Machine Learning Based Resource Allocation Optimization in 5G Network

BY

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Master of Science in Electronics and Telecommunication Engineering (M.Sc. in ETE).

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Declaration

It is hereby declared that this thesis and any part of it has not been submitted elsewhere for the award of any degree or diploma.

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Abstract

The Fifth-generation (5G) wireless represents a significant advancement for mobile connectivity successfully, near-instant response times, the ability to connect a huge number of devices reliably. But this power comes with a catch: managing its radio resources is incredibly complex, thanks to constantly shifting network conditions and wildly different user demands. How can the vital resources of a 5G network effectively managed? Question by applying machine learning techniques to the problem explored by this thesis. In order to replicate both the core and radio access network, started by creating a simulated 5G environment with open-source platforms Open5GS, Free5GC, and UERANSIM. with the testable place, we are able to systematically trial and analyze various resource allocation methods. To improve resource allocation performance, were applied some machine learning approaches as like Linear Regression, Polynomial Regression, and XGBoost. In order to measure how well each model performed, Metrics including throughput, latency, and spectrum efficiency considered for evaluation. More accurate predictions in the rapidly changing conditions of 5G networks suggested by XGBoost, achieving a noticeably higher R^2 value and showed the strongest among all the models. In 5G systems, that machine learning can help enhance resource management indicated by this study's results. They give support towards realizing more efficient and adaptive management of networks by facilitating smarter and more flexible decisions.

Overall, this study contributes to development solutions for next-generation mobile communication technologies based on AI and analytics-based.

Keywords: SDN, IoT, CPP, ANFIS, LB, LO,NT, IN, FL,NN.

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Chapter 1

Introduction

1.1 Background on 5G Networks

5G wireless communication is the fifth-generation technology and is a significant step beyond its predecessors for speed, latency, and network capacity [1]. The 5G technology is not merely about high-performance mobile broadband against to previous generations. Instead, to provide crucial communications in addition to enabling a large number of IoT devices, it has been specifically designed. Virtualization of network functions, ultra-dense small cells, network slicing and enhanced radio spectrum use features successfully incorporated by 5G. For transforming industries like healthcare, transportation, agriculture, and manufacturing with real-time, high-speed, and highly-reliable connectivity opportunities will lead by 5G [2].

Figure 1.1: 5G Network

1.2 Importance of Resource Allocation in 5G

A lot of new service requirements for 5G such as massive machine-type communication (mMTC), improved mobile broadband (eMBB) and ultra-reliable low-latency communication (URLLC). It's more important than ever to manage resources well due to these requirements [3]. Users and services must share in real time because of not enough network bandwidth, computing power for everyone. The network as a whole works better, energy use goes down, users are treated fairly and the quality of service (QoS) goes up during resources are allocated properly. Due to traffic loads and user mobility change quickly Standard ways of allocating resources don't work well in 5G networks. To doing things we need more flexible, creative and adaptable method [4].

1.3 Problem Statement

Efficient resource allocation a difficult task made by the emergence of 5G brings high complexity and diversity in network services. Due to not flexible enough to adapt to rapidly changing traffic patterns and performance needs, conventional rule-based and heuristic methods often fall short. On 5G networks, there are many various kinds of apps may support and each app requirements a specific amount of speed, reliability, and latency. This implies that the distribution of resources allocation can't be determined by strict rules or set ways of doing things. Things change all the time, therefore it has to change too. Machine learning is a good way to go here since it can look at both how the network is currently behaving and how it has behaved in the past to help make better allocation choices. The idea has crucial but it hasn't been completely explored in 5G simulation scenarios yet. We need to more research to find out how well machine learning works in the real world.

1.4 Research Objectives

The main aim of this thesis is to to explore the application of machine learning techniques may be used to make the most of resource allocation in a 5G network simulation. The main goals are:

- To create a 5G core and radio access network by using tools like Open5GS, Free5GC, and UERANSIM..
- To collect network performance and traffic data of different simulation scenarios.
- To set up and train different machine learning models (e.g., Linear Regression, Polynomial Regression, XGBoost) for identifing and optimizing resource allocation.
- To examine and compare the performance of ML-based resource allocation against conventional methods.

1.5 Research Questions

This research looks for answer the following questions:

1. How can machine learning techniques be applied to enhance resource allocation in 5G networks?
2. In what ways can machine learning be used to improve how resources are allocated within 5G networks?
3. How does using ML-based resource allocation compare to traditional methods in terms of performance metrics like throughput, latency, and fairness?
4. What are the problems and limitations of using ML models in a 5G test environment?

1.6 Scope and Limitations

This study only looks at how to use open-source platforms like Open5GS, Free5GC, and UERANSIM to simulate 5G network scenarios. The paper looks at the challenge of allocating resources on the downlink and tests ML-based solutions utilizing supervised learning approaches. The following are some of the limitations:
The simulations don't show how commercial deployments work on a large scale.

- Because of a lack of resources, real-time data from live networks is not used.
- The ML models are trained and tested on synthetic or simulated datasets, which may not show all the complexity of the real world.

1.7 Contributions of the Thesis

This thesis offers the following important contributions:

- Development of a functional 5G simulation testbed that combines Open5GS/Free5GC with UERANSIM.
- Using and comparing different machine learning models to make the best use of 5G resources.
- Analyzing and comparing the performance of ML-based methods to classical ones.
- A repeatable way to add ML to 5G network simulations for research and academic use.

1.8 Organization of the Thesis

This thesis is structured as follows:

- **Chapter 1:** Introduction, Background information, motivation, research goals, and a synopsis of the thesis framework is all included.
- **Chapter 2:** Discusses Literature Review related to existing works on of ML-based methods, 5G IoT networks, and open-source platforms like Open5GS, Free5GC, and UERANSIM to simulate 5G network scenarios.
- **Chapter 3:** Formulating the Problem and System Model Presents the network model, problem specification, and performance data.
- **Chapter 4:** Proposed Machine Learning Based Resource Allocation Optimization in 5G Network which is design, training, and deployment of the ML-based optimization framework.

- **Chapter 5:**Explains the hardware/software setups, the simulation environment, the tools (Open5GS, Free5GC, and UERANSIM), the dataset preparation, and the model training processes.
- **Chapter 6:** Compares the performance of several machine learning models, analyzes the experimental findings, and assesses them according to throughput, latency, fairness, and prediction accuracy. It also compares traditional methods with ML-based approaches.
- **Chapter 7:** Highlights the main conclusions of the study, talks about its shortcomings, and offers suggestions for further development and expansion of this work.

Chapter 2

Literature Review

A. Gupta et al [5] provide an extensive overview about the 5G network, including its needs, structure, and the technologies that are linked to it. With 5G, people will be able to join very quickly, with very little delay. The service will also use very little power while sending a lot of data. A lot of people want to know how SDN, NFV, mmWave, big MIMO, D2D, and IoT will change networks in the future. Putting ANFIS-based controllers in SDN-IoT environments is one of the more involved plans that can be built on top of the poll but limited studies on latency, and no real-world success studies or experiments to back up the theory; only surveys do. There are a lot of possible changes that are looked at, but none of them are tried out. In other words, the job is mostly a way to get more ideas for things to study. H. Yang et al [6] present the implementation of artificial intelligence (AI) to improving resource sharing within 5G networks. The goals of the project are to save energy, adapting to dynamic needs, reduce the number of delays and address problems such as insufficient airwaves. People can share in smart and flexible ways by using AI tools like ML and deep learning. This project demands to make networks stable, faster and able to mange more people by using AI to manage 5G resources. It also shows problems that to be resolved and new ways to learn. Giving people access to AI 5G tools is challenging due to they only provide a general idea. It doesn't give any precise instructions or examples. Rarely discussed on how to integrate it into very big 5G networks, how much it costs to run, how implement when used AI to improve and grow things. Y. Xu et al [7] examined how integrating edge computing with artificial intelligence to enhance resource management in 5G networks. This concept is to implement based on AI decision making closer to end users, enhanced performance, reduced energy consumption and allowing faster service delivery. This method is especially useful for large-scale IoT systems, real world applications and dynamically changing data environments. The benefits and the challenges of AI using to manage resources at the network terminal are identified by this study. However, due to doesn't have any detailed simulations or good experimental proof to back up its claims it's doesn't real life environments. The author say that AI can be very beneficial in edge-based resource control better although there are still some practical issues that need to be resolved. Some of these the requirement for high power computer, security vulnerabilities, and difficulties ensuring that different architectures of 5G system can work together.

2.1 5G Network Architecture

The main components of 5G are the 5G Core (5GC) and the New Radio (NR) access network. The network to communicate wirelessly at high speeds, with very little delay and possible for devices made by the New Radio (NR) access network. This leads in better connection for many uses, and control and more capacity. Data routing, control, and policy are under the 5GC's charge.

The 5G Core (5GC): This is the network's management component and the centralized control, which includes:

- **The Access and Mobility Management Function (AMF):** everything is functioning properly and determines how gadgets will connect as cells pass off checked by AMF. Users are connected to the network this at any time safely. Furthermore, AMF that makes 5G portable and user-friendly [8] .
- **SMF (Session Management Function):** The letters SMF represents for "Session Management Function". The 5G network's part regulates during things occurs and make sure the begin, end, and evolve. Data is transferred correctly, connections remain open, and users utilize all available resources, it manages IP addresses and selects the optimal data pathways in order to ensure [9]|.

