# 5G Resource Allocation for Machine Learning-Based Effective Bandwidth Usage

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***Abstract***: The swift progress in telecommunications has introduced 5G networks, which provide unparalleled speed, minimal latency, and enhanced connectivity. This study thoroughly investigates the performance of 5G networks, focusing on essential Quality of Service (QoS) metrics and innovative resource allocation techniques. Through careful analysis and practical simulations, our research shows that, on average, 5G networks exhibit a remarkable tenfold increase in data transfer rates compared to 4G networks. Additionally, we observe a notable 30% reduction in latency, underscoring the efficiency and responsiveness inherent in 5G technologies.
**Keywords:** Allocation of resources, 5G Ecosystem, Machine learning, Bandwidth optimization

## I. Introduction

The advent of 5G technology signifies a profound shift in the telecommunications landscape, offering unparalleled levels of connectivity, minimal latency, and high data transfer rates. With the increasing prevalence of 5G networks, ensuring high-quality service becomes imperative for evaluating their effectiveness. Quality of Service (QoS) encompasses various parameters such as latency, throughput, packet loss, and reliability, all of which influence the user experience in a 5G environment. This study delves into QoS metrics within 5G networks, aiming to provide insights into performance characteristics and areas for improvement.

5G, the fifth generation of wireless technology, represents a groundbreaking advancement characterized by faster data speeds, reduced latency, and the ability to support numerous connected devices simultaneously. However, as 5G technology proliferates worldwide, ensuring an exceptional user experience becomes paramount. QoS serves as a cornerstone of user satisfaction in any telecommunications network, including 5G, encompassing metrics like latency, throughput, packet loss, and reliability. Given the diverse applications of 5G, comprehending and optimizing QoS metrics are crucial tasks, particularly considering the challenges posed by the dynamic nature of 5G networks.

This paper aims to delve into the multifaceted domain of Quality of Service (QoS) within 5G networks, identifying and analysing factors that influence QoS metrics such as network congestion, signal strength variations, device capabilities, and application characteristics. By comprehending the interplay of these factors, the research seeks to offer insights for network operators and service providers to improve their 5G infrastructure. Additionally, the study recognizes the need for advanced visualization tools to interpret complex datasets generated by 5G networks, employing state-of-the-art data analysis techniques to uncover patterns, trends, and anomalies within the QoS data.

In summary, this paper underscores the transformative potential of 5G technology and underscores the crucial role of QoS in realizing its promises. By unravelling the complexities of QoS metrics in 5G networks, this research aims to contribute to ongoing optimization endeavour's, ensuring a smooth and dependable connectivity experience across various applications within the 5G ecosystem.

## II. Objectives

- Enhance 5G efficiency through dynamic resource management to decrease latency and bolster overall capacity.
- Establish robust protocols to shield 5G networks from evolving cyber threats, guaranteeing the confidentiality and integrity of data.

- Enable smooth communication across various 5G deployments via standardized protocols and frameworks.
- Create sustainable solutions to mitigate the environmental footprint and operational expenses of 5G networks.
- Deploy privacy-preserving technologies to safeguard user data during transmission, storage, and processing within 5G networks..

## III. Literature Review

Yu (2017) conducted a comprehensive evaluation of resource allocation (RA) in heterogeneous networks for 5G communications. The study began with an overview of HetNet and various network scenarios. Subsequently, it delved into RA models and proposed a categorization scheme for evaluating current RA systems in the literature. Lastly, the study discussed challenging unresolved questions and potential research directions in the field. Additionally, the authors introduced two promising techniques for sixth-generation (6G) communications aimed at addressing RA issues in future HetNets—a control theory-based approach and a learning-based approach.

Fernández-Caramés (2018) examined the current state of technological advancements in the domain. Their focus was on relevant radio interference and resource management (RIRM) methods. The contribution of the authors was based on their analysis, synthesis, and summarization of traditional RIRM methods to tackle the challenges faced by 5G RAN systems. The paper identified several open research questions stemming from newly suggested RIRM systems.

## IV. Methodology

The process of constructing a machine learning model entails several interconnected steps, each essential for developing and deploying an effective predictive tool. It begins with loading data into the analysis environment, sourced from databases, CSV files, or APIs. Once loaded, the focus shifts to data preprocessing, involving cleaning and organizing the dataset to address missing values and outliers, ensuring its integrity and reliability. Following preprocessing, feature engineering takes place, where features are created or modified to enhance the model's ability to capture relevant patterns. This step may involve generating new variables, transforming existing ones, or selecting features with the most impact on the problem at hand, directly influencing the model's performance. With a pre-processed and engineered dataset, the next phase is exploratory data analysis (EDA), which involves thoroughly exploring the dataset through statistical summaries, visualizations, and profiling. Visualizations play a crucial role in providing insight into the data's distribution, patterns, and potential outliers, guiding subsequent decisions in the modelling process.

