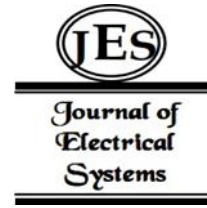


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Resource Allocation in 5G Networks - Machine Learning Approach



Abstract: - The influx of fifth generation [5G] technology marks the commencement of a fresh era in wireless communication, offering unparalleled data speeds, extremely low latency and extensive device connectivity. Realizing the full potential of 5G, efficient resource allocation strategies that optimize the use of the available spectrum is studied. This research paper proposes an efficient approach to optimize resource allocation in 5G networks by leveraging the power of machine learning (ML). We probe into the challenges of traditional resource allocation methods and present a novel idea ML-driven approach that adapts and learns from network dynamics to predict the allocation of resources dynamically. The utilization of ML models including supervised learning, enables the system to anticipate the improvisation of performance of 5G network, enhance spectral efficiency, and improve quality of service (QoS). This research offers valuable insights into the role of ML in 5G networks. In the study, we have analyzed and evaluated each model against key metrics such as mean square value (MSE), R2 values. It is found that the real time captured data exhibit efficiency. Finally, we discuss future research directions and possible applications of ML to optimize resource allocation in 5G networks.

Keywords: 5G, ML, QoS, Resource allocation, MSE

I. INTRODUCTION

The emergence of 5G networks has brought about a paradigm shift in the field of wireless communication, presenting numerous opportunities and challenges [32]. The emergence of 5G wireless technology has transformed connectivity and interaction, enabling innovative applications like autonomous vehicles, smart cities, enhanced mobile broadband, and the Internet of Things. Efficient allocation of network resources is crucial for maximizing the performance and ensuring a smooth user experience. As the next generation of wireless communication technology, is expected to revolutionize various aspects of our lives [15], from enabling high bandwidth applications to supporting massive machine-type communication, 5G is designed to meet the growing demands of today's high bandwidth users. Furthermore, 5G networks will not only enhance the throughput and capacity over 4G, but also optimize network performance for human-to-human communication and deliver solutions for machine-type communication. However, along with these advancements come the challenges of efficient resource allocation in 5G networks.

II. BACKGROUND OF 5G

The rise in wireless devices connecting to mobile networks is one of the main causes of the increase in mobile traffic worldwide. Data transfer between at least two devices using radio waves, rather than electrical connections, is referred to as wireless communication. One of the key reasons for the increase in mobile traffic globally is the development in wireless devices connecting to mobile networks.

Millions of new devices with various form factors and expanded capacity are released every year. The number of mobile devices and connections increased by over half a billion (526 million) in 2013, and by 2018, 15.9 Exabyte of data will be transmitted from mobile devices each month, roughly an increase of 11 times over 2013 [2]. The amount of mobile data and linked devices is increasing at a rate never before seen, which has new needs for the 5G wireless access networks, which are anticipated to be commercially accessible around 2020. According to Market observe, the global 5G market will expand at a 17% CAGR from now until 2028. We should expect more bandwidth and faster data rates with 5G. This is anticipated to lead to a large rise in the number of linked devices that depend on quick, dependable data transmissions. ITU-R's Recommendation

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ITU-R M.2083 outlines the following primary IMT utilization scenarios for 2020 and beyond as shown in Figure 1[1].

The fifth-generation (5G) of wireless communication technology represents a revolutionary leap forward in the realm of mobile and wireless networks. It promises to deliver significantly enhanced data rates, ultra-low latency, massive device connectivity, and reliability, enabling a plethora of applications ranging from enhanced mobile broadband (eMBB) to mission-critical services and massive machine-type communications (mMTC)[1]. However, realizing the true potential of 5G necessitates a fundamental reevaluation and optimization of the way network resources are allocated. By analyzing the performance of each algorithm, we aim to identify the best model for specific 5G network scenarios.

