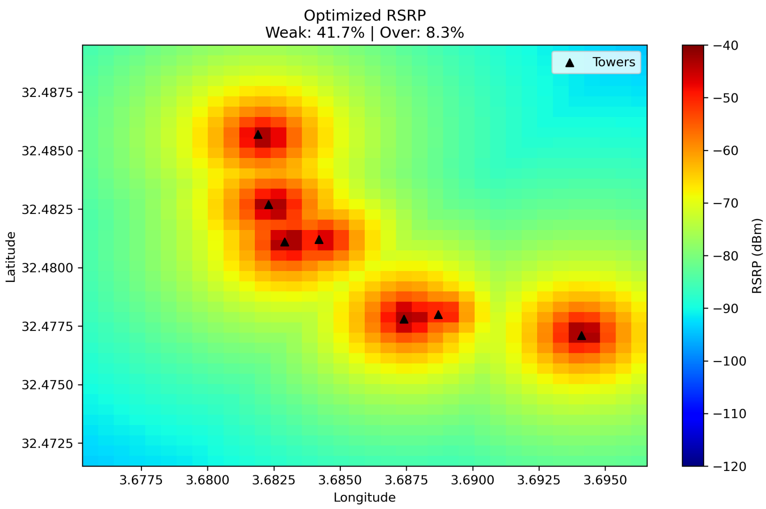

Figure 4.11: RSRP heatmap after first BO run

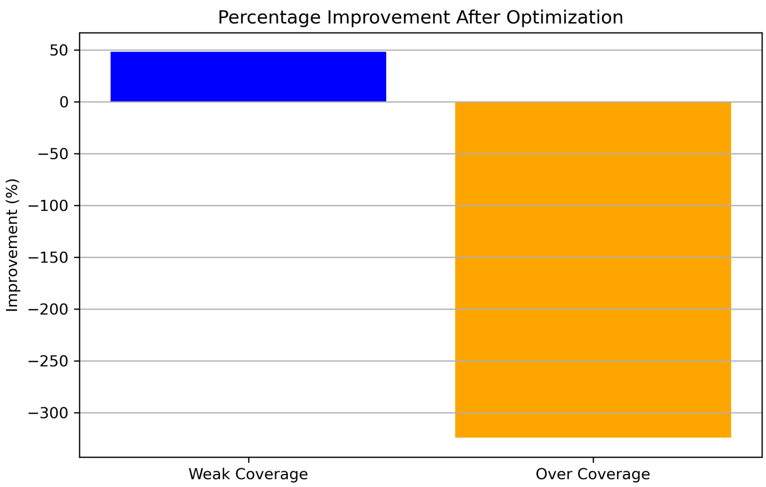

Figure 4.12: Improvement after first BO run

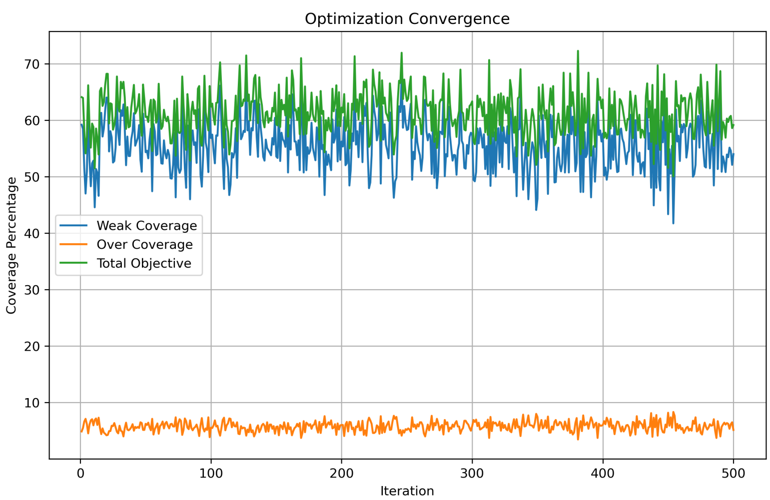

Figure 4.13: BO convergence for the first run

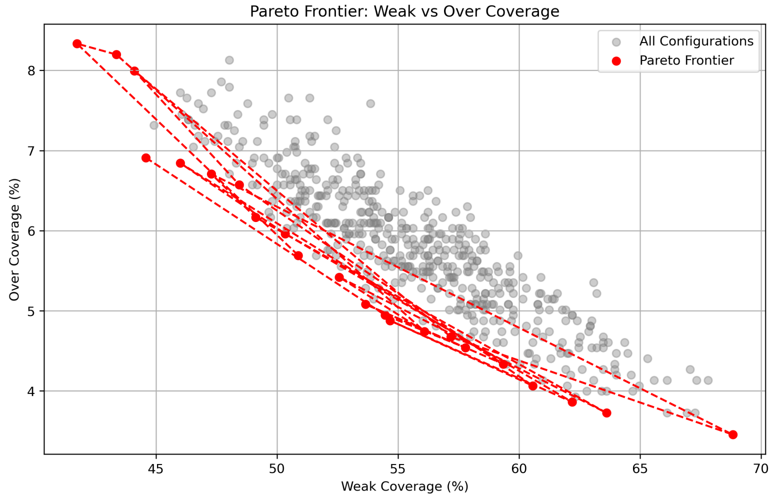

Figure 4.14: Pareto frontier after first BO run

As the stop condition was not met, the GA module proposed a new tower, and the BO was rerun. The second run resulted in 32.9% weak coverage and 9.0% over-coverage, as shown in Figure 4.15. The optimization was still insufficient to meet the stop criteria.