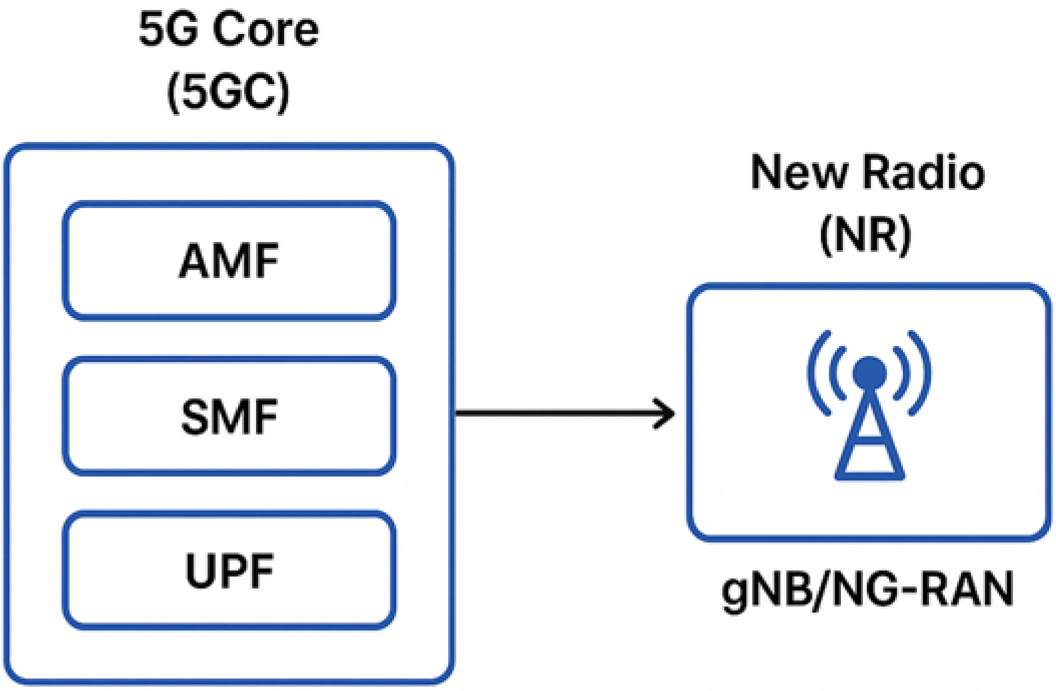

Figure 2.1: 5G Network Architecture

- **The User Plane Function (UPF):** In in 5G networks the User Plane Function (UPF) helps transfer of user data. ensuring that the service is good and monitoring over them are duties of UTF. The delay is not much. a lot of 5G apps and fast contact are enable by this [10].

- **The New Radio (NR), or gNB/NG-RAN:** On the 5G radio access network (RAN), things can communicate with the 5G Core. Connect wirelessly fast and properly, send data correctly made by the radio waves. Who is moving, and make sure that data is handled correctly to offer instructions, monitor. This makes well connected, more capable, faster different 5G apps [11].

2.2 Resource Allocation Challenges in 5G

Resource allocation in 5G faces unique with varying quality of service (QoS) requirements is challenged because of heterogeneous services.

Key challenges include:

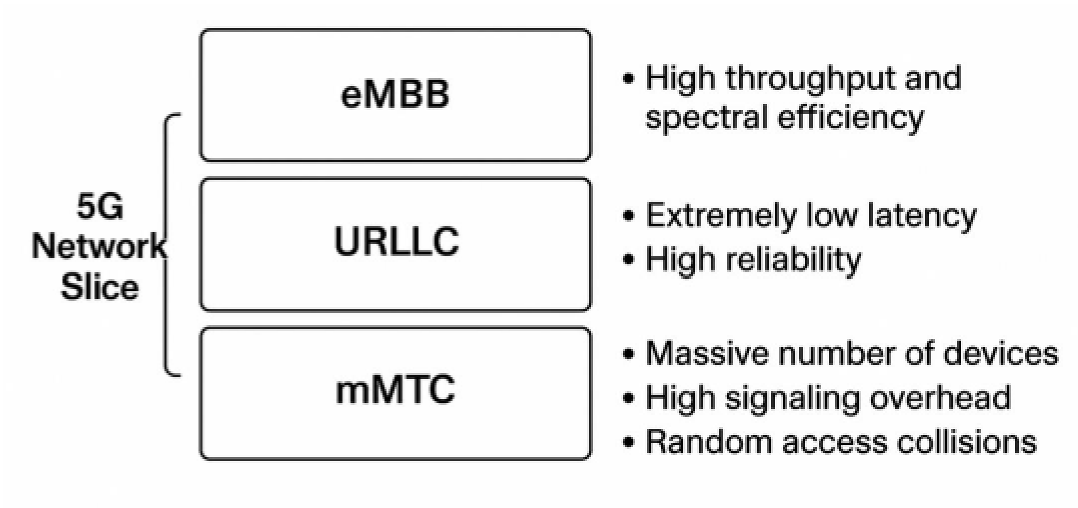

Figure 2.2: Resource Allocation Challenges

- **Network Slicing:** To distribute resources among separate virtual slices without interfering with one another required coordination techniques.
- **URLLC: URLLC:** High reliability and very low latency (less than 1 ms) are needed that is difficulties to do with with traditional method.
- **mMTC: mMTC:** Access control harder and scheduling made by a lot of devices send data at random times.
- **eMBB:** Particularly crowded areas need a large of data to flow effectively and quickly.

When many service types coexist in the same network environment , these Complex trade-offs result from these disparate requirements. Effective resource management must guarantee service uniqueness, flexibility, and equity under changing circumstances.

2.3 Traditional vs. Modern Resource Allocation Techniques

Traditional resource allocation methods as like include fixed allocation, round-robin scheduling, and heuristic-based methods which are very simple and easy to implement but frequently lack flexibility and function poorly in changing network settings.

More intelligent and adaptable methods are provided by contemporary techniques:

- **Game-theoretic models:** For limited resources this model used to model competition among users.
- **Optimization-based approaches:** theoretical securities but frequently face computational limitations in real-time scenarios.
- **Machine Learning (ML)-based methods:**:To make adaptive and predictive decisions without programming that is explicit learn from data.

ML method in 5G networks in particular, supervised and reinforcement learning have demonstrated promise in power allocation, resource scheduling, and traffic prediction.

2.4 Optimization Techniques in 5G

There are different ways to optimize 5G to solve problems with resource allocation:

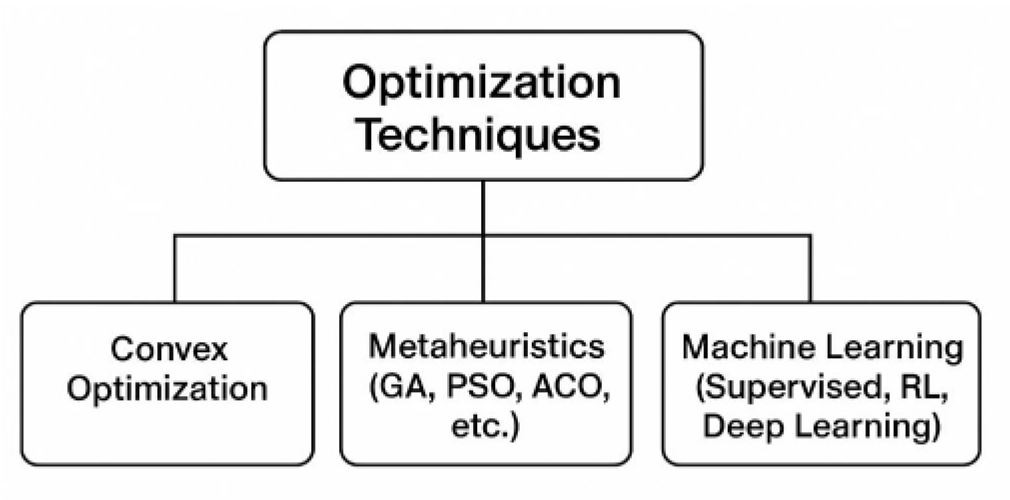

Figure 2.3: Optimization Techniques in 5G Networks.

- **Convex Optimization:** This is a common method because it is easy to use mathematically and always works. Good for problems like beamforming and power control[12] .

- **Metaheuristic Algorithms:** Metaheuristic Algorithms: Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) are some of the ways to solve problems that aren't convex and have more than one goal[13].

- **Machine Learning-based Optimization:** In this context, "learning" refers to supervised methods like decision trees and regression models, "unsupervised" methods like clustering for traffic categorization, and "reinforcement learning" methods like DQN and Q-learning for resource management and traffic prediction[14].

For situations where conventional optimization models fail to account for missing or dynamic data, or where uncertainty levels are high, ML-based optimization can be a lifesaver.