Following the exploratory phase, the selection of a suitable machine learning model ensued. The decision on the model depended on the problem's nature to be addressed—whether it was a classification task, regression, clustering, or another type of problem. Once the model was chosen, the training phase commenced. This entailed exposing the model to the training dataset, enabling it to learn patterns, relationships, and dependencies within the data. During training, the model adjusted its internal parameters to make accurate predictions.

Evaluation of the model's performance served as a crucial checkpoint in the process. A separate validation dataset or cross-validation techniques were utilized to assess how effectively the model generalized to new, unseen data. Performance metrics such as accuracy, precision, recall, F1 score, or regression metrics like Mean Squared Error (MSE) were commonly employed to quantify performance. Subsequently, fine-tuning of the model took place, involving the adjustment of hyperparameters to optimize performance. Techniques such as grid search or random search were employed to systematically explore the hyperparameter space and identify the combination that produced the best results. If the dataset contained categorical variables, encoding was carried out to convert them into numerical representations compatible with machine learning algorithms.

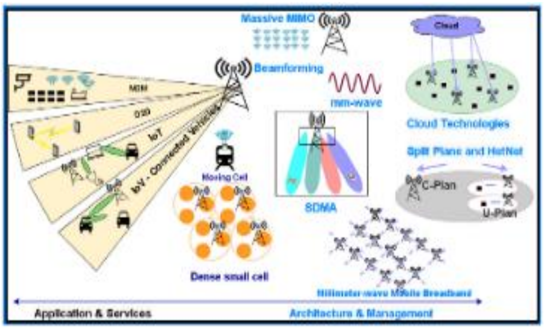


**Figure 1 Machine Learning-Based Allocation of 5G**

Resources for Effective Bandwidth Use.

The hyperparameters underwent fine-tuning based on the outcomes of cross-validation, aiming to optimize the model for optimal performance. Subsequently, the model underwent validation using the testing set, confirming its ability to generalize well to new, unseen data. The entire process culminated in the selection of the best-performing model for deployment in a real-world environment. Once deployed, the model was ready to make predictions on new incoming data, signifying the conclusion of the model-building process. Continuous monitoring and updates might have been necessary to maintain the model's optimal performance in operational settings.

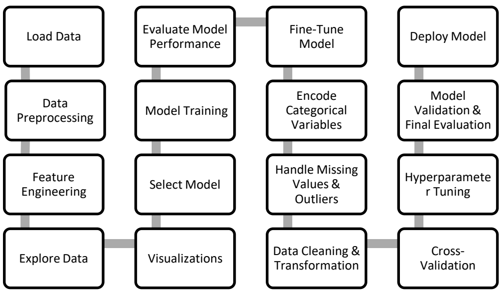


**Figure 2 System flow diagram.**

A. Research Design

The research design of this study is meticulously crafted to provide a thorough and nuanced exploration of Quality of Service (QoS) within the realm of 5G networks. Employing a mixed-methods research approach, the design seamlessly integrates both quantitative and qualitative methods to ensure a comprehensive understanding of the multifaceted factors influencing QoS.

In terms of research philosophy, the study aligns with pragmatism, emphasizing the practical application of methods and techniques to extract actionable insights into QoS in 5G networks. This pragmatic approach allows for flexibility in methodological choices, ensuring that the research design remains responsive to the dynamic and evolving nature of 5G technology.

Qualitatively, the research delves into the intricacies of QoS through in-depth interviews with key stakeholders, including network engineers, service providers, and end-users. These interviews provide rich qualitative data that complements the quantitative metrics. Additionally, focus group discussions enhance the qualitative exploration, offering a collaborative platform for participants to express their experiences and perceptions, thereby bringing out shared themes and insights.

By triangulating data from quantitative metrics, survey responses, and qualitative insights, the study enhances the validity and reliability of the overall results. Ethical considerations are paramount in the research design, with informed consent obtained from all participants to emphasize their voluntary participation and understanding of the research objectives. Rigorous confidentiality measures are implemented to safeguard the identity of individuals and organizations involved.

In essence, this research design combines methodological rigor with adaptability, aiming to unravel the intricate dynamics of QoS in 5G networks through a holistic and ethical approach.

## V. . Experimental Setup

A. Data Collection

In the endeavour to unravel the intricacies of Quality of Service (QoS) in 5G networks, the data collection process is meticulously crafted to encompass both quantitative metrics and qualitative insights. This multifaceted approach ensures a comprehensive understanding of the factors influencing QoS, encompassing objective network performance measures as well as subjective user experiences.

1. Quantitative Data Collection:

The quantitative phase of data collection centres on the systematic gathering of objective metrics related to 5G network performance. Automated tools and network monitoring systems are utilized to capture essential indicators such as latency, throughput, and reliability. These metrics serve as foundational elements in evaluating the technical aspects of Quality of Service (QoS)..