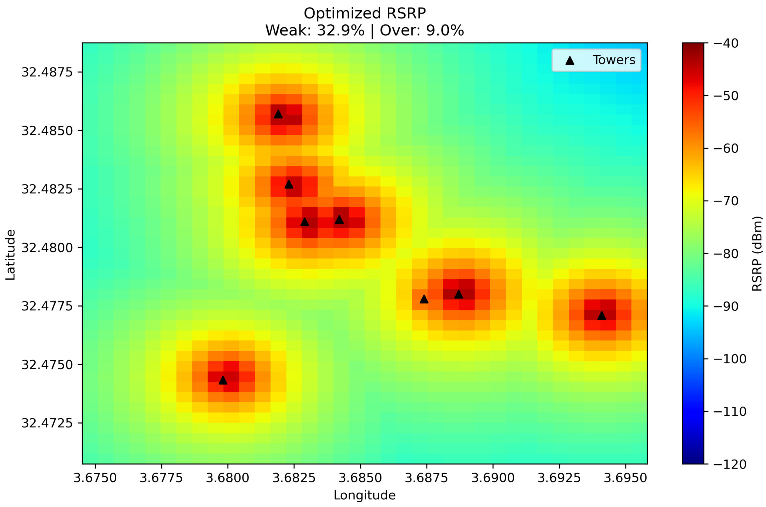

Figure 4.15: RSRP heatmap after second BO run

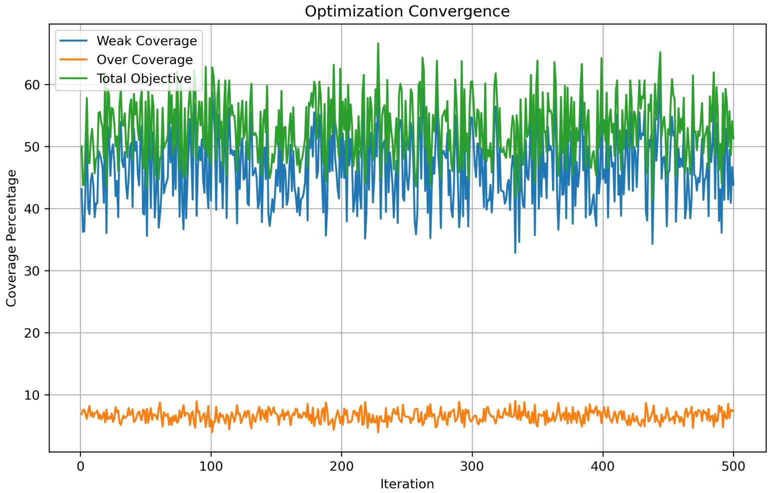

Figure 4.16: BO convergence for the second run

A third GA iteration was then executed, resulting in a final BO optimization phase. This third optimization achieved performance that satisfied the predefined coverage criteria. Figure 4.17 shows the optimized RSRP distribution, while Figures 4.18 and 4.19 illustrate the convergence and Pareto frontier, respectively.