III. INSIGHTS OF 5G

A. Features

- 5G operates across a wide range of frequency bands, including: Sub-6 Use either SI (MKS) GHz bands: 3.5 GHz, 2.5 GHz, and 2.3 GHz, 1.8 GHz. mmWave bands: 24 GHz, 28 GHz, 39 GHz, 47 GHz, and 60 GHz.
- Latency: Ultra-low latency is a crucial aspect of 5G, as low as 1 millisecond (ms), which is vital for real-time applications like augmented reality (AR), virtual reality (VR), and critical communications.
- Data Rates: 5G has higher data rates compared to previous generations, reaching up to several gigabits per second (Gbps) for enhanced mobile broadband (eMBB) applications.
- Spectral Efficiency - The amount of data that can be transmitted per unit of bandwidth.
- Network Slicing: allows the making of multiple slices network within a common infrastructure, for specific use cases such as eMBB, massive IoT, critical communications), with tailored characteristics and resource allocations.
- Massive MIMO (Multiple-Input, Multiple-Output): Utilizes a large number of antennas at base stations to improve spectral efficiency, coverage, and overall network capacity.
- Beam forming: technology is used to focus radio signals in specific directions, optimizing signal strength.
- Carrier Aggregation (CA): combines multiple carriers in different frequency bands to increase overall data rates and improve network capacity.
- Security and Privacy Enhancements includes improved security measures to ensure the integrity, confidentiality, and authenticity of transmitted data, protecting against various cyber threats.

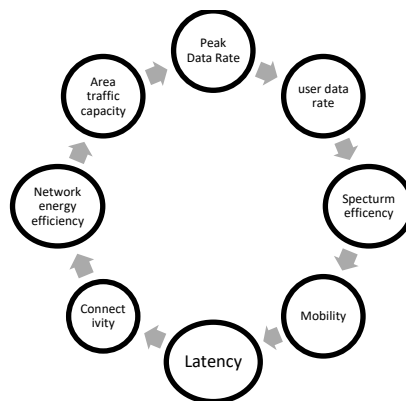


Figure. 1. 5G requirements [1]

- Quality of Service (QoS): 5G provides better QoS at various service levels such as latency, reliability, and data rates. Different radio access networks like Wi-Fi, 5G, LTE uses single interface for their communications. The aggregator is situated at the controller such as Base station and radio network, aggregates all its traffics and routes to gateway. Each terminal has its own interface to access its spectrum.

B. Resource Allocation

Resource allocation, a critical aspect of network management, involves judiciously distributing limited network resources such as spectrum, time slots to cater to the diverse needs of users and applications. With a significantly broader spectrum and higher frequency bands, 5G offers the potential for improved spectral efficiency and increased capacity.

Resource blocks (RBs) are fundamental units of resource allocation in 5G wireless communication systems for effectively managing and allocating resources to users and devices in the network. Each resource block in 5G consists of a group of consecutive subcarriers in the frequency domain and a specific number of time slots in the time domain. The width in the frequency domain defines the bandwidth available for the communication, and the duration in the time domain manage the duration of the transmission. The size of a resource block comprises of 12 subcarriers in the frequency domain and 14 symbols in the time domain, for flexible allocation based on application's requirements.

In recent years machine learning (ML)-based approaches have emerged over traditional complex algorithms to support these challenges optimally and efficiently. ML based methods work on data-driven approaches rather than model-based approaches as shown in the Figure 2. These methods take data from real hardware in a real-world environment and optimize the system for the best performance.

In this research paper, we leverage machine learning to optimize resource allocation, like bandwidth, to ensure high Quality of Service (QoS) and network efficiency in diverse user demands. This research aims to compare and evaluate the performance of various machine learning models, from regression algorithms to neural networks, in dynamically allocating bandwidth within 5G networks, identifying the most suitable model for specific scenarios based on key metrics.

C. Equations

Mathematical expressions are used to model resource allocation process in 5G.

$$F(\text{Allocation}) = \sum_{i=1}^{NU} U_i(\text{Resource Allocation } i) \tag{Eq. (1)}$$

Where,

F(Allocation): represents a function F

$\sum_{i=1}^{NU}$: indicates the summing of the index i starting from 1 and NU

NU represents the total number of units.

$U_i(\text{Resource Allocation}_i)$ represents that U_i is a function or quantity associated with Resource Allocation_i for the i-th unit.

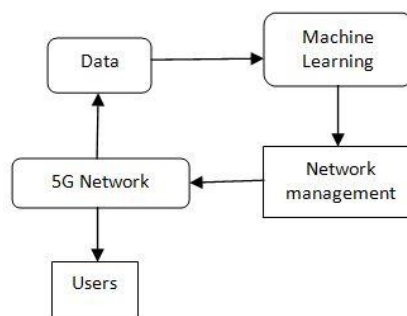


Figure 2 . ML approach to Optimization of resource allocation in 5G Networks

Optimization for resource allocation in 5G is represented as

$$\text{Resource Allocation} = \beta_0 + \beta_1 * \text{Parameter1} + \beta_2 * \text{Parameter2} + \dots + \beta_n * \text{Parameter } n \tag{Eq. (2)}$$

Where,

Resource Allocation represents the amount of the specific resource being allocated

β_0 is the y-intercept

$\beta_1, \beta_2, \dots, \beta_n$ are the coefficients associated with each parameter.