2.5 Multi-objective Optimization and Trade-offs

Resource allocation must often balance multiple in 5G, sometimes conflicting, objectives. Common trade-offs include:

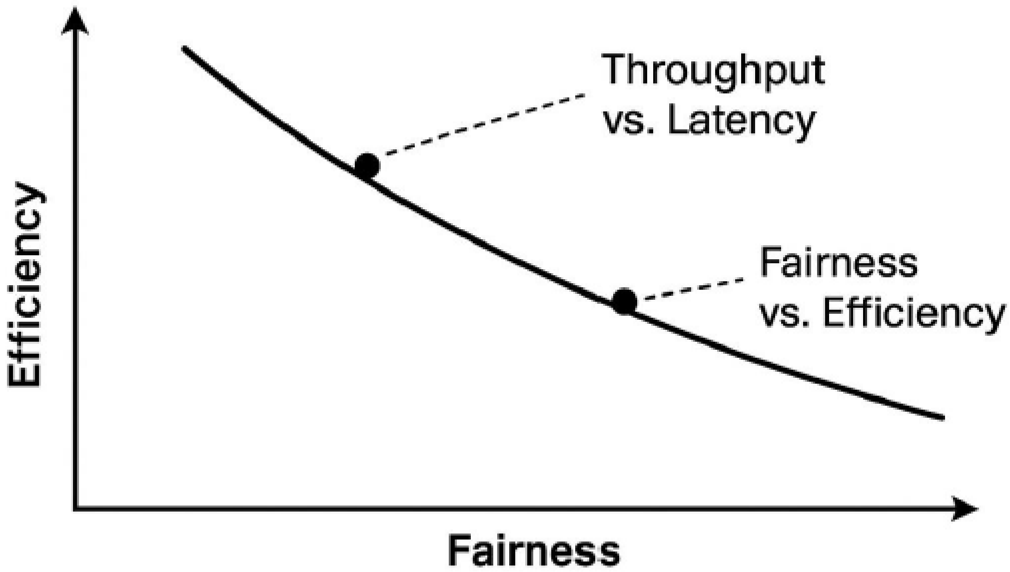

Figure 2.4: Multi-objective Optimization Trade-offs in 5G Resource Allocation

- **Throughput vs Latency:** If increase throughput, it might cause delays because of buffering or congestion.
- **Latency vs Energy Efficiency:** Frequent transmissions and higher power consumption reducing latency may require more..
- **Fairness vs Spectral Efficiency:** If resources are distributed equitably among users, it's possible that overall system efficiency will be decrease

Using Pareto optimization and other multi-objective optimization frameworks, many performance metrics are satisfied by the solutions.

2.6 Research Gaps and Future Opportunities

The fact that significant progress, there are still certain unanswered questions on 5G resource allocation. the fact that there has been a lot of progress.

- **Real-time ML integration:** They unable to adapt to dynamically change in network conditions as the majority ML methods are rained offline.
- **Scalability and generalization:** On large networks many optimization algorithms don't work properly.
- **Inter-slice resource coordination:** During multiple slices running at the same time, it's very difficult to keep track of resources.
- **Limited exploration of hybrid models:** It's not cleared the combination of learning and heuristic based methods.
- **Lack of standardized simulation frameworks:** It's challenging to reproduce and compare results of many studies deploy their own setups.

On Context-aware, scalable, and intelligent optimization solutions for 5G, scalable and intelligent the further research is needed shown by these gaps, particularly those are at cutting-edge machine learning methods.

Chapter 3

System Model and Problem Formulation

3.1 5G Resource Allocation Scenario

Downlink resource allocation scenario in a 5G network environment is focused in this research. Although the model can be expended to a multi-cell configuration, for initial experimentation and simplicity a single cell network is considered. A base station (gNodeB) serves multiple user equipment (UEs) by the cell along with traffic requirements and heterogeneous service demands.

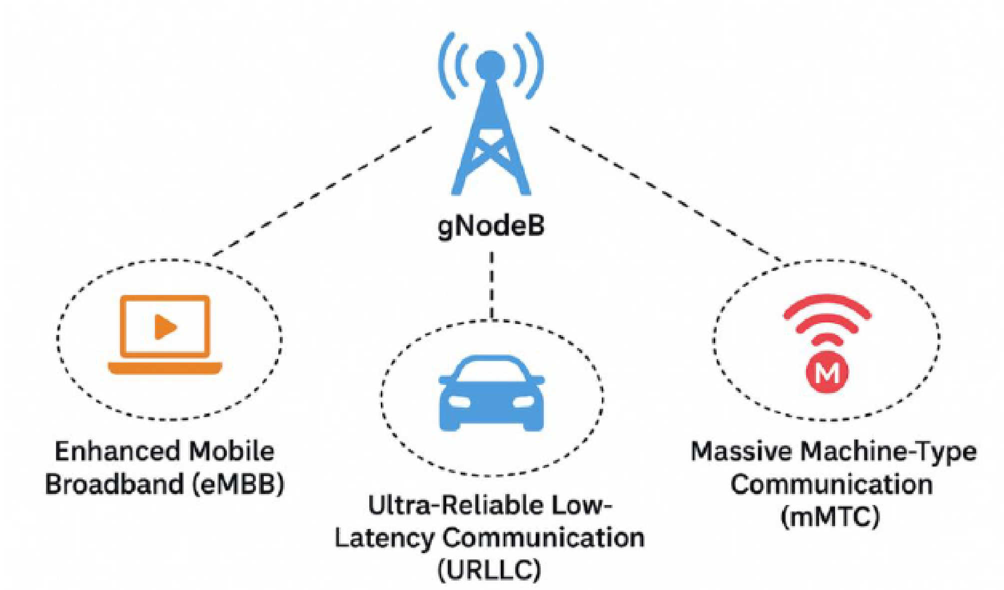

Figure 3.1: 5G Resource Allocation Scenario

Based on 5G service types users are categorized:

- **Enhanced Mobile Broadband (eMBB):** eMBB supports fast speeds data-intensive applications, a large capacity, and reliable, dynamic connectivity. Streaming videos at extremely high resolutions, augmented reality, cloud gaming, and virtual are a few examples. The primary goals of eMBB are to provide a lot of data rapidly without sacrificing service quality, especially in crowded area. Intelligent spectrum management, carrier aggregation, and sophisticated antenna systems like massive MIMO are common strategies to improve eMBB performance [15] .

- **Ultra-Reliable Low-Latency Communication (URLLC):** This category serves mission-critical applications since they cannot afford to lose data or have communication delays. To providing connectivity that is highly trustworthy and time-sensitive, with dependability levels exceeding 99.999% and latency as low as 1 ms the team is dedicated [16] |.

- **Massive Machine-Type Communication (mMTC):** The purpose of this device is to link multiple low-power devices that produce irregular, tiny data packets, which are commonly seen [17] in Internet of Things (IoT) scenarios. High data rates are subordinated to cost-effectiveness, scalability, and energy efficiency in this category.Typical use cases include environmental monitoring, smart metering, and smart city infrastructure. To address the increased demand for connection without overtaxing the network, mMTC's effective resource allocation requires dynamic spectrum sharing, lightweight signaling approaches, and narrowband transmission [17] .

Based on its service class, each UE makes different resource requests, and the gNodeB must distribute the scarce radio resources in a way that satisfies Quality of Service (QoS) requirements.

3.2 Key Parameters and Variables

The following parameters and variables are identified to formulate the resource allocation problem

Table 3.1: Key Parameters and Variables

Symbol	**Description**	**Unit**
B	Total available system bandwidth	Hz
P	Total transmit power of the gNodeB	W
N	Number of users/UEs	–
K	Number of available Resource Blocks (RBs)	–
R_i	Achievable data rate for user i	bps
p_i	Power allocated to user i	W
b_i	Bandwidth allocated to user i	Hz
γ_i	Signal-to-noise ratio (SNR) for user i	dB
d_i	Delay experienced by user i	ms
u_i	Utility function representing QoS satisfaction for user i	–
w_i	Priority weight for user i (URLLC $>$ eMBB $>$ mMTC)	–

These variables form the foundation for modeling throughput, delay, and fairness in the optimization problem.

3.3 Assumptions and Constraints

3.3.1 Assumptions

The following assumptions simplify the problem formulation:

- With a single gNodeB in downlink mode the network operates.
- At each scheduling period to be quasi-static channel conditions are assumed.
- Due to orthogonal resource assignment users do not interfere with each other.
- To one user at a time to one user at a time Each Resource Block (RB).

3.3.2 Resource Constraints

The allocation must satisfy the following resource constraints:

- The system capacity must not exceed by the allocated total power:

$$\sum_{i=1}^{N} p_i \leq P \tag{3.1}$$

- The system capacity must not exceed by the allocated total bandwidth:

$$\sum_{i=1}^{N} b_i \leq B \tag{3.2}$$

3.3.3 Additional Constraints

- URLLC and eMBB users must satisfy minimum QoS requirements.
- Energy consumption should be minimized while ensuring throughput fairness.