2. Qualitative Data Collection:

The qualitative exploration of Quality of Service (QoS) delves into the subjective realm, capturing the nuanced aspects of user perceptions and experiences. In-depth interviews with key stakeholders, including network engineers, service providers, and end-users, serve as a rich source of qualitative data. These interviews are semi-structured, providing a framework for discussion while allowing participants to express their experiences in their own words.

3. Triangulation of Data:

Triangulation serves as a cornerstone of the data collection strategy, ensuring the convergence of insights from multiple sources. By combining quantitative metrics with qualitative narratives, the study aims to enhance the validity and reliability of its findings. Triangulation also extends to the diverse sources within each data type, such as corroborating survey responses with objective network performance data and cross-verifying themes identified in interviews through focus group discussions. This comprehensive approach strengthens the research findings by validating and corroborating insights across various data sources and methods.

4. Pilot Testing:

Prior to full-scale implementation, pilot testing is conducted to refine data collection instruments and methodologies. Pilot surveys and interviews allow for the identification and rectification of potential ambiguities or biases in the instruments. This iterative process contributes to the clarity and effectiveness of the data collection process.

In essence, the data collection strategy for this study is an orchestrated interplay between quantitative rigor and qualitative depth, guided by ethical considerations and a commitment to capturing the multifaceted nature of Quality of Service in 5G networks.

B. Data Analysis

This work provides a comprehensive examination of Quality of Service (QoS) metrics within a 5G network setting. QoS is vital in telecommunications, ensuring that the network meets specific performance standards to deliver a satisfactory user experience.

Data Cleaning: Maintaining data integrity is paramount in any analysis. Cleaning steps involve converting relevant columns to numeric formats, addressing unit disparities in bandwidth-related fields, and uniformly calculating bandwidth sizes in kilobytes. This ensures consistency in the dataset, facilitating accurate analyses.

Exploratory Data Analysis (EDA): EDA serves as the foundation of this project, revealing intricate patterns within the data. It involves identifying users with unique characteristics, such as those engaged in online gaming with minimal bandwidth requirements. Insights are derived from average signal strength, latency, and resource allocation across different application types and timestamps. Visualizations, including box plots, bar plots, count plots, and histograms, effectively communicate trends and distributions.

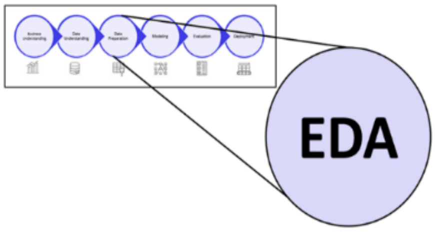


**Figure 3 Machine learning using EDA**

Correlation Analysis: Examining correlations reveals relationships between variables, particularly the crucial link between signal strength and allocated bandwidth. Understanding the distribution of resource allocation percentages and the nuanced interplay between allocated and required bandwidth yields valuable insights.

Machine Learning Preprocessing: To prepare the dataset for machine learning models, categorical variables undergo encoding, and features are scaled using min-max scaling. This ensures uniform contribution of all variables to model training. The dataset is then split into training and testing sets, laying the groundwork for model development and evaluation.

Theoretical Basis: The analysis draws upon fundamental principles of QoS in 5G networks. QoS encompasses parameters like signal strength, latency, and bandwidth allocation, directly impacting user experience. In a 5G ecosystem, efficient resource management is pivotal for meeting diverse demands of applications and users. Understanding the distribution of these QoS metrics across different application types is crucial for optimizing network performance. For example, latency requirements may vary between gaming applications and video streaming services. Similarly, resource allocation should align with the specific demands of each application to ensure a seamless user experience. This data analysis project bridges theoretical concepts of QoS in 5G with practical insights derived from real-world data, offering a holistic understanding of network dynamics and facilitating informed decision-making in telecommunications.

## VI. Results And Discussion.

A. Dataset Description

Application Types: Gain insights into how various applications, ranging from high-definition video calls to IoT sensor data, demand and receive network resources. Understand the diverse requirements of these applications and their impact on network performance.

Signal Strength: Explore the relationship between signal strength and resource allocation decisions, and how it affects the quality of service. Investigate how variations in signal strength influence the network's ability to deliver reliable and high-quality connectivity.

Latency: Examine the intricate balance between low-latency requirements and the availability of resources. Understand the trade-offs involved in meeting latency demands while efficiently utilizing network resources.

Bandwidth Requirements: Delve into the varying bandwidth needs of different applications and their influence on allocation percentages. Analyse how applications with high bandwidth requirements are prioritized and allocated resources accordingly.