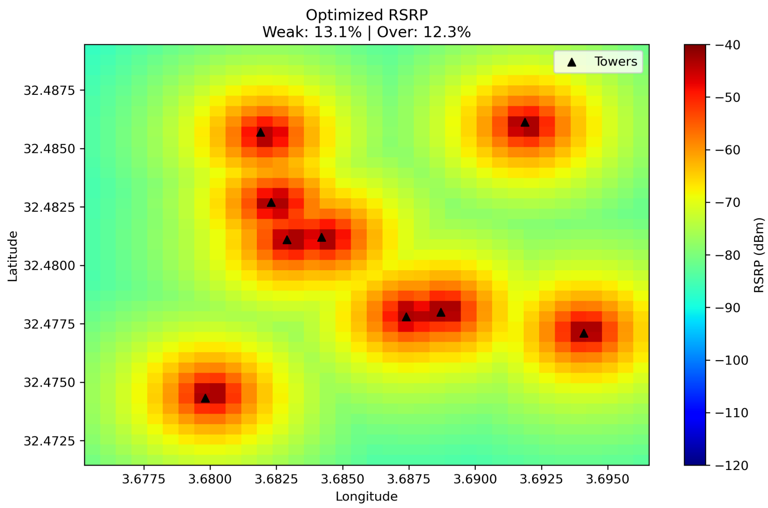

Figure 4.17: RSRP heatmap after third BO run

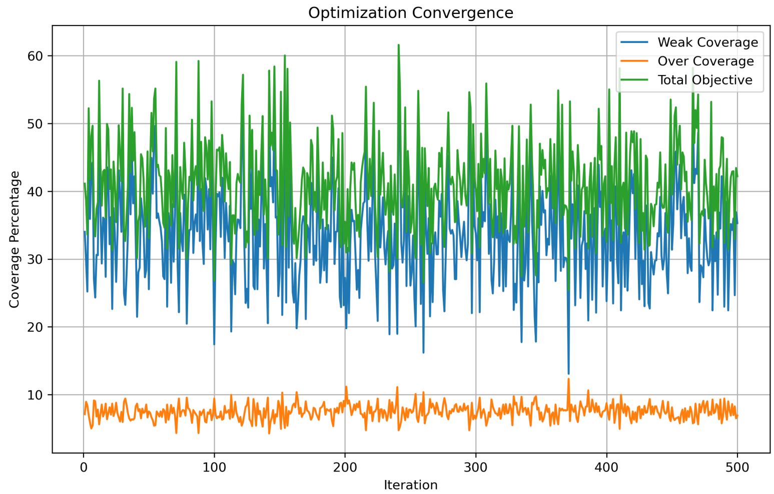

Figure 4.18: BO convergence for the third run

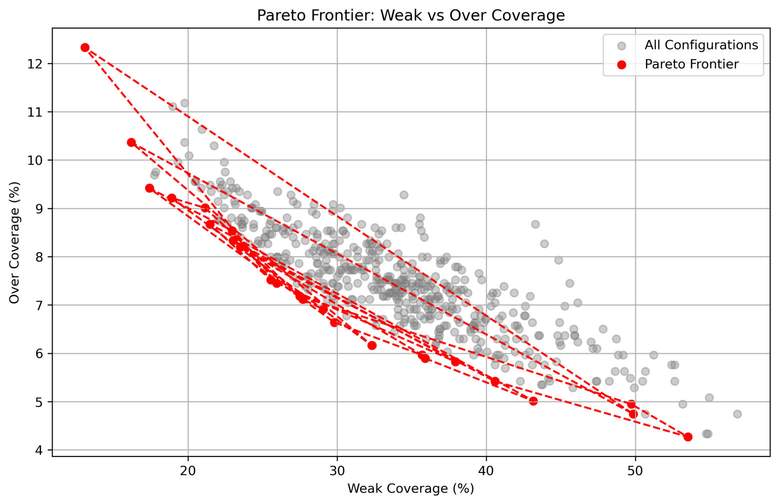

Figure 4.19: Pareto frontier after third BO run

Table 4.4: Optimized Tower Configuration in Experiment 2

Tower ID	Latitude	Longitude	Power 1	Angle 1	Power 2	Angle 2	Power 3	Angle 3
0	32.4780	3.6887	50.00	3.40	38.54	10.00	40.21	6.38
1	32.4778	3.6874	32.72	2.62	50.00	0.00	50.00	1.93
2	32.4771	3.6941	40.87	10.00	43.16	10.00	50.00	1.80
3	32.4827	3.6823	50.00	10.00	48.29	8.16	39.49	0.00
4	32.4857	3.6819	34.36	5.43	39.98	0.00	49.39	6.59
5	32.4812	3.6842	50.00	0.00	38.24	1.00	41.42	0.41
6	32.4811	3.6829	41.01	6.62	50.00	0.00	37.43	1.08
7	**32.4743**	**3.6798**	**39.42**	**5.82**	**50.00**	**5.43**	**35.53**	**6.22**
8	**32.4861**	**3.6919**	**34.88**	**0.41**	**31.06**	**2.92**	**50.00**	**6.17**

Table 4.4 summarizes the final optimized configuration of the nine towers, including two newly introduced towers Tower 7 (located at latitude 32.4743, longitude 3.6798) and Tower 8 (at latitude 32.4861, longitude 3.6919) which were added to improve coverage in previously underserved regions. The table provides detailed values for transmit power and downtilt angle across the three sectors of

each tower. Power levels range from 31.06 to 50.00 dBm, while downtilt angles span from 0.00° to 10.00°, complying with 3GPP and system constraints [1].

In particular, Tower 7 demonstrates a balanced configuration with moderate transmit powers (35.53 to 50.00 dBm) and mid-range downtilt angles (5.43 to 6.22 °), effectively enhancing coverage while minimizing interference. Tower 8, on the other hand, is characterized by lower transmit powers (31.06–34.88 dBm for sectors 1 and 2) and various down-tilt settings (0.41–6.17 °), tailored to complement the surrounding network topology. This optimized configuration, visualized in Figure 4.17, achieved a significantly improved RSRP distribution, satisfying the optimization termination criteria with notable reductions in weak coverage and controlled over-coverage. The results demonstrate the system's ability to incrementally enhance coverage through combined optimization and strategic deployment of additional infrastructure. The qEHVI-based multi-objective Bayesian Optimization framework efficiently explored trade-offs between weak coverage and over-coverage, guiding the optimization process toward more balanced and robust configurations that adhere to predefined performance thresholds.

4.4.3 Results and Discussion

This section presents a comprehensive analysis of the outcomes obtained from the two experiments conducted in this study. The evaluation is based on the optimization of radio parameters primarily transmit power and downtilt as well as the strategic placement of new towers to improve network coverage and capacity. The two experiments differ in their optimization strategies: the first uses a sequential Bayesian Optimization (BO) with Expected Improvement (EI) and Genetic Algorithm (GA), while the second employs a true multi-objective Bayesian Optimization using the q-Expected Hypervolume Improvement (qEHVI) acquisition function.

Experiment 1: Sequential Optimization with EI and GA Initially, the network exhibited 80.3% weak coverage and 2.0% over-coverage, as visualized in Figure 4.3. This poor performance highlighted the necessity for optimization, particularly in improving signal strength across underserved areas.

After applying BO for 220 iterations, the network improved to 39.8% weak coverage and 8.6% over-coverage. The resulting heatmap in Figure 4.4 demonstrates a significant expansion of signal strength coverage, especially in previously weak zones. This is further illustrated in Figure 4.6, which shows a 50% reduction in weak coverage, albeit with a 320% increase in over-coverage. While this trade-off is expected due to signal overlapping between neighboring sectors, it raises potential interference concerns.

Figure 4.5 confirms this, displaying increased interference in zones where signal strength from multiple sectors overlaps. Figure 4.13 shows that the BO algorithm converged early, around the 40th iteration, indicating stable improvements and diminishing returns in subsequent iterations. The Pareto frontier (Figure 4.14), although used here primarily for illustration, shows the trade-off surface between weak and over-coverage under single-objective optimization.

Since the optimization did not meet the stop conditions ($\leq$ 20% weak and $\leq$ 10% over-coverage), a new tower was added using GA (30 generations, 20 population size). The new deployment, shown in Figure 4.9, helped further densify the network. This additional tower reduced the weak coverage to 13.1% and increased over-coverage to 12.3%, as shown in Figure 4.9. Interference behavior post-GA is illustrated in Figure 4.10, which indicates a more balanced coverage footprint, though over-coverage slightly exceeded the target threshold.

Experiment 2: Multi-Objective Optimization with qEHVI The second experiment began with the same initial network conditions as Experiment 1. However, this experiment aimed to jointly minimize weak coverage and over-coverage using true multi-objective Bayesian Optimization with qEHVI, reflecting a more realistic operator scenario.

After 500 iterations, the first BO run achieved 41.7% weak coverage and 8.3% over-coverage, as shown in Figure 4.11. Although coverage improved, the stop condition was not met. Figure 4.12 and Figure 4.13 display the performance improvements and convergence. Figure 4.14 shows the Pareto front indicating balanced optimization trade-offs across the two objectives.

A new tower was introduced using GA, and a second BO run was performed. As shown in Figure 4.15, the optimization further reduced weak coverage to 32.9%, although over-coverage slightly increased to 9.0%. The convergence of the second BO run is illustrated in Figure 4.16.

In the third and final phase, another tower was added, and BO was executed again. Figure 4.17 shows the resulting optimized heatmap, achieving significantly enhanced signal distribution. The convergence and Pareto frontier are detailed in Figures 4.18 and 4.19, respectively. This final run showed a more favorable trade-off curve and converged closer to the target performance metrics, satisfying the predefined coverage criteria.