Parameter 1, Parameter 2, Parameter n is the dependant parameters

The optimization is formulated as:

$$\text{Min } \theta L(X, y; \theta) \quad \text{Eq. (3)}$$

Where, θ represents the model parameters.

Model Training:

Machine learning model is trained on a labeled dataset containing input features (X) and corresponding target variable (y). During training, the model adjusts its parameters to minimize the loss function and improve its predictive performance using gradient descent variants

$$\theta_{t+1} = \theta_t - \alpha \nabla L(X, y; \theta_t) \quad \text{Eq. (4)}$$

Where,

α is the learning rate

$\nabla L(X, y; \theta_t)$ is the gradient of the loss function with respect to the model parameters.

Model Prediction:

Given the input features (X), the model predicts the corresponding resource allocations (\hat{y}):

$$(\hat{y}) = f(X; \theta) \quad \text{Eq. (5)}$$

Where,

$f(\cdot)$ represents the learned mapping from input features to resource allocations.

Evaluation:

Finally, we evaluate the performance of the trained model on a separate validation or test dataset to assess its generalization ability and predictive accuracy. We measure metrics such as accuracy, precision, recall, or F1-score to quantify the model's performance.

D. Methodology

In this study, we employed a comprehensive methodology to investigate and optimize resource allocation strategies in 5G networks, with the aim of enhancing network performance and user experience. Our methodology encompassed the following key steps:

- 1) Data Acquisition and Preprocessing
- 2) Dataset Download :A relevant dataset (400 rows) from Nokia containing features related to 5G network resource allocation, such as signal strength, required bandwidth, latency and allocated
- 3) Data Augmentation: To increase data size and potentially improve model performance, create a new dataset (800 rows) by applying data augmentation techniques suitable for the specific features.
- 4) Feature Engineering
 - a) Case 1: Combine signal strength and required bandwidth into a single feature and resource allocation as another separate feature.
 - b) Case 2: Combine latency and latency signal interaction into a single feature and resource allocation as another separate feature
 - c) Data Split : Divide each dataset (400 rows and 800 rows) into training, validation, and test sets using a consistent split ratio (e.g., 70/20/10).
- 5) Model Training and Evaluation
- 6) Model Selection: Implement and train various machine learning models on each dataset .
 - a) Linear Regression
 - b) Polynomial Regression
 - c) Decision Tree
 - d) Random Forest
 - e) Gradient Boosting Regressor

- f) Support Vector Machine
- g) KNN
- h) Neural Networks with different epochs(100, 200, 300)

E. Steps involved in adopting a machine learning model for resource allocation:

Adopting a machine learning (ML) model for resource allocation in 5G networks involves a series of systematic steps to ensure the effectiveness and reliability of the model. Below are the key steps:

1. Define Input Features (X) and Target Variable (y)
 - a) Input Features (X): These are the parameters or attributes that describe the current network state, user requirements, and system constraints. For example, signal strength, channel conditions, user QoS requirements, and available resources.
 - b) Target Variable (y): This represents the resource allocation decisions that the model aims to predict. It could be the allocated bandwidth, transmit power levels, time slots, etc.
2. Model Representation:
 - a) We represent the resource allocation problem using a machine learning model, such as a neural network, decision tree, or support vector machine. The model takes the input features (X) as input and predicts the target variable (y) as output.
3. Loss Function (L):
 - b) We define a loss function that measures the difference between the predicted resource allocations (\hat{y}) and the actual resource allocations (y) in the training data. The loss function quantifies the model's performance and guides the learning process. The choice of loss function depends on the nature of the target variable. For example, mean squared error (MSE) loss is commonly used for regression tasks, while cross-entropy loss is used for classification tasks.
4. Optimization: The goal is to minimize the loss function by adjusting the model. So optimization algorithms are used to iteratively update the model parameters and minimize the loss.
5. Model Training: During training, the model adjusts its parameters to minimize the loss function and improve its predictive performance.
6. Model Prediction: Once the model is trained, we can use it to make resource allocation decisions for new data instances.
7. Evaluation: Finally, we evaluate the performance of the trained model on a separate validation or test dataset to assess its generalization ability and predictive accuracy.