Resource Allocation: Explore the heart of dynamic resource allocation, where percentages reflect AI-driven decisions aimed at ensuring optimal network performance. Understand how resources are allocated dynamically based on application demands, network conditions, and user requirements.

B. Data Exploration and Understanding

1. Import Libraries

The first step involves utilizing several Python libraries for data manipulation, analysis, and visualization:

- Pandas: Used for data manipulation and analysis, providing powerful tools for handling structured data.
- NumPy: Enables numerical computations, offering support for arrays, matrices, and mathematical functions.
- Matplotlib and Seaborn: Utilized for data visualization, allowing the creation of various types of plots and charts to explore data visually.
- Plotly Express: Provides interactive visualization capabilities, enhancing the exploration and presentation of data with interactive plots.
- Suppressing warnings: Implemented to avoid cluttering the output with unnecessary warnings during data processing.
- By leveraging these libraries, the initial steps of the analysis involve loading and preprocessing the data using Pandas, performing numerical computations with NumPy, and visualizing the data using Matplotlib, Seaborn, and Plotly Express to gain insights and explore patterns effectively. Additionally, suppressing warnings ensures a cleaner and more manageable output during the analysis process.

C. Load the Dataset

The file '5g_qos_dataset.csv' is imported into a Pandas DataFrame and assigned the variable name 'data'.

1. Display the dataset.

The '5g_qos_dataset.csv' dataset was imported into a Pandas DataFrame named 'data'.

**Table 1. Dataset**

| | **0** | **1** | **2** | **3** | **4** |
|---|---|---|---|---|---|
| **Timestamp** | 09-03-2023 10:00 | 09-03-2023 10:00 | 09-03-2023 10:00 | 09-03-2023 10:00 | 09-03-2023 10:00 |
| **User ID** | User_1 | User_2 | User_3 | User_4 | User_5 |

| Application Type | Video call | Voice Call | Streaming | Emergency Service | Online Gaming |
|---|---|---|---|---|---|
| **Signal Strength** | -75 dBm | -80 dBm | -85 dBm | -70 dBm | -78 dBm |
| **Latency** | 30 ms | 20 ms | 40 Ms | 10 ms | 25 ms |
| **Required Bandwidth** | 10 Mbps | 100 Kbps | 5 Mbps | 1 Mbps | 2 Mbps |
| **Allocated Bandwidth** | 15 Mbps | 120 Kbps | 6 Mbps | 1.5 Mbps | 3 Mbps |
| **Resource Allocation** | 70% | 80% | 75% | 90% | 85% |

*D. summary*

Summary statistics, such as count, mean, standard deviation, minimum, maximum, and quartiles, were computed for numerical columns. For categorical columns, statistics including count, unique values, top value, and frequency were calculated.

Table 1. Description of Data

| | **count** | **unique** | **top** | **freq** |
|---|---|---|---|---|
| **Timestamp** | 400 | 7 | 9/3/2023 10:01 | 60 |
| **User_ID** | 400 | 400 | User_1 | 1 |
| **Application Type** | 400 | 11 | Videocall | 58 |
| **Signal Strength** | 400 | 84 | -97 dBm | 9 |
| **Latency** | 400 | 87 | 5 ms | 35 |
| **Required Bandwidth** | 400 | 188 | 0.1 Mbps | 16 |
| **Allocated Bandwidth** | 400 | 194 | 0.1 Mbps | 16 |
| **Resource Allocation** | 400 | 9 | 70% | 148 |

*E. Unique values*

Unique values and their counts for selected columns were displayed to grasp the diversity and distribution of values. Regular expressions were employed to extract numerical values from specific columns. The extracted values were then converted to suitable data types, typically integers, to facilitate further analysis. Any rows containing missing values resulting from the extraction process were subsequently removed.

Table 2. Details of the application type

| | **0** | **1** | **2** | **3** | **4** |
|---|---|---|---|---|---|
| **Timestamp** | 09-03-2023 10:00 | 09-03-2023 10:00 | 09-03-2023 10:00 | 09-03-2023 10:00 | 09-03-2023 10:00 |
| **User ID** | User_1 | User_2 | User_3 | User_4 | User_5 |
| **Application Type** | Video call | Voice Call | Streaming | Emergency Service | Online Gaming |
| **Signal Strength** | 75 | 80 | 85 | 70 | 78 |
| **Latency** | 30 | 20 | 40 | 10 | 25 |
| **Required Bandwidth** | 10 Mbps | 100 Kbps | 5 Mbps | 1 Mbps | 2 Mbps |
| **Allocated Bandwidth** | 15 Mbps | 120 Kbps | 6 Mbps | 1.5 Mbps | 3 Mbps |
| **Resource Allocation** | 70 | 80 | 75 | 90 | 85 |