The multi-objective approach (Experiment 2) allowed for more refined control over both objectives, leading to more consistent improvement in weak coverage while managing the increase in over-coverage. In contrast, Experiment 1 showed faster convergence but exhibited higher variance in the balance between objectives.

in order to compare the performance of the proposed AI-driven framework, it is instructive to consider how Bayesian Optimization (BO) for parameter tuning and Genetic Algorithms (GA) for tower placement compare to traditional heuristic or rule-based methods, as discussed in the literature. Traditional approaches, such as Local Search and Simulated Annealing, iteratively explore solution spaces to adjust base station parameters like antenna tilt, often relying on predefined rules or heuristic evaluations. These methods, while computationally feasible for smaller networks, are prone to converging at local optima, limiting their effectiveness in dynamic urban environments with high user density and complex topography. Rule-based methods, commonly employed in Self-Organizing Networks, depend on static configurations and manual adjustments, which struggle to adapt to real-time changes in network demand or interference patterns. Other metaheuristic techniques, such as Tabu Search, offer improved exploration but face scalability challenges and sensitivity to parameter tuning, making them less suitable for large-scale urban deployments.

In contrast, the BO-based approach in this study dynamically optimizes base station parameters, achieving significant improvements in signal distribution. In Experiment 1, BO reduced weak coverage from 80.3% to 39.8%, and with GA's addition of a new tower, further to 13.1%, demonstrating robust adaptability to urban network challenges. Experiment 2's multi-objective BO approach, by jointly optimizing weak and over-coverage, achieved a balanced configuration with two new towers, meeting target criteria. These results highlight BO's ability to efficiently navigate complex solution spaces, avoiding the local optima traps common in traditional heuristics like Local Search. The GA-based tower placement further enhances performance by strategically addressing coverage gaps, incorporating regulatory constraints (exclusion zones near sensitive areas) that rule-based methods often handle manually or oversimplify.

The literature suggests traditional methods, such as Simulated Annealing, can reduce interference or pilot power but require extensive iterations and careful parameter tuning, which may not scale well in dense networks. Tabu Search, while effective for smaller networks, incurs high computational costs and memory demands, limiting its practicality for real-time applications. The proposed framework, by leveraging BO's probabilistic modeling and GA's evolutionary search, offers greater flexibility and efficiency, as evidenced by the rapid convergence in Experiment 1 (after 40 iterations) and the balanced trade-offs in Experiment 2. Unlike rule-based methods that rely on static thresholds, the AI-driven approach adapts to dynamic conditions, reducing the need for manual intervention.

However, the AI-based solutions share some challenges with traditional methods, such as computational complexity in large-scale networks. The reliance on a simplified propagation model and simulated terrain data may also introduce inaccuracies, a limitation also present in heuristic approaches that use idealized assumptions. Even with the existing of this challenges, the proposed framework's ability to integrate real-time parameter tuning with strategic infrastructure planning positions it as a more adaptive and effective solution for urban LTE optimization compared to traditional methods, with potential scalability to future technologies like 5G. This discussion underscores the advantages of AI-driven optimization in addressing the complexities of modern cellular networks, providing a foundation for further advancements in intelligent network management.

Overall, the experiments validate the effectiveness of using Bayesian Optimization (with EI and qEHVI) in combination with Genetic Algorithms for both parameter tuning and cell placement. Table 4.5 details the transmit power (in dBm) and downtilt angles (in degrees) for each sector across all towers in Experiment 1 (EI) and Experiment 2 (qEHVI), highlighting distinct optimization approaches. Experiment 1 frequently employs extreme power settings (e.g., 50 dBm in 15 sectors across towers 0–7), whereas Experiment 2 uses more intermediate values (e.g. 34.36–50 dBm for tower 4). Key differences include tower 4, sector 2, where EI sets 50 dBm and 10°, but qEHVI opts for 39.98 dBm and 0°, reducing overspill to balance coverage and interference. Another notable case is tower 5, sector 1, with EI at 30 dBm and 0°, contrasted by qEHVI's 50 dBm and 0°, enhancing signal strength in weak areas. These refined settings in qEHVI contribute to achieving the target coverage thresholds, unlike EI's higher over-coverage. The visual results demonstrate substantial signal distribution improvements, reduced weak coverage zones, and increased area-wide coverage uniformity.

Table 4.5: Comparison of Transmit Power and Downtilt Settings for All Towers in Experiment 1 (EI) and Experiment 2 (qEHVI)

Tower ID	**Sector**	**Experiment 1 (EI)**		**Experiment 2 (qEHVI)**		**Power Diff. (dBm)**	**Downtilt Diff. (°)**
		Power	Downtilt	Power	Downtilt		
0	1	46.94	10.00	50.00	3.40	+3.06	-6.60
	2	48.54	10.00	38.54	10.00	-10.00	0.00
	3	36.26	0.00	40.21	6.38	+3.95	+6.38
1	1	50.00	0.00	32.72	2.62	-17.28	+2.62
	2	50.00	0.00	50.00	0.00	0.00	0.00
	3	50.00	6.55	50.00	1.93	0.00	-4.62
2	1	42.96	10.00	40.87	10.00	-2.09	0.00
	2	50.00	1.91	43.16	10.00	-6.84	+8.09
	3	38.17	10.00	50.00	1.80	+11.83	-8.20
3	1	30.00	10.00	50.00	10.00	+20.00	0.00
	2	36.14	0.00	48.29	8.16	+12.15	+8.16
	3	35.54	0.00	39.49	0.00	+3.95	0.00
4	1	40.61	10.00	34.36	5.43	-6.25	-4.57
	2	50.00	10.00	39.98	0.00	-10.02	-10.00
	3	50.00	1.66	49.39	6.59	-0.61	+4.93
5	1	30.00	0.00	50.00	0.00	+20.00	0.00
	2	44.97	10.00	38.24	1.00	-6.73	-9.00
	3	50.00	0.00	41.42	0.41	-8.58	+0.41
6	1	50.00	0.00	41.01	6.62	-8.99	+6.62
	2	36.34	0.00	50.00	0.00	+13.66	0.00
	3	40.20	0.00	37.43	1.08	-2.77	+1.08
7	1	50.00	0.00	39.42	5.82	-10.58	+5.82
	2	50.00	10.00	50.00	5.43	0.00	-4.57
	3	50.00	0.00	35.53	6.22	-14.47	+6.22
8	1	-	-	34.88	0.41	-	-
	2	-	-	31.06	2.92	-	-
	3	-	-	50.00	6.17	-	-

4.5 Conclusion

In this chapter, we evaluated the proposed optimization techniques within a simulated LTE network environment tailored to the urban context of Ghardaia. The experiments demonstrated the capacity of Bayesian Optimization to enhance network performance by adjusting existing tower parameters, significantly reducing weak and over-coverage areas. Concurrently, the Genetic Algorithm-based placement of a new tower proved effective in identifying optimal locations that balance coverage enhancement with interference control and regulatory compliance. The simulation results confirm that intelligent parameter tuning and infrastructure planning can substantially improve signal distribution and network efficiency in a realistic urban macrocell scenario. The combination of real-world data, a validated propagation model, and domain specific constraints ensures that the outcomes are both scientifically grounded and practically relevant.