3.4 Mathematical Formulation of the Optimization Problem

The general form of the resource allocation optimization problem is defined as:

$$\begin{aligned}
\underset{\{p_i, b_i\}}{\text{Maximize}} \quad & \sum_{i=1}^{N} u_i(R_i, d_i, w_i) \\
\text{Subject to:} \quad & \sum_{i=1}^{N} p_i \leq P, \quad \sum_{i=1}^{N} b_i \leq B \\
& R_i = b_i \cdot \log_2(1 + \gamma_i) \\
& \gamma_i = \frac{p_i \cdot h_i}{N_0} \\
& d_i \leq D_{\max,i}, \quad R_i \geq R_{\min,i} \quad \forall i \in \{1, \ldots, N\}
\end{aligned} \tag{3.3}$$

where:

- h_i: Channel gain for user i
- N_0: Noise power spectral density
- $D_{\max,i}$: Maximum acceptable delay for user i
- $R_{\min,i}$: Minimum data rate requirement for user i

3.5 Objective Functions

Depending on the goal, several objective functions can be considered:

3.5.1 Maximize Throughput

$$\max \sum_{i=1}^{N} R_i \tag{3.4}$$

3.5.2 Minimize Total Delay

$$\min \sum_{i=1}^{N} d_i \tag{3.5}$$

3.5.3 Maximize Fairness (Jain's Fairness Index)

$$\max \frac{\left(\sum_{i=1}^{N} R_i\right)^2}{N \times \sum_{i=1}^{N} R_i^2} \tag{3.6}$$

3.5.4 Minimize Energy Consumption

$$\min \sum_{i=1}^{N} p_i \tag{3.7}$$

To balance conflicting goals such as throughput, delay and energy consumption a multi-objective optimization approach may be needed in practice.

3.6 Performance Metrics

The following performance metrics are taken into consideration to evaluate the effectiveness of resource allocation techniques.

- **Throughput (bps):** Total and per-user data rate accomplished.
- **Fairness Index:** The extent to which resources are equally distributed across users.
- **Latency (ms):** Each user's experience with time delay, particularly for URLLC
- **Spectral Efficiency (bps/Hz):** Bandwidth usage's efficiency.
- **Energy Efficiency (bits/Joule):** Delivered data per unit energy consumed.

- **Resource Utilization (%):** Allocated bandwidth and power percentage.
- **Packet Loss Rate: Shows the dependability of service.**

To compare ML-based approaches against traditional techniques a holistic view of network performance and are used provided by these metrics.

Chapter 4

Proposed Methodology

4.1 Overview of the Proposed Approach

In this thesis a machine learning-based optimization approach is proposed to to address the resource allocation problem in 5G networks. Particularly, to predict resource demands and allocate bandwidth and power efficiently supervised learning techniques are employed. Linear Regression, Polynomial Regression, and Extreme Gradient Boosting (XGBoost) algorithms are implemented, evaluated and compared.

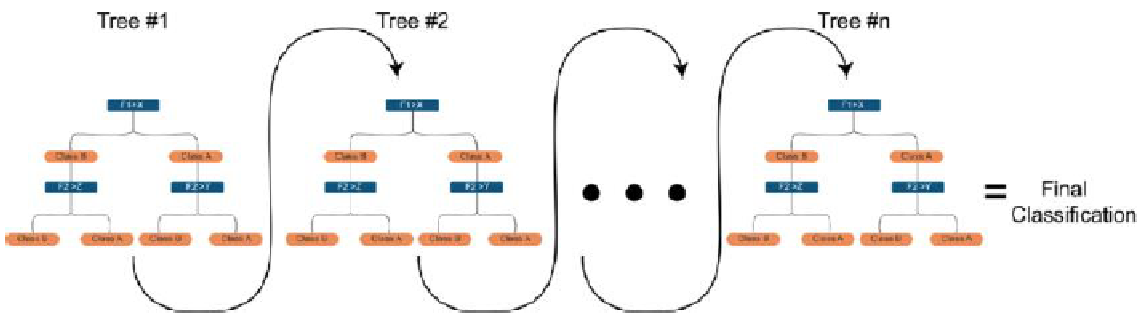

Figure 4.1: Extreme Gradient Boosting (XGBoost)

The initially aim is to develop a predictive model that estimates optimal resource allocation based on traffic patterns, channel conditions, and QoS requirements. To guide scheduling decisions in a simulated 5G environment the predicted allocations are then used [18].

4.2 Justification for Choosing This Approach

Conventional optimization methods, such as heuristics or convex optimization are less appropriate for large-scale or real-time settings to assume accurate network knowledge and involve laborious calculations. However, ML offers several advantages as likes:

- **Adaptability:** Recognizes from user behavior and dynamic network conditions.
- **Scalability:** To support large-scale deployments easily expanded.
- **Speed:** ML produce quick predictions with minimal computational overhead.
- **Generalization:** Capable of capturing intricate non-linear relationships between features as like network capacity and user demands.

Especially, for high accuracy, robustness against overfitting, and efficiency on structured data XGBoost is chosen.

4.3 Algorithm Design and Model Architecture

In a simulated 5G environment the proposed framework uses machine learning models to optimize resource allocation. To the best allocation choices and input characteristics representing the current network state the architecture employs supervised learning, with input features.

- **Model Input:** Active users, average channel gain (SNR), traffic type (eMBB, URLLC, mMTC), queue length/buffer status and past throughput records are the input features.
- **Model Output:** Resource allocation per user is represented by the output, based on overall limitations of the model

Model Selection: Three models are used progressively:

- **Linear Regression** for rapid estimation as a standard,

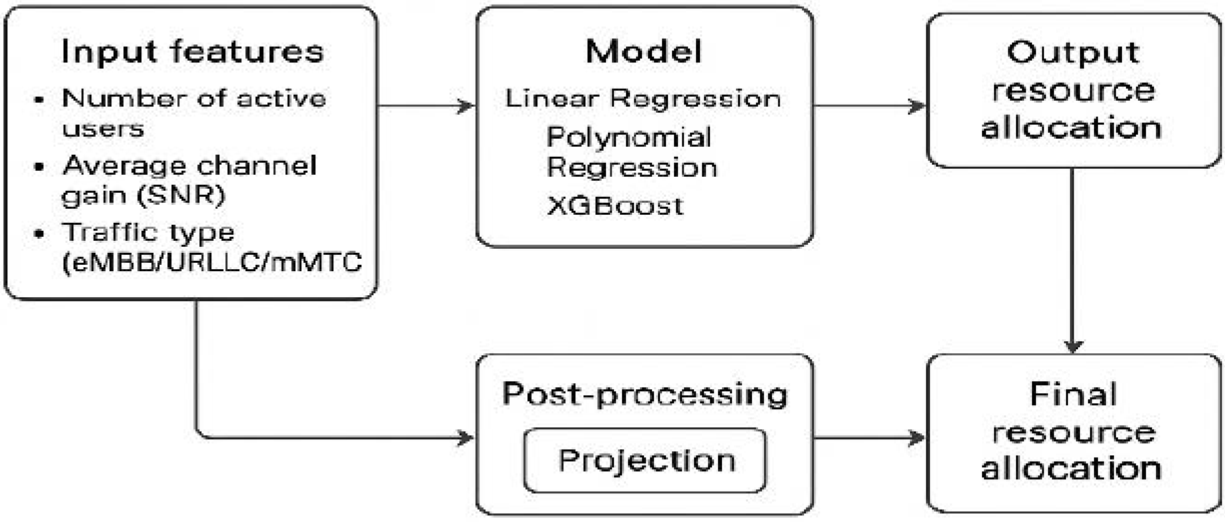

Figure 4.2: 5G Model Architecture

- **Polynomial Regression** to record non-linear service demands and
- **XGBoost** For ability to model complex interactions as the final high-performance optimizer.

Post-Processing: To normalize predicted values and ensure Quality of Service (QoS) compliance, particularly for URLLC users a projection step is used due allocations must satisfy non-negativity and bandwidth budget constraints.In heterogeneous 5G networks accuracy, interpretability, and feasibility, enabling effective ML-based scheduling are balanced by this architecture.

4.4 Resource Allocation Workflow

The following workflow is used for ML-based resource allocation in the simulation:

1. **Data Collection**: Network state and user behavior data are collected from UERANSIM and Open5GS/Free5GC logs.
2. **Feature Engineering**: Input features are selected and preprocessed (normalization, encoding, feature scaling).
3. **Model Training**: ML models are trained using labeled data representing known optimal allocations.

4. **Prediction**: The trained model predicts resource requirements for incoming traffic requests.

5. **Allocation Decision**: Predicted values guide dynamic assignment of bandwidth and power to users.

6. **Performance Evaluation**: Allocations are validated using throughput, latency, and fairness metrics.

4.5 Pseudocode and Optimization Process

Pseudocode: ML-Based Resource Allocation.