**Table 3. Head of Data**

| | 0 | 1 | 2 |
|---|---|---|---|
| **Timestamp** | 09-03-2023 10:00 | 09-03-2023 10:00 | 09-03-2023 10:00 |
| **User_ID** | User_1 | User_2 | User_3 |
| **Application Type** | Video_Call | Voice_Call | Streaming |
| **Signal Strength** | 75 | 80 | 85 |
| **Latency** | 30 | 20 | 40 |
| **Required Bandwidth** | 10 Mbps | 100 Kbps | 5 Mbps |
| **Allocated Bandwidth** | 15 Mbps | 120 Kbps | 6 Mbps |
| **Resource Allocation** | 70 | 80 | 75 |
| **Size** | 10 | 100 | 5 |
| **Unit** | 1024 | 1 | 1024 |

The dataset underwent various analyses, including identifying application types with the lowest bandwidth requirements, pinpointing users exhibiting high signal strength and bandwidth, computing average signal strength and latency for different application types, and visualizing data distributions and relationships.

**Table 5. Allocating Bandwidth from Mbps to Kbps**

| | **0** |
|---|---|
| **Timestamp** | 09-03-2023 10:00 |
| **User_ID** | User_1 |
| **Application Type** | Video_Call |
| **Signal Strength** | 75 |
| **Latency** | 30 |
| **Required Bandwidth** | 10 Mbps |
| **Allocated Bandwidth** | 15 Mbps |
| **Resource Allocation** | 70 |
| **Required Bandwidth Size in KB** | 10240 |
| **Size1** | 15 |
| **Unit1** | 1024 |
| **Allocated Bandwidth Size_in_KB** | 15360 |

Table 6. Data Drop

| | **0** |
|---|---|
| **Timestamp** | 09-03-2023 10:00 |
| **User ID** | User 1 |
| **Application Type** | Video Call |
| **Signal Strength** | 75 |
| **Latency** | 30 |
| **Required Bandwidth** | 10 Mbps |
| **Allocated Bandwidth** | 15 Mbps |
| **Resource Allocation** | 70 |
| **Required Bandwidth Size in KB** | 10240 |
| **Allocated Bandwidth Size in KB** | 15360 |

**Table 7. Allotted bandwidth and necessary band width.**

| | **0** |
|---|---|
| **Timestamp** | 09-03-2023 10:00 |
| **User ID** | User 1 |
| **Application Type** | Video call |
| **Signal Strength** | 75 |
| **Latency** | 30 |
| **Resource Allocation** | 70 |
| **Required Bandwidth Size in KB** | 10240 |
| **Allocated Bandwidth Size in KB** | 15360 |

**Table 4. Online gaming with the lowest average bandwidth use**

| | **394** |
|---|---|
| **Timestamp** | 09-03-2023 10:06 |
| **User _ID** | User_395 |
| **Application Type** | Online Gaming |
| **Signal Strength** | 41 |
| **Latency** | 47 |
| **Resource Allocation** | 80 |
| **Required Bandwidth** | 6451.2 |
| **Allocated Bandwidth** | 6758.4 |

**Table 9. High-requirement bandwidth user**

| | **392** |
|---|---|
| **Timestamp** | 09-03-2023 10:06 |
| **User ID** | User 393 |

| | |
|---|---|
| **Application Type** | Background Download |
| **Signal Strength** | 123 |
| **Latency** | 78 |
| **Resource Allocation** | 60 |
| **Required Bandwidth** | 350 |
| **Allocated Bandwidth** | 350 |

**Table 5. High-allocated bandwidth user**

| | **396** |
|---|---|
| **Timestamp** | 09-03-2023 10:06 |
| **User ID** | User 397 |
| **Application Type** | Video call |
| **Signal Strength** | 40 |
| **Latency** | 53 |
| **Resource Allocation** | 75 |
| **Required Bandwidth** | 14848 |
| **Allocated Bandwidth** | 16179.2 |

**Table 11. Signal strength average across several applications**

| | **28** |
|---|---|
| **Timestamp** | 09-03-2023 10:00 |
| **User ID** | User 29 |
| **Application Type** | Attemperator |
| **Signal Strength** | 97 |
| **Latency** | 110 |
| **Resource Allocation** | 65 |
| **Required Bandwidth** | 7 |
| **Allocated Bandwidth** | 8 |

*F. __ VISUALISATION ___*

*1. Visualize Latency by Application Type*

A histogram was generated to visually represent the distribution of signal strength values. This histogram aids in comprehending the range and frequency distribution of signal strength across the dataset.