Conclusion and Perspectives

This thesis presents a transformative AI-driven framework for optimizing coverage and capacity in LTE cellular networks, specifically tailored to urban macrocell environments like Ghardaia, Algeria. By integrating Bayesian Optimization (BO) and Genetic Algorithms (GA), it offers a robust, adaptive solution to enhance network performance, providing actionable insights for operators seeking to meet escalating user demands efficiently. We recommend this approach for urban LTE deployments and as a foundation for future 5G networks, emphasizing its scalability and practical relevance.

The rapid increase in mobile data traffic, fueled by smart devices and multimedia services, places unprecedented stress on LTE networks, particularly in high-density urban environments of complex topographies. It is challenging to offer strong coverage and sufficient capacity due to dynamic interference, user densification, and regulatory constraints. This issue is significant because proper connectivity is the backbone of today's communication, trade, and public safety and requires new solutions to bypass the shortcomings of conventional rule-based approaches dependent on static settings and human tuning, resulting in inefficiency and high operational expense.

The proposed framework addresses these challenges by leveraging AI to optimize network performance dynamically and strategically. BO adjusts transmit power (30–50 dBm) and antenna downtilt (0–10°) of existing base stations, using Expected Improvement (EI) for rapid single-objective optimization and q-Expected Hypervolume Improvement (qEHVI) for multi-objective trade-offs, minimizing weak coverage (RSRP $<$ -80 dBm) and over-coverage (RSRP $>$ -60 dBm). When parameter tuning is insufficient, GA optimizes new tower placement, balancing coverage, capacity, interference, and regulatory constraints like proximity to sensitive areas (e.g., schools, hospitals). This dual approach outperforms traditional heuristic methods, offering adaptability, cost-effectiveness, and scalability, with insights applicable to 5G and beyond.

The motivation to develop an AI-driven solution stems from the need for adaptive, efficient network management in dynamic urban environments. The framework answers key research questions posed in the introduction: BO effectively tunes parameters to balance coverage and capacity, reducing weak coverage by up to 50% in simulations; real-time adjustments mitigate interference in dense areas; GA optimizes new tower locations, adhering to regulatory constraints; and the integrated BO-GA approach outperforms traditional methods in flexibility and performance. These results validate the potential of AI to transform network optimization, delivering robust, scalable solutions.

Despite its advancements, the framework faces limitations inherent to wireless networks and AI applications. The computational complexity of BO and GA poses challenges for real-time, large-scale deployments, requiring significant processing power. The reliance on cleaned OpenCelliD data and synthetic terrain models introduces potential inaccuracies, as real-world data may be incomplete or inconsistent. Regulatory and logistical constraints, such as zoning restrictions and installation costs, complicate tower placement, demanding precise integration into the GA fitness function. Additionally, the COST-231 Hata model, while effective, simplifies propagation dynamics, potentially overlooking complex urban effects like multipath fading.

The experiments, conducted in a 2 km $\times$ 2 km simulated urban area in Ghardaia, demonstrate significant improvements. Experiment 1 (EI-based BO and GA) reduced weak coverage from 80.3% to 13.1% and increased over-coverage to 12.3% after adding one tower, with rapid convergence after 40 iterations. Experiment 2 (qEHVI-based BO) achieved a final configuration with two additional towers, meeting target criteria (weak coverage $<$ 20%, over-coverage $<$ 10%) through refined multi-objective optimization. These results, visualized in RSRP and interference maps, confirm enhanced signal distribution, reduced coverage gaps, and controlled interference, validating the framework's effectiveness in urban LTE settings.

This work lays a robust foundation for self-optimizing cellular networks, with far-reaching implications for wireless communications. Future research will explore two primary directions: network scaling and risk-averse optimization. Scaling to larger geographic areas with hundreds or thousands of cells is critical for real-world deployment, where centralized optimization may be infeasible. Distributed or hierarchical AI approaches could address this, leveraging parallel processing to manage large search spaces. Risk-averse optimization will ensure parameter configurations avoid unacceptable service quality, such as large coverage gaps, by incorporating robust constraints into BO and GA models. Additionally, updating the propagation model to include ray-tracing or advanced techniques will enhance realism, capturing complex urban effects like reflections and diffraction. Other extensions include adding reinforcement learning to enable real-time adaptability, leveraging crowdsourced user information or satellite imagery for improved accuracy, and ensuring energy efficiency and self-healing capabilities for green, resilient networks. Ghardaia or similar city field trials will validate these extensions, bridging the gap between simulation and real-world deployment, and extending the framework to 5G and beyond.

Bibliography

[1] Study on scenarios and requirements for next generation access technologies. Technical Report TR 38.913 V14.3.0, 3rd Generation Partnership Project (3GPP), 2017. Available at: https://www.3gpp.org/ftp/Specs/archive/38_series/38.913/38913-e30.zip.

[2] Roger Abou-Jaoude, Naveed Ulhaq, and Christian Hartmann. Hsdpa throughput optimization with antenna tilt and pilot power in a moving hot-spot scenario. In *2009 IEEE 70th Vehicular Technology Conference Fall*, pages 1–5, 2009. doi: 10.1109/VETECF.2009.5378895.

[3] Ruslan V. Akhpashev and Andrey V. Andreev. Cost 231 hata adaptation model for urban conditions in lte networks. In *2016 17th International Conference of Young Specialists on Micro/Nanotechnologies and Electron Devices (EDM)*, pages 64–66, 2016. doi: 10.1109/EDM.2016.7538693.