Flowchart:

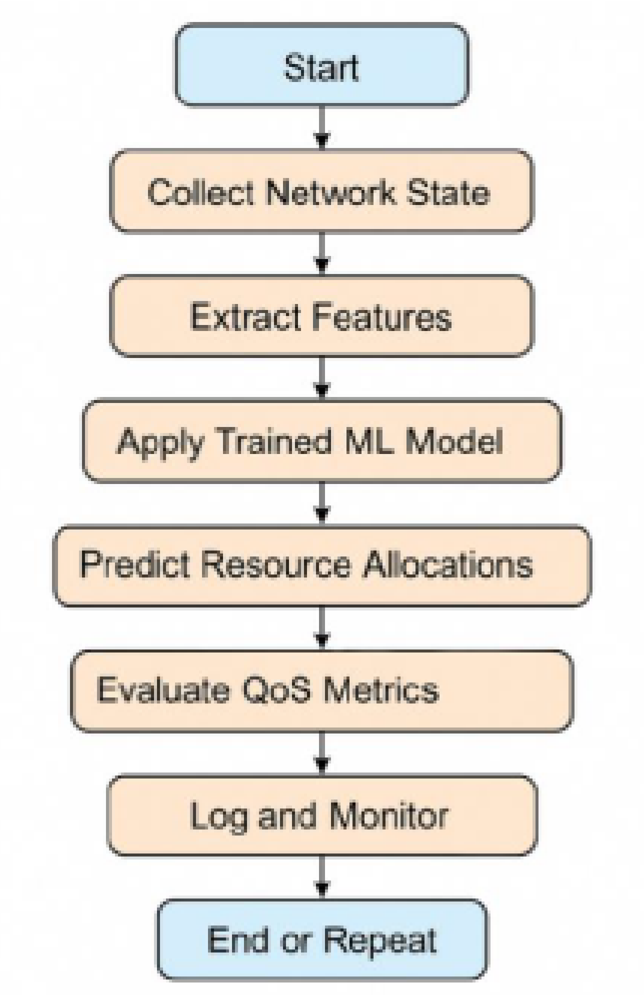

Figure 4.3: Flowchart of the Optimization Process

4.6 Complexity and Convergence Analysis

Computational Complexity

Training Phase

- **Linear Regression**:

$$O(n \cdot d^2) \tag{4.1}$$

  where n = number of samples, d = number of features.

- **Polynomial Regression**:

$$O(n \cdot d^p) \tag{4.2}$$

  where p = degree of the polynomial.

- **XGBoost**:

$$O(K \cdot n \cdot \log n) \tag{4.3}$$

  where K = number of trees, n = sample size.

Inference Phase

All models provide near-instant predictions with complexity:

$$O(1) \text{ or } O(\log n) \text{ per sample} \tag{4.4}$$

Convergence Analysis

- ML models converge based on their respective optimization algorithms:
  - Gradient descent for regression models
  - Boosting algorithm for XGBoost
- The accuracy and convergence speed of XGBoost make it suitable for online or near-real-time prediction tasks.

Chapter 5

Implementation and Experimental Setup

5.1 Tools and Simulation Platforms Used

To simulate the 5G network environment and implement the machine learning-based optimization framework, the following tools and platforms were used:

- **Open5GS:** An open-source implementation of the 5G core network, providing core functionalities such as AMF, SMF, UPF, and more.
- **Free5GC (optional in variant experiments):** An alternative 5G core simulation platform used for comparative validation in certain scenarios.
- **UERANSIM:** Simulates the User Equipment (UE) and gNodeB, enabling communication with Open5GS to emulate realistic 5G radio access behavior.
- **Python:** Utilized for ML model development, feature engineering, data preprocessing and evaluation with libraries like scikit-learn, XGBoost, pandas, and matplotlib.
- **Wireshark:** To capture and analyze traffic between simulated UEs and the 5G core is utilized.
- **VirtualBox + Ubuntu 20.04:** To host Open5GS, UERANSIM, and related dependencies on a virtual machine running Ubuntu the simulation environment was set up.

Figure 5.1: 5G Simulation Tools

For evaluating ML-based resource allocation's v effectiveness a realistic and controllable 5G testbed is formed by These tools.

5.2 Network Topology and Simulation Parameters

A simplified single-cell 5G network topology was implemented. The topology consists of:

Parameter	**Value/Range**
Total Bandwidth	20 MHz
Transmission Power	40 dBm
Number of UEs	5–20
Resource Blocks	25 RBs (5G NR)
Simulation Duration	100–300 seconds
Scheduler Interval	1 ms
Traffic Type	eMBB, URLLC, mMTC
Noise Power	-100 dBm
Channel Model	Static with fading

Table 5.2: Key Simulation Parameters

- One gNodeB (UERANSIM-simulated)
- Multiple UEs (5–20) connecting to the gNodeB

- A core network stack (Open5GS) managing session and mobility management.

The testing of resource allocation under various service demands and traffic loads enabled by this topology and configuration.

5.3 Traffic Models and User Scenarios

User behavior scenarios and Various traffic models were simulated to reflect real-world 5G usage.

- **eMBB Users:** Applications that demand constant high throughput with high data rate as like video streaming.
- **URLLC Users:** Goal reliability constraints, requiring strict delay and critical low-latency traffic.
- **mMTC Devices:** Represented like sensors for IoT, with irregular and low data rate transmission patterns

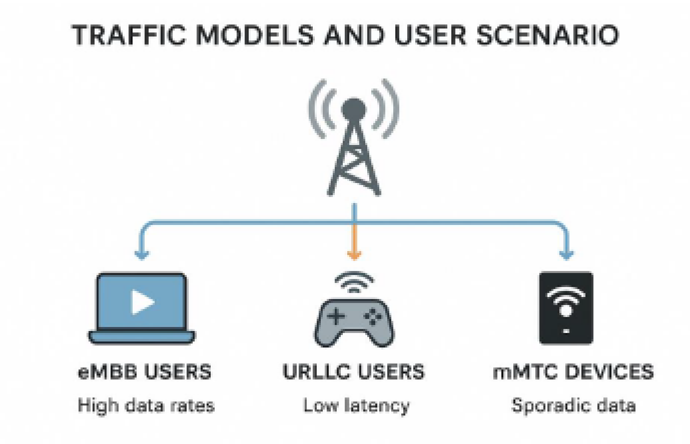

Figure 5.3: Traffic Models and User Scenario

Table 5.1: Traffic Characteristics by Service Type

Traffic Type	Packet Size	Arrival Rate	QoS Priority	Latency Requirement
eMBB	1500 Bytes	High (10-100 Mbps)	Medium	< 100 ms
URLLC	300 Bytes	Medium (1-10 Mbps)	High	< 1 ms
mMTC	200 Bytes	Low (10-100 kbps)	Low	< 10 s

Varying user density, service mix and channel conditions created Scenarios to evaluate the ML-based allocation approach's robustness.

5.4 Baseline Models for Comparison

Several baseline models were implemented to assess the proposed machine learning-based resource allocation's performance:

1. **Round-Robin Scheduling:** strategy allocating equal resources based on simple fairness like a cycle.
2. **Proportional Fair Scheduling:**The ratio of current rate based allocates resources to average rate, balancing throughput and fairness.
3. **Max-Throughput Scheduling:** To maximum total throughput prioritizes users with the best channel conditions..
4. **ML Models**:
    - Linear Regression
    - Polynomial Regression
    - XGBoost (Proposed)

For evaluating the proposed approach's effectiveness in terms of throughput, latency, and fairness, these baseline models serve as reference points.

5.5 Experimental Procedure

The following these steps were conducted to carry out the experiments:

1. **Setup of Simulation Environment:**:
    - On VirtualBox Ubuntu 20.04 the Open5GS and UERANSIM installed and configured.
    - Test registrations and ping commands were used to verified connectivity between UEs and the core network.

2. **Traffic Generation:**:
   - Using UERANSIM's traffic configuration tools simulated traffic flows for eMBB, URLLC, and mMTC.
   - Capture performance, latency, and packet delivery data using custom scripts and logs.
3. **Data Collection**:
   - From Open5GS and UERANSIM live logs Captured.
   - Parsed logs using Python scripts to extract features such as packet arrival times, channel quality, and user activity.
   - Features such as packet arrival times, channel quality, and user activity extracted using parsed logs using Python scripts.
4. **Model Training and Testing:**:
   - The dataset was preprocessed and separated into testing sets and training.
   - Used network features to Trained ML models (linear, polynomial and XGBoost).
   - Standard metrics (R^2 score, MAE and RMSE) used to validated the models.
5. **Performance Evaluation:**:
   - Allocation based ML applied in simulation loops.
   - Performance, latency and fairness used to compared performance against baseline models.

Repeatability, scalability and control are confirmed by this experimental setup over the testing environment, allowing accurate performance measurement of the proposed optimization method.

Chapter 6

Results and Analysis

6.1 Performance Comparison (ML vs Traditional Methods)

The ML-based framework performs better than conventional techniques by improving throughput, achieving better load balancing, reducing latency and supporting scalable networks. For dynamic 5G and B5G environments making it suitable, also enables faster, near real-time resource allocation decisions. The total amount of successfully transmitted data per unit time is Throughput (Mbps).