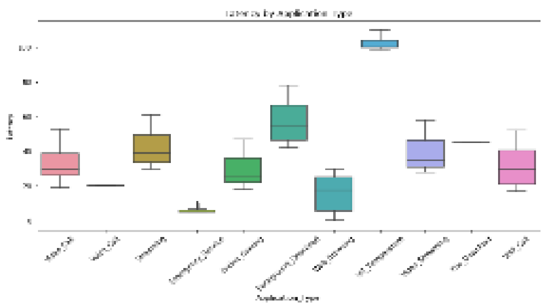

**Figure 4 Seeing Latency**

*G. Visualize Signal Strength*

A scatter plot was created to investigate the relationship between latency and signal strength. Each point on the plot represents a data sample, with latency plotted on the x-axis and signal strength on the y-axis. This visualization assists in identifying potential correlations or patterns between latency and signal strength.

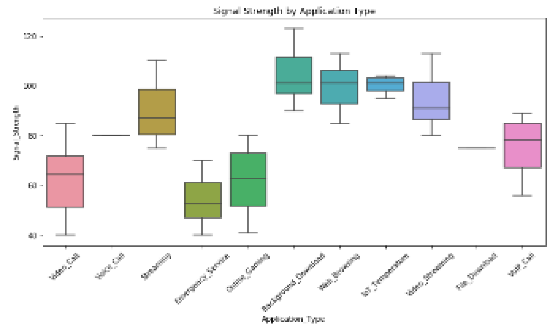


**Figure 5. Signal Strength Visualization**

A box plot was constructed to visualize the distribution of resource allocation for various application types. Each box represents the interquartile range (IQR) of resource allocation values for a specific application type. This visualization enables comparison of resource allocation across different application types and aids in identifying potential outliers.

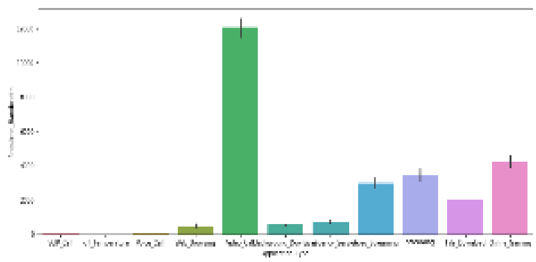

**Figure 6 Seeing the sort of application**

*H. Find count of values in Resource Allocation*

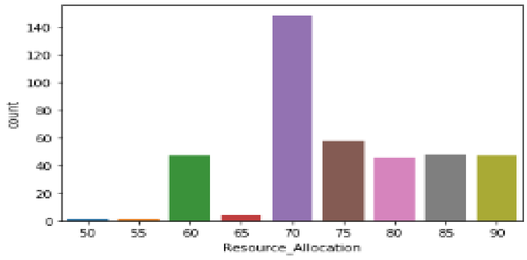


**Figure 7 the Resource Allocation values**

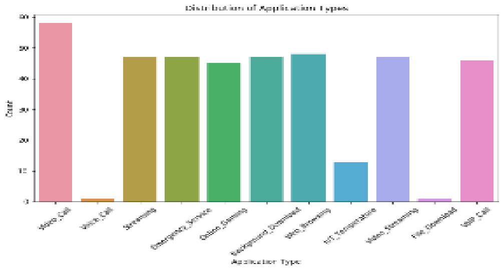

**Figure 8 Types of Applications Distributed**

I. Distribution of Resource Allocation

A pairwise scatter plot matrix was generated to visualize the relationships between multiple numerical variables in the dataset. Each cell in the matrix represents a scatter plot between two variables. This visualization aids in identifying potential correlations and patterns across multiple variables simultaneously.