[4] Md Farhad Alam, Md Arifuzzaman, and Debabrata Sarddar. Ant colony optimization-based solution to optimize load balancing and throughput for 5g and beyond heterogeneous networks. *EURASIP Journal on Wireless Communications and Networking*, 2024(1):48, 2024. doi: 10.1186/s13638-024-02376-2. URL https://jwcn-eurasipjournals.springeropen.com/articles/10.1186/s13638-024-02376-2.

[5] Mohammed Jaber Alam, Md Rahat Hossain, Salahuddin Azad, and Ritesh Chugh. An overview of lte/lte-a heterogeneous networks for 5g and beyond. *Transactions on Emerging Telecommunications Technologies*, 34(8): e4806, 2023. doi: https://doi.org/10.1002/ett.4806.

[6] S.M. Allen, S. Hurley, and R.M. Whitaker. Automated decision technology for network design in cellular communication systems. In *Proceedings of the 35th Annual Hawaii International Conference on System Sciences*, pages 8 pp.–, 2002. doi: 10.1109/HICSS.2002.994002.

[7] E. Amaldi, A. Capone, and F. Malucelli. Radio planning and coverage optimization of 3g cellular networks. *Wireless Networks*, 14(4):435–447, 2008.

[8] M. Amirijoo, Ljupco Jorguseski, Thomas Kürner, Remco Litjens, Michaela Eden, Lars Schmelz, and U. Turke. Cell outage management in lte networks. pages 600 – 604, 10 2009. doi: 10.1109/ISWCS.2009.5285232.

[9] H. Arslan, M. Hossain, D. Niyato, and E. Hossain. Optimizing resource allocation and antenna configuration in heterogeneous cellular networks using genetic algorithms. *IEEE Transactions on Wireless Communications*, 16(7): 4806–4819, 2017. doi: 10.1109/TWC.2017.2699363.

[10] B. Badic, T. O'Farrell, P. Loskot, and J. He. Effect of the base station antenna beam tilting on energy consumption in cellular networks. In *2010 IEEE 72nd Vehicular Technology Conference Fall, VTC2010-Fall - Proceedings*, IEEE Vehicular Technology Conference. IEEE, 2010. ISBN 9781424435746. doi: 10.1109/VETECF.2010.5594153. 2010 IEEE 72nd Vehicular Technology Conference Fall, VTC2010-Fall ; Conference date: 06-09-2010 Through 09-09-2010.

[11] Vishaka Basnayake, Hakim Mabed, Dush Nalin Jayakody, and Philippe Canalda. *Ph.D Thesis: Reliable Emergency Service for 5G Networks*. PhD thesis, 06 2023.

[12] Naga Bhushan, Junyi Li, Durga Malladi, Robert Gilmore, Dean Brenner, Aleksandar Damnjanovic, Ravi Sukhavasi, Chirag Patel, and Stefan Geirhofer. Network densification: The dominant theme for wireless evolution into 5g. *IEEE Communications Magazine*, 52(2):82–89, 2014. doi: 10.1109/MCOM.2014.6736747.

[13] Oliver Blume, Harald Eckhardt, Siegfried Klein, Edgar Kuehn, and Wieslawa M. Wajda. Energy savings in mobile networks based on adaptation to traffic statistics. *Bell Labs Technical Journal*, 15(2):77–94, 2010. doi: 10.1002/bltj.20442.

[14] Bruno Campos, Luiz F. G. Soares, Sergio Colcher, Luiz A. Villas, Luiz H. A. Monteiro, and Hugo C. Lovisolo. Genetic algorithm-based cellular network optimization considering positioning applications. *IET Communications*, 13 (11):1657–1665, 2019. doi: 10.1049/iet-com.2018.5125.

[15] Rafael Saraiva Campos and Lisandro Lovisolo. Genetic algorithm-based cellular network optimisation considering positioning applications. *IET Communications*, 13(7):879–891, 2019. doi: https://doi.org/10.1049/iet-com.2018.5125. URL https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-com.2018.5125.

[16] Nikolay Dandanov, Hussein Al-Shatri, Anja Klein, and Vladimir Poulkov. Dynamic self-optimization of the antenna tilt for best trade-off between coverage and capacity in mobile networks. *Wireless Personal Communications*, 90(2):279–311, 2016. doi: 10.1007/s11277-016-3849-9. URL https://doi.org/10.1007/s11277-016-3849-9.

[17] Samuel Daulton, Maximilian Balandat, and Eytan Bakshy. Parallel bayesian optimization of multiple noisy objectives with expected hypervolume improvement, 2021. URL https://arxiv.org/abs/2105.08195.

[18] Supratim Deb, Pantelis Monogioudis, Jerzy Miernik, and James P. Seymour. Algorithms for enhanced inter-cell interference coordination (eicic) in lte hetnets. *IEEE/ACM Transactions on Networking*, 22(1):137–150, 2014. doi: 10.1109/TNET.2013.2246820.

[19] Ryan M. Dreifuerst, Samuel Daulton, Yuchen Qian, Paul Varkey, Maximilian Balandat, Sanjay Kasturia, Anoop Tomar, Ali Yazdan, Vish Ponnampalam, and Robert W. Heath. Optimizing coverage and capacity in cellular networks

using machine learning. In *ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 8138–8142, 2021. doi: 10.1109/ICASSP39728.2021.9414155.

[20] Lin Du, John Bigham, Laurie Cuthbert, C. Parini, and Petrit Nahi. Using dynamic sector antenna tilting control for load balancing in cellular mobile communications. 01 2002.

[21] Harald Eckhardt, Siegfried Klein, and Markus Gruber. Vertical antenna tilt optimization for lte base stations. pages 1–5, 05 2011. doi: 10.1109/VETECS.2011.5956370.

[22] Su Feng and Edward Mao. Self-optimizing networks: The role of son in lte and beyond. *IEEE Communications Magazine*, 55(5):122–128, 2017. doi: 10.1109/MCOM.2017.1600735.

[23] M. Garcia-Lozano, S. Ruiz, and J.J. Olmos. Umts optimum cell load balancing for inhomogeneous traffic patterns. In *IEEE 60th Vehicular Technology Conference, 2004. VTC2004-Fall. 2004*, volume 2, pages 909–913 Vol. 2, 2004. doi: 10.1109/VETECF.2004.1400153.