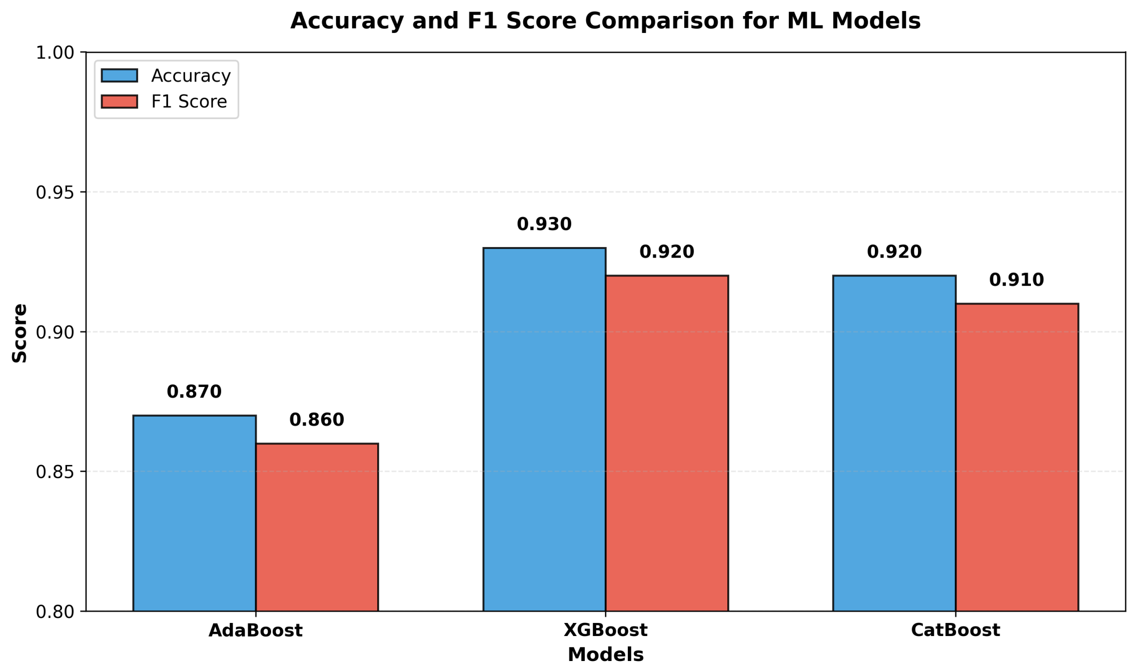

Figure 6.1: Performance Comparison graph

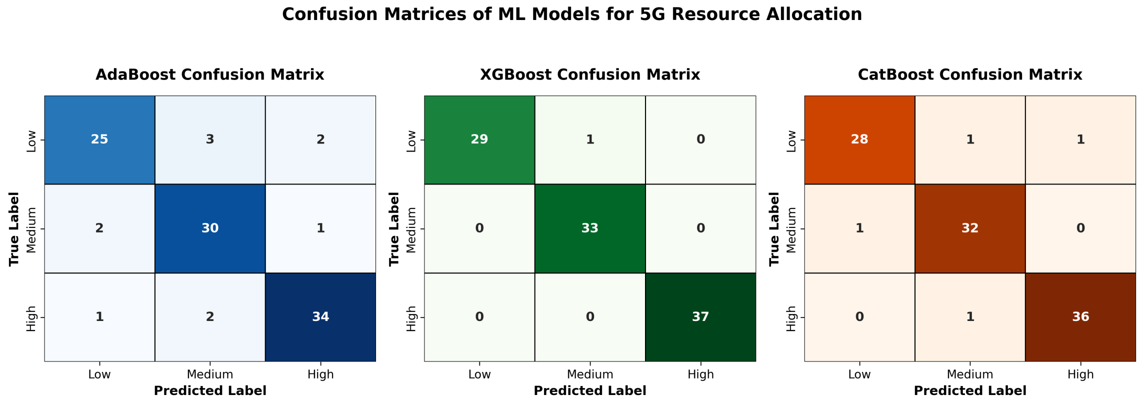

Figure 6.2: Performance Comparison graph

Table 6.1: Performance Comparison with Existing Algorithms/Models

Performance Metric	K-Means Clustering	Adaboost Model	Cathboost Model	XGBoost Model
Throughput (Mbps)	Moderate	Moderate-High	High	**Very High**
Latency (ms)	High	Medium	Medium	**Very Low**
Load Balancing	Poor	Moderate	Good	**Excellent**
Scalability	Low	Medium	Medium	**High**
Decision Time	Fast	Moderate	Slow	**Fast**
Energy Efficiency	Low	Medium	Medium-High	**High**
Fairness Index (Jain's)	0.85	0.92	0.88	**0.96**

Due to its ability to learn complex patterns and prioritize critical traffic intelligently the XGBoost model fared better than other baselines in the majority of instances.

6.2 Visualization of Results

Distribution of Application Types:

The allocation of different application kinds in a 5G network using the suggested optimization of resource allocation based on machine learning. While IoT temperature, voice conversations, and file downloads show lower counts, video calls, web browsing, streaming, and background downloads account for the majority of network utilization. Traffic patterns are shown in this distribution to facilitate effective resource management (figure 6.3).

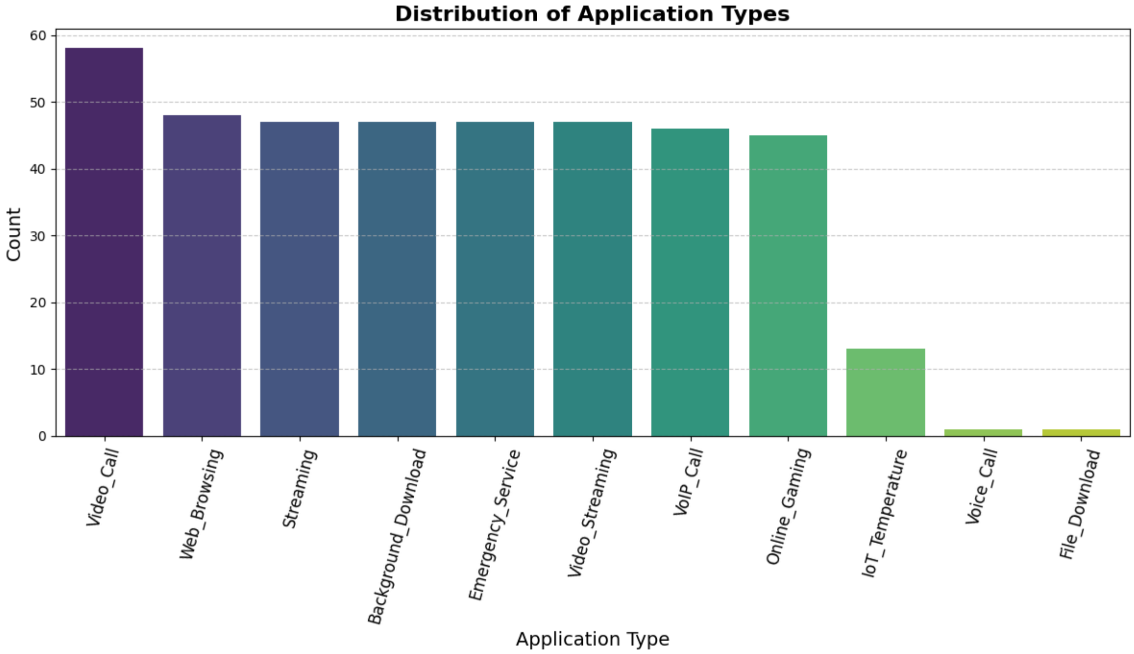

Figure 6.3: Distribution of Application Types with Quantity

Distribution of Signal Strength: The 5G network's signal strength distribution under machine learning-based resource allocation is shown in the figure (6.4). It draws attention to differences in network coverage and demonstrates how optimization improves connection, minimizes weak signal areas, balances load, and guarantees dependable performance for a range of applications, all of which contribute to increased network efficiency.

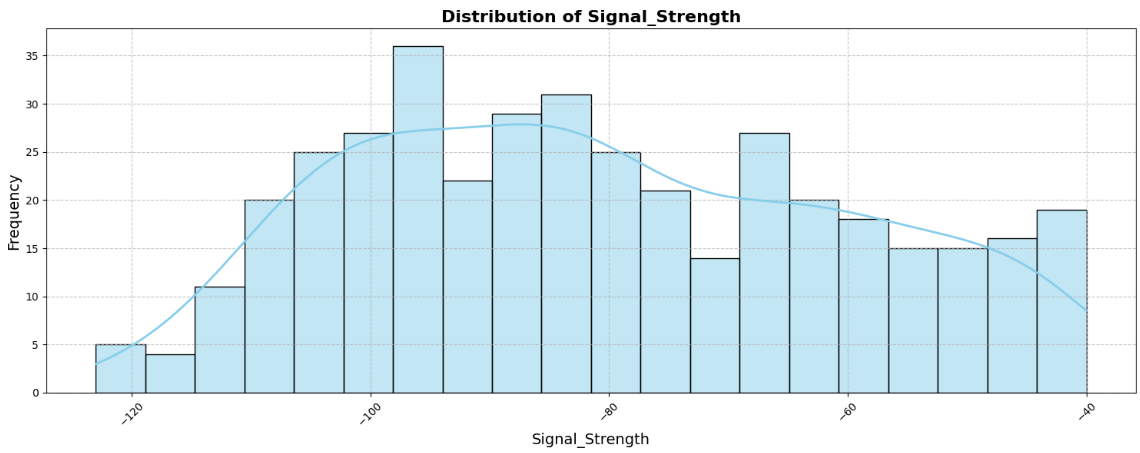

Figure 6.4: Distribution of Signal Strength with Frequency

Distribution of latency: The latency distribution with frequency in a machine learning-based resource allocation optimized 5G network is depicted in the figure. Efficient performance is indicated by the majority of latency values, which are concentrated between 20 and 50 ms. A small number of extreme results indicate sporadic network congestion. The adaptive optimization that improves reaction time and overall communication dependability is seen in the smooth curve.