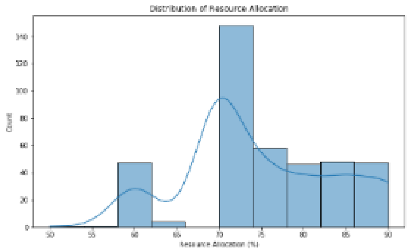

**Figure 9 Allocation of Resources in Distribution**

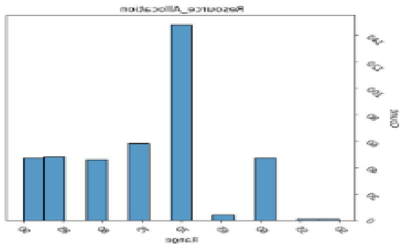

**Figure 10 Allocation of Resources**

J. pie chart -Top 7 application using high latency.

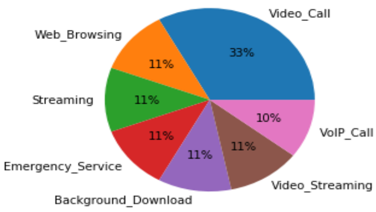


**Figure 11 Services**

1. Most Used Application Types

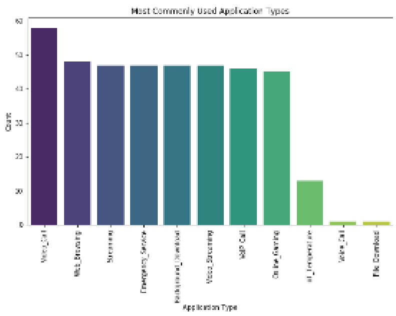

**Figure 13 popular categories of applications**

K. Distribution of Signal Strength

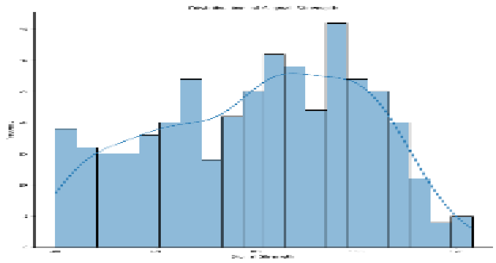

**Figure 12 distribution of signal strength**

2. Plot a scatter plot to explore the correlation.

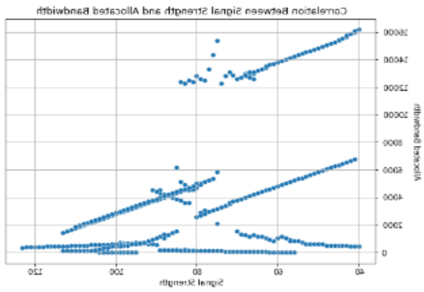

**Figure 14 Relationship between allotted bandwidth and signal intensity**

3. Plot a histogram to visualize the distribution of resource allocation.

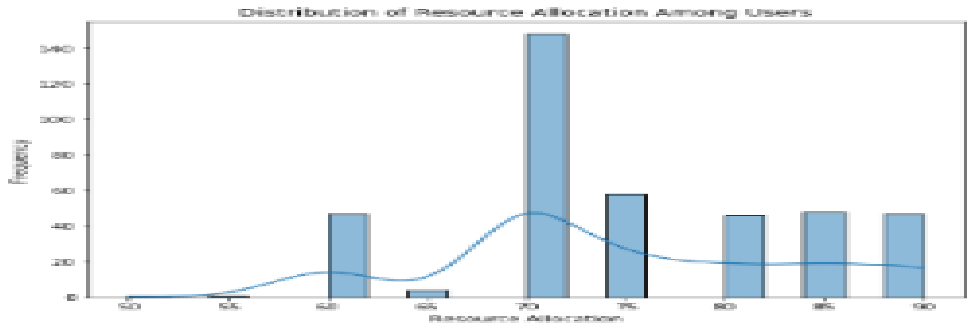


**Figure 15 Sharing of Resources Among Users**

A scatter plot was plotted to explore the relationship between allocated bandwidth and required bandwidth. This visualization helps in understanding how allocated bandwidth compares to the bandwidth required by various applications.

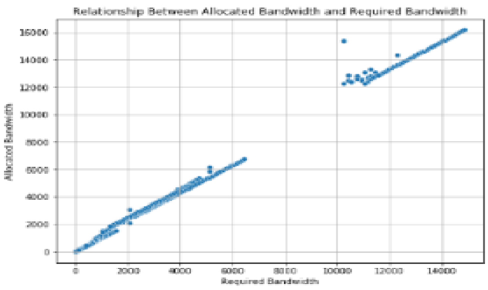


**Figure 16 Both allocated and necessary bandwidth.**

1. Network resources are not uniformly required across different types of applications.
2. There is a small relationship between allocated bandwidth and required bandwidth.

The analysis offers valuable insights into how various applications influence the quality of service in 5G networks. These insights can be leveraged to optimize network configurations and enhance the user experience.