[24] Amitabha Ghosh, Nitin Mangalvedhe, Rapeepat Ratasuk, Bishwarup Mondal, Mark Cudak, Eugene Visotsky, Timothy A. Thomas, Jeffrey G. Andrews, Ping Xia, Han Shin Jo, Harpreet S. Dhillon, and Thomas D. Novlan. Heterogeneous cellular networks: From theory to practice. *IEEE Communications Magazine*, 50(6):54–64, 2012. doi: 10.1109/MCOM.2012.6211486.

[25] F. Gunnarsson, M. N. Johansson, A. Furuskar, M. Lundevall, A. Simonsson, C. Tidestav, and M. Blomgren. Downtilted base station antennas — a simulation model proposal and impact on hspa and lte performance. In *Vehicular Technology Conference, 2008. VTC 2008-Fall. IEEE 68th*, pages 1–5. IEEE, September 2008.

[26] Emre Gures, Ibraheem Shayea, Sawsan Saad, Mustafa Ergen, Ayman El-Saleh, Nada Sid Ahmed, and Mohammad Alnakhli. Load balancing in 5g heterogeneous networks based on automatic weight function. *ICT Express*, 9, 03 2023. doi: 10.1016/j.icte.2023.03.008.

[27] Hardy Halbauer, Stephan Saur, David Teichmann, and Martin Weckerle. Interference avoidance with dynamic vertical beamsteering in real deployments. In *IEEE Vehicular Technology Conference (VTC Fall)*, pages 1–6, 2011. doi: 10.1109/WCNCW.2012.6215509.

[28] Lennart Hardell, Mona Nilsson, and Tarmo Koppel. Aspects on the international commission on non-ionizing radiation protection (icnirp) 2020 guidelines on radiofrequency radiation. *Journal of Cancer Science and Clinical Therapeutics*, 05, 01 2021. doi: 10.26502/jcsct.5079117.

[29] Zeeshan Hasan, Hamidreza Boostanimehr, and Vijay K. Bhargava. Green cellular networks: A survey, some research issues and challenges. *IEEE Communications Surveys Tutorials*, 13(4):524–540, 2011. doi: 10.1109/SURV.2011.092311.00031.

[30] Zhi-Jiang He, Meng Hou, Kai Niu, Wei-Ling Wu, and Sen Xu. Coverage and capacity optimization in lte network based on non-cooperative games. *Journal of China Universities of Posts and Telecommunications*, 19(4):14–21, 2012. doi: 10.1016/S1005-8885(11)60277-X.

[31] Jakob Hoydis, Mari Kobayashi, and Mérouane Debbah. Green small-cell networks. *IEEE Vehicular Technology Magazine*, 6(1):37–43, 2011. doi: 10.1109/MVT.2010.939910.

[32] S. B. Jamaa, Z. Altman, J. M. Picard, and B. Fourestié. Combined coverage and capacity optimisation for umts networks. In *Proceedings of the 11th International Telecommunications Network Strategy and Planning Symposium (NETWORKS 2004)*, pages 175–178. IEEE, 2004. doi: 10.1109/NETWKS.2004.1431456.

[33] S.B. Jamaa, Z. Altman, J.M. Picard, and B. Fourestie. Combined coverage and capacity optimisation for umts networks. In *11th International Telecommunications Network Strategy and Planning Symposium. NETWORKS 2004,*, pages 175–178, 2004. doi: 10.1109/NETWKS.2004.240881.

[34] Siegfried Klein, Ingo Karla, and Edgar Kuhn. Potential of intra-lte, intra-frequency load balancing. In *2011 IEEE 73rd Vehicular Technology Conference (VTC Spring)*, pages 1–5, 2011. doi: 10.1109/VETECS.2011.5956281.

[35] D. J. Y. Lee and Ce Xu. Mechanical antenna downtilt and its impact on system design. In *Proceedings of the IEEE 47th Vehicular Technology Conference (VTC)*, volume 2, pages 447–451. IEEE, May 1997.

[36] Seungseob Lee, SuKyoung Lee, Kyungsoo Kim, and Yoon Hyuk Kim. Base station placement algorithm for large-scale lte heterogeneous networks. *PLoS ONE*, 10(10):e0139190, 2015. doi: 10.1371/journal.pone.0139190.

[37] I. Luketić, D. Šimunić, and T. Blajić. Optimization of coverage and capacity of self-organizing network in lte. In *2011 Proceedings of the 34th International Convention MIPRO*, pages 612–617, 2011.

[38] Jane Musengya. *COMMON PILOT CHANNEL POWER CONTROL FOR 3G CELLULAR NETWORKS TRAFFIC LOAD BALANCING BASED ON FUZZY LOGIC CONTROL*. PhD thesis, 03 2017.

[39] J. Niemela, T. Isotalo, J. Borkowski, and J. Lempiainen. Sensitivity of optimum downtilt angle for geographical traffic load distribution in wcdma. In *Proceedings of the IEEE 62nd Vehicular Technology Conference (VTC-Fall)*, volume 2, pages 1202–1206. IEEE, September 2005.

[40] OpenCelliD. Opencellid: The world's largest open database of cell towers geolocation. https://www.opencellid.org/downloads.php, 2025. Accessed: 2025-04-13.

[41] Jolly Parikh. Impact of base station antenna height and antenna tilt on performance of lte systems. *IOSR Journal of Electrical and Electronics Engineering*, 9:06–11, 01 2014. doi: 10.9790/1676-09450611.

[42] R. Razavi, S. Klein, and H. Claussen. Self-optimization of capacity and coverage in lte networks using a fuzzy reinforcement learning approach. In *21st Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, pages 1865–1870. IEEE, 2010. ISBN 978-1-4244-8016-6. doi: 10.1109/PIMRC.2010.5671869.

[43] Mohamed Selim, Ahmed Kamal, Khaled Elsayed, Heba M. Abdel-Atty, and Mohamed Alnuem. *Self-Healing in 5G HetNets: A Research and Development Perspective*, pages 149–177. 04 2016. ISBN 978-1-4987-3954-2. doi: 10.1201/b19698-11.