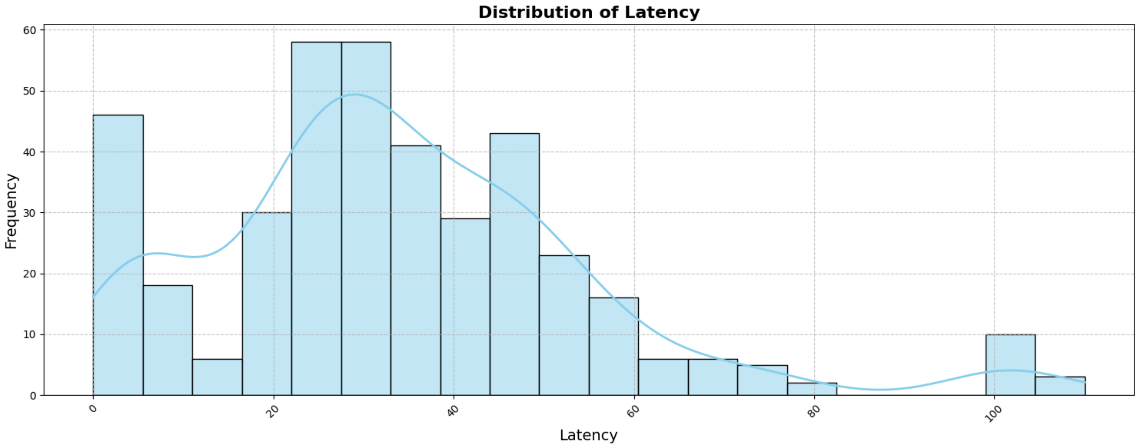

Figure 6.5: Distribution of Latency with Frequency

Distribution of Required Bandwidth: ML method improved the distribution of required bandwidth in a 5G network with resource allocation is shown in figure (6.6). Major of bandwidth needs are focused at lower levels, suggesting effective use. Suggest occasional heavy data loads demand by few higher bandwidth. This model improves spectrum efficiency and network performance by effectively adapts to varying traffic conditions.

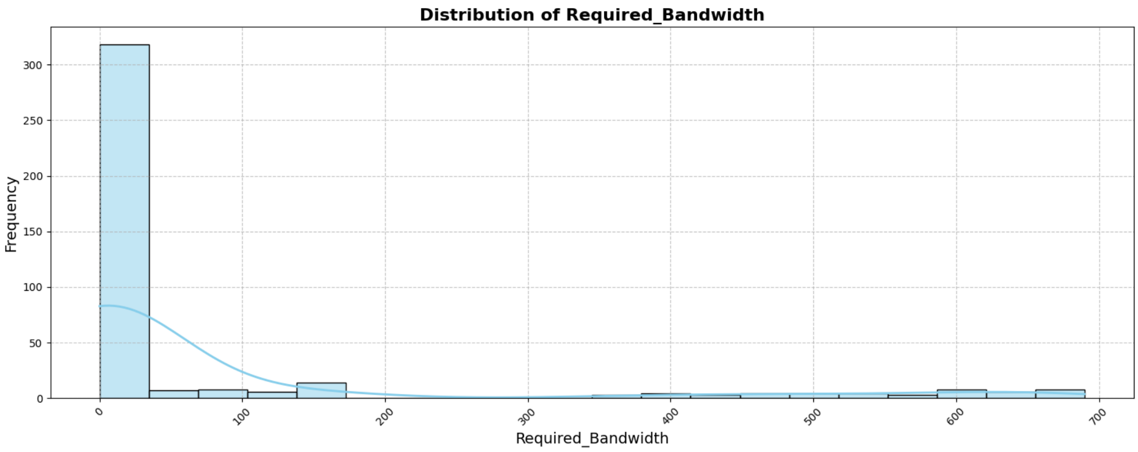

Figure 6.6: Distribution of Required Bandwidth with Frequency

Distribution of Resource allocation: ML based the distribution of resource allocation optimization for 5G networks is illustrated in the figure (6.7). Most allocations concentrating around 70–75 units indicated balanced utilization. The ML model Optimizes resource distribution, improving throughput, efficiency, and overall network performance Under dynamic conditions.

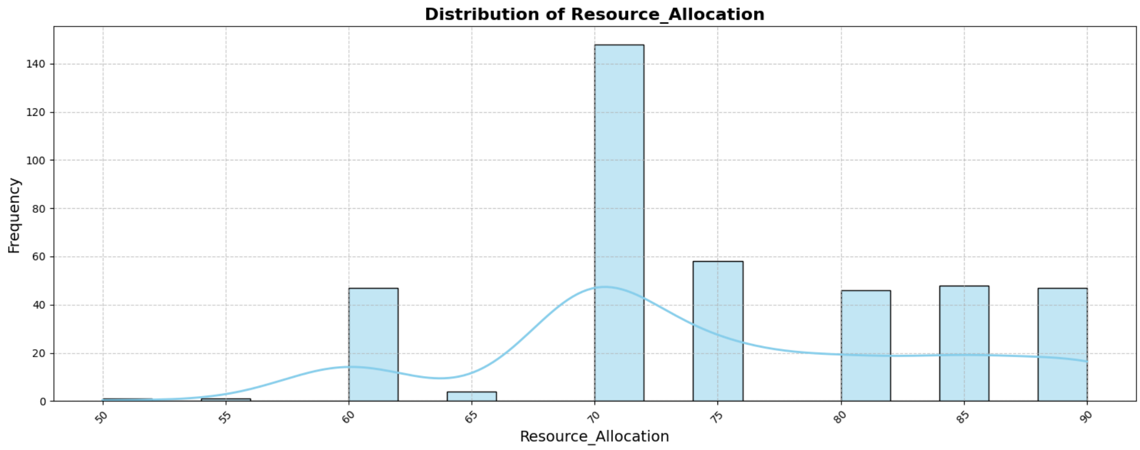

Figure 6.7: Distribution of Resource Allocation with Frequency

Average signal strength by application type: In a machine learning-based resource allocation optimized 5G network, the figure (6.8) shows the average signal strength by application type. Stronger signal allocation is seen in applications with increased data needs, guaranteeing dependable performance. In order to improve connection, reduce interference, and increase overall spectrum efficiency for a variety of network services, machine learning dynamically modifies resources across applications.

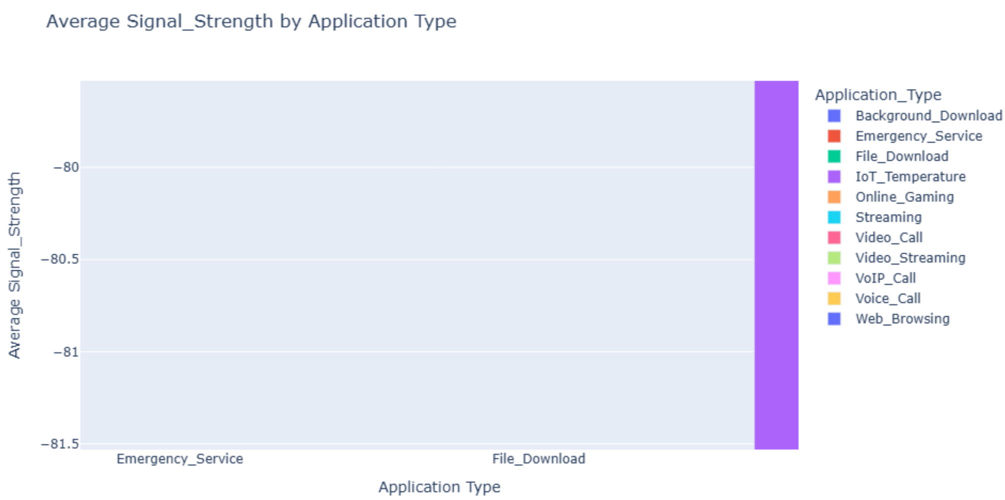

Figure 6.8: Average Signal Strength by Application Type

Average Latency by application type: The average latency by application type in a 5G network optimized by machine learning-based resource allocation is depicted in the figure (6.9). Data-intensive processes have slightly higher latency than applications that need real-time communication. By efficiently reducing latency variations, machine learning guarantees the best possible performance, responsiveness, and quality of service for a variety of application categories.