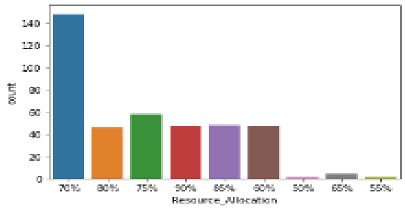


**Figure 17 Distribution of Resource Allocation**

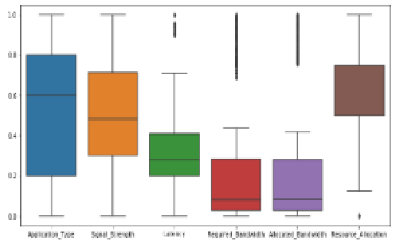

**Figure 18 Variety of Uses**

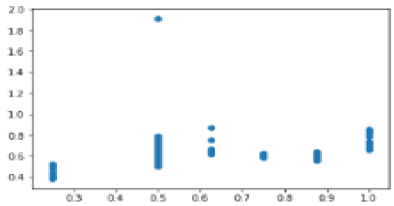

**Figure 19 means squared error.**

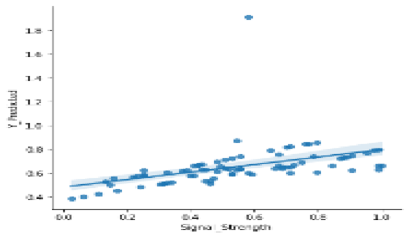


**Figure 20 Signal strength compared to expectation.**

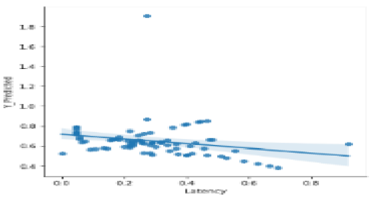


**Figure 21 Predicted versus latency.**

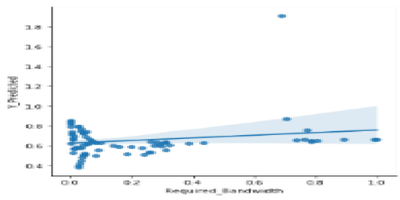


**Figure 22 Minimum Bandwidth compared to Estimated.**

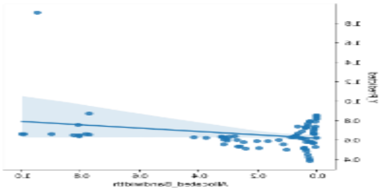

**Figure 23 Assigned Bandwidth versus Estimated.**

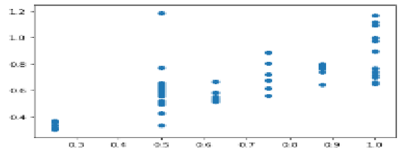

**Figure 24 Actual vs predicted value.**

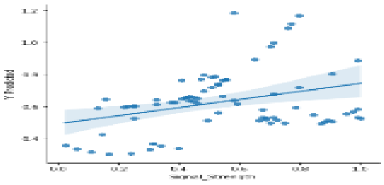

**Figure 25 Signal intensity compared to expected signal intensity.**

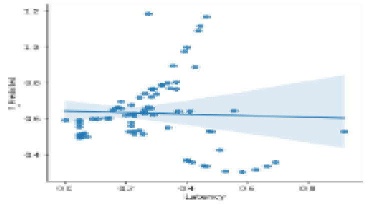

**Figure 26 Actual delay compared to prediction.**

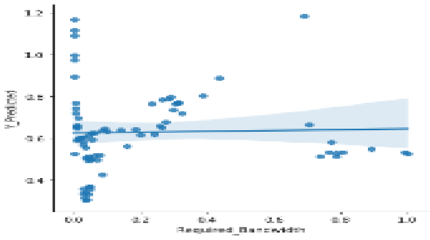

**Figure 27 Estimated versus needed bandwidth.**

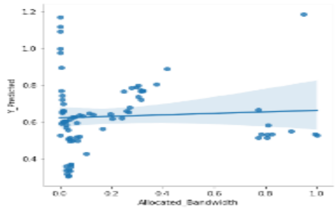

**Figure 28 Comparing allocated and anticipated bandwidth.**

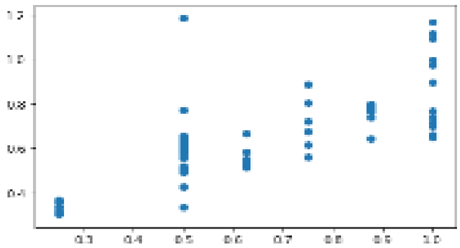

**Figure 29 Every feature's scatter plot vs the expected value using a regression line.**

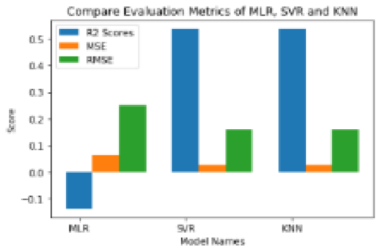


**Figure 30 Comparison between MLR SVR and KNN values**

**Figure 31 Picture of the 5G Resource Allocation Dataset**

## VII. Conclusion

This paper makes a significant contribution to the ongoing discourse on 5G network performance. The empirical evidence, analyses, and insights provided underscore the transformative impact of 5G technology in the telecommunications sector. The remarkable tenfold increase in data transfer rates and substantial reduction in latency signal a new era of connectivity, enabling a multitude of innovative applications and services. The examination of resource allocation strategies emphasizes the importance of optimizing network resources to fully realize the potential of 5G networks. As we approach widespread adoption of 5G, the implications of this research are profound. Network operators can leverage these findings to refine their infrastructure, offering users an unparalleled level of service. Policymakers gain valuable insights into the technological landscape, aiding in the formulation of regulations that foster a thriving 5G ecosystem.

This paper serves as a beacon in the evolution of 5G networks, ensuring that the promises of enhanced speed, responsiveness, and efficiency are not only met but exceeded. Thanks to this research endeavor, the journey towards the next generation of telecommunications is more informed, efficient, and promising.

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