[44] Md. Shahin Alom Shuvo, Md. Azad Rahaman Munna, Sujan Sarker, Tamal Adhikary, Md. Abdur Razzaque, Mohammad Mehedi Hassan, Gianluca Aloi, and Giancarlo Fortino. Energy-efficient scheduling of small cells in 5g: A meta-heuristic approach. *Journal of Network and Computer Applications*, 178:102986, 2021. ISSN 1084-8045. doi: https://doi.org/10.1016/j.jnca.2021.102986. URL https://www.sciencedirect.com/science/article/pii/S1084804521000138.

[45] I. Siomina, P. Värbrand, and D. Yuan. An effective optimization algorithm for configuring radio base station antennas in umts networks. In *Vehicular Technology Conference, 2006. VTC-2006 Fall. 2006 IEEE 64th*, pages 1–5. IEEE, September 2006.

[46] Iana Siomina. P-cpich power and antenna tilt optimization in umts networks. In *Proceedings of the Advanced Industrial Conference on Telecommunications/Service Assurance with Partial and Intermittent Resources Conference/E-Learning on Telecommunications Workshop*, pages 1–8, Lisbon, Portugal, July 2005. IEEE. ISBN 0-7695-2388-9. doi: 10.1109/AICT.2005.66. © 2005 IEEE.

[47] Iana Siomina and Di Yuan. Enhancing hsdpa performance via automated and large-scale optimization of radio base station antenna configuration. In *VTC Spring 2008 - IEEE Vehicular Technology Conference*, pages 2061–2065, 2008. doi: 10.1109/VETECS.2008.463.

[48] Iana Siomina, Peter Varbrand, and Di Yuan. Automated optimization of service coverage and base station antenna configuration in umts networks. *IEEE Wireless Communications*, 13(6):16–25, 2006. doi: 10.1109/MWC.2006.275194.

[49] Jasper Snoek, Hugo Larochelle, and Ryan P. Adams. Practical bayesian optimization of machine learning algorithms, 2012. URL https://arxiv.org/abs/1206.2944.

[50] Catherine Nayer Tadros, Mohamed R. M. Rizk, and Bassem Mahmoud Mokhtar. Software defined network-based management for enhanced 5g network services. *IEEE Access*, 8:53997–54008, 2020. doi: 10.1109/ACCESS.2020.2980392.

[51] Andras Temesvary. Self-configuration of antenna tilt and power for plug play deployed cellular networks. In *2009 IEEE Wireless Communications and Networking Conference*, pages 1–6, 2009. doi: 10.1109/WCNC.2009.4917961.

[52] M. Naseer ul Islam, R. Abou-Jaoude, C. Hartmann, and A. Mitschele-Thiel. Self-optimization of antenna tilt and pilot power for dedicated channels. In *2010 Proceedings of the 8th International Symposium on Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks (WiOpt)*, pages 196–203. IEEE, May–June 2010.

[53] A. Wang and V. Krishnamurthy. Mobility enhanced smart antenna adaptive sectoring for uplink capacity maximization in cdma cellular network. In *Proceedings of the 2006 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, volume 4, page IV. IEEE, May 2006.

[54] Shalitha Wijethilaka and Madhusanka Liyanage. Survey on network slicing for internet of things realization in 5g networks. *IEEE Communications Surveys Tutorials*, 23(2):957–994, 2021. doi: 10.1109/COMST.2021.3067807.

[55] G. Wilson. Electrical downtilt through beam-steering versus mechanical downtilt [base station antennas]. In *Proceedings of the IEEE 42nd Vehicular Technology Conference (VTC)*, volume 1, pages 1–4. IEEE, May 1992.

[56] Ruixiao Wu, Zhigang Wen, Chunxiao Fan, Jie Liu, and Zhenjun Ma. Self-optimization of antenna configuration in lte-advance networks for energy saving. In *2010 3rd IEEE International Conference on Broadband Network and Multimedia Technology (IC-BNMT)*, pages 529–534, 2010. doi: 10.1109/ICBNMT.2010.5705146.

[57] X. Wu, A. Maeder, and A. Klein. Genetic algorithm based antenna parameter optimization in lte networks. In *Proceedings of the 2011 IEEE Wireless Communications and Networking Conference (WCNC)*, pages 1526–1530. IEEE, 2011. doi: 10.1109/WCNC.2011.5779421.

[58] Osman N. C. Yilmaz, Jyri Hämäläinen, and Seppo Hämäläinen. Self-optimization of remote electrical tilt. In *21st Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, pages 1128–1132, 2010. doi: 10.1109/PIMRC.2010.5672065.

République Algérienne Démocratique et Populaire
وزارة التعليم العالي و البحث العلمي
Ministère de l'Enseignement Supérieur et de La Recherche Scientifique
كلية العلوم والتكنولوجيا
Faculté des Sciences et de la Technologie
قسم الرياضيات و الإعلام الآلي
Département des Mathématiques & de l'Informatique
جامعة غرداية
Université de Ghardaia

شهادة الترخيص بالإيداع

أنا الأستاذ : سعيدي أحمد

بصفتي رئيس و المسؤول عن تصحيح مذكرة الماستر الموسومة ب:

Al-Driven Optimization of Cellular Network Coverage and Capacity: Tower Placement and Dynamic Parameter Tuning

والمُنجزة من طرف الطالبين:

1. الطالب :قربوزمحمد علاء الدين
2. الطالب :دوادي سليمان عبد الرحيم

الكلية: العلوم والتكنولوجيا
القسم: الرياضيات والإعلام الآلي
الشعبة: إعلام آلي

التخصص: الأنظمة الذكية لاستخراج المعارف
تاريخ المناقشة: 2025/06/30

أُشهد بموجب هذا أن الطالبين قد قاما بجميع التصحيحات المطلوبة من طرف لجنة المناقشة، وأن النسخة الإلكترونية مطابقة تمامًا للنسخة الورقية، وفقًا للمعايير المعتمدة.

إمضاء المسؤول عن التصحيح

مصادقة رئيس القسم

مساعد رئيس قسم الرياضيات والإعلام الآلي مكلف بالتدريس والتعليم في التدرج
بوشقوف أسماء

جامعة غرداية
قسم الرياضيات و الإعلام الآلي
كلية العلوم و التكنولوجيا