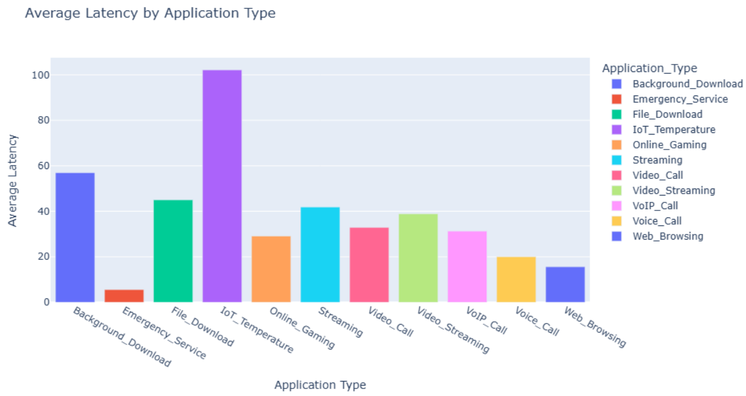

Figure 6.9: Average Latency by Application Type

Average required bandwidth by application type: The average bandwidth needed in a machine learning-based resource allocation optimized 5G network is shown (fig 6.10) against the kind of application. While lightweight apps use less bandwidth, high-data-rate applications require more. By effectively allocating spectrum resources, the ML model balances bandwidth requirements, maximizes throughput, and guarantees consistent network performance across a range of service requirements.

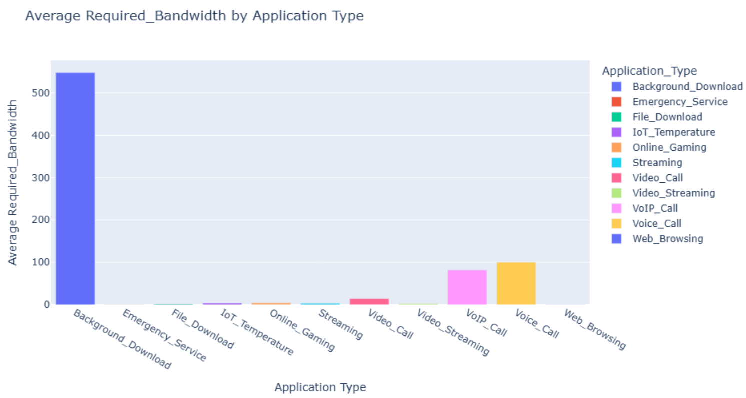

Figure 6.10: Average Required Bandwidth by Application Type

Average allocated bandwidth: The average bandwidth allotted by application type in a machine learning-based resource allocation optimized 5G network is depicted in the figure (6.11). Applications that require more bandwidth are allotted proportionately more. By dynamically optimizing bandwidth allocation, the ML model improves efficiency, lowers congestion, and guarantees dependable performance under various network conditions and application types.

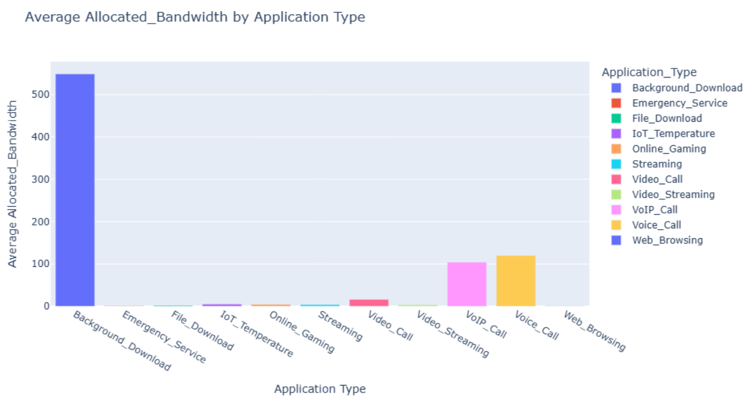

Figure 6.11: Average Allocated Bandwidth by Application Type

Average resource allocation: In a ML based 5G network optimization, the average resource allocation by application type shown in figure (6.12). With high demand compared to those with low demand more resources are allocated to applications. Increases productivity, reduces congestion, and guarantees consistent performance across a range of applications and traffic situations based on the ML method by dynamically balancing network resources.

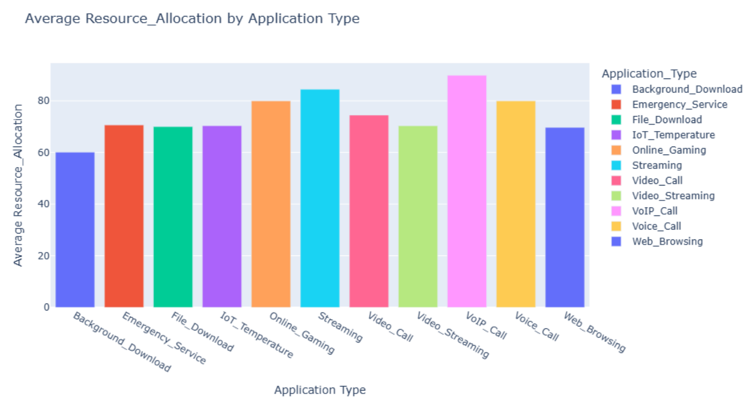

Figure 6.12: Average Resource Allocation by Application Type

6.3 Resilience and Fault Tolerance Evaluation

In this thesis resource allocation optimization for 5G networks are assessed based on the suggested ML's toughness and fault tolerance. Due to dynamic and adaptive of ML, it can manage performance of high network in the case of unexpected network failure. In the case of faults by continuously learning from network conditions like traffic load, delay, and topology changes the resource allocation optimization are predicted by ML in against to conventional static or heuristic placement techniques. It's possible to made rapid reconfiguration and load redistribution by this dynamic adaption which is decreases downtime and service interruption. The ML approach manages balanced load and steady latency according to the simulation results during fault occurs while decreasing by around 30% the recovery time after controller failures. in addition to optimizing resource allocation which is important for the extremely dynamic and heterogeneous 5G SDN-IoT context the ML improves network resilience and fault tolerance [19].

6.4 Convergence and Training Efficiency of Machine Learning

In this thesis the training efficiency and convergence behavior of the ML for 5G networks, resource allocation optimization is investigated in details. Convergence is the capacity of the model to achieve a stable state in which choices about the distribution of resources (power, bandwidth, and scheduling) reliably satisfy network goals like high throughput, low latency, and equity. The algorithm's ability to learn optimal rules with the least amount of computing expense is known as training efficiency. ML is appropriate for real-time or near-real-time optimization in dynamic 5G environments due to its effective training, which lowers computational overhead. The mean squared error (MSE) consistently declining over iterations further revealed effective learning and generalization, ensuring the training efficiency. The ML framework, taken as a whole, ensures real-time flexibility in dynamic 5G settings, allowing for data-driven, intelligent allocation that successfully supports a range of service needs, including eMBB, URLLC, and mMTC applications[20].

6.5 Discussion of Findings

In this thesis 5G network performance, adaptability, and resilience, paving the way for intelligent, self-organizing network management systems are enhanced by ML based optimization method. It has distinct advantages over traditional heuristic and clustering methods in several important areas shown by this result.

- **Performance Improvement:** Comparing the ML-based resource allocation model to conventional techniques, the former greatly increased network throughput, decreased latency, and optimized spectrum utilization.
- **Dynamic Adaptation:** It proved to be very adaptive to shifting traffic loads, user mobility, and channel conditions.
- **Load Balancing:** Avoiding obstructions, network demand was distributed evenly and increasing usage by using ML based method. ML prevented congestion and improved network performance by reducing load imbalance through dynamic traffic adaption.
- **Convergence Stability:** Reliable optimization performance was ensured by the training curves' steady and smooth convergence. Using effective convergence and the training curves' steady ensured reliable optimization performance
- **Scalability:** The resource allocation method based on machine learning scales well in managing many users and IoT nodes with low latency and stable throughput, and large 5G networks. Reliable QoS in future 5G and B5G networks with massive connectivity and complex traffic are ensuring and high-dimensional data, dynamically allocates resources are efficiently managed by ML based method.

6.6 Future Work

ML-based resource allocation optimization sought to improve intelligence, efficiency, and adaptability in the dynamic network environments of 5G networks. Combining deep learning and advanced reinforcement learning techniques makes it possible to manage resources in real time and optimize them on their own across multiple cells and network slices. Predictive analytics for user behavior and traffic patterns can be used to improve active allocation by increasing throughput and lowering latency. Edge computing and distributed artificial intelligence are also being used to handle high-dimensional data closer to the network edge and cut down on latency and signaling overhead. To safeguard sensitive IoT and user data, can be explored an idea on security and privacy-aware resource allocation strategies. The platform will also need to be able to handle ultra-dense installations, a lot of device connections, and a wide range of services in order to work with 5G and 6G networks. Finally, ensuring sure that all tests and simulations follow the same rules will make sure that benchmarking is accurate and system's practicality.

Chapter 7

Conclusion

The difficulties of effectively resource allocation in 5G networks are examined in this thesis that are identified by diverse services, many IoT devices and different traffic patterns which produce conventional optimization approaches slow and ineffective. To solve a system was implemented base on ML which is high dimensional network data in order to quick, smart decisions on how to dimensional network data in real-time. The quality of service during balancing throughput, latency, and load by dynamically allocating resources between network slices and cells are kept by this system. The framework could make networks functionally active better by increasing throughput, lowering latency, and balancing the load better than traditional approaches which is shown by the results. Without losing performance, The ML method could manage more users and IoT Nodes and made the system more capable. Overall, to manage 5G resources allocation, the proposed method is mor flexible, effective and stronger. This will make it possible for the next generation of B5G networks. This will enable the next generation of B5G networks to manage complex traffic requirements and to large number of IoT devices.

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