IV. LITERATURE SURVEY

The author Rahul Pandya [6] proposes the machine learning (ML) oriented route modulation format aware spectrum for resource allocation (RA) that reduces the impact of the physical layer impairments, inter core cross-talk, differential mode delay, and mode dependent losses. The author Sasweth C [5] proposed algorithm to achieve low latency low power-Bit Error Rate (BER) and data rate optimization by a dynamic modulation scheme selection using machine learning. By Medhat Elsayed [4] proposed Q-learning algorithm (LR-Q) that performs joint power and resource allocation in improving reliability and latency performance of URLLC users by 29% increase and by 21 times increase in throughput. Gang Wang[8] has developed a optimization framework in which slice customer's problem maximizes the resource efficiency. The author Peng Yu[9] proposes the corresponding slice resources allocation architecture based on the concept of a self-organizing network in the 5G wireless cloud network (C-RAN) scenario using deep learning model named LSTM (long short-term memory) to construct the dynamic traffic model. The author Farhad Meshkati in [13] focuses on distributed algorithms with emphasis on energy efficiency. A family of power control games is presented for energy-efficient resource allocation in wireless code-division multiple-access (CDMA) networks. Authors in several papers have tried to show the way to optimize the resource allocation in 5G networks with various algorithms, deep learning and reinforcement learning. D. Zavyalova [24] has developed and shown the performance of Reinforcement Learning based agent based scheduler of the air interface resources in 5G networks learned to find the best scheduling strategy without any knowledge and predefined algorithms.

V.RESULTS

Distribution count of application type from the dataset is shown in Figure 3 and Figure 4 as bar graph and pie chart. By analyzing the real time dataset of the service provider as shown in the Figure 5, it reveals from the graph that 90% of the resource allocation is achieved for voice calls. Online gaming and streaming data takes 80% to 85%, video streaming at 70% of allocation in the real world channel with minimal impairment. So here we observed quite an efficient QoS. There is less dropping of resources to be allocated.

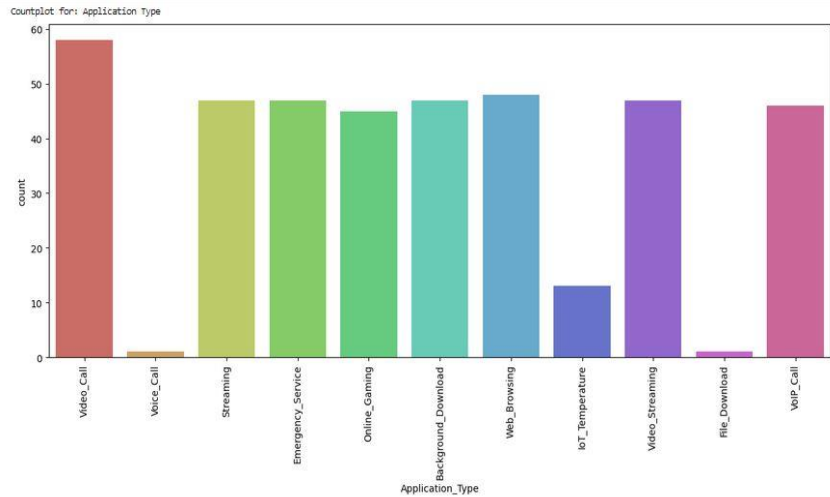


Figure 3 Count Plot for application type

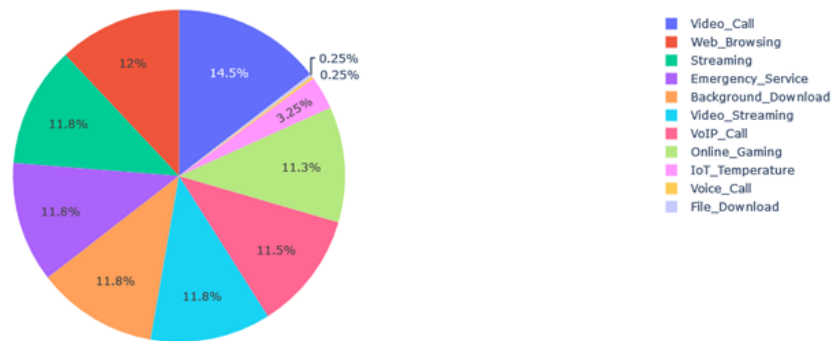


Figure 4. Distribution on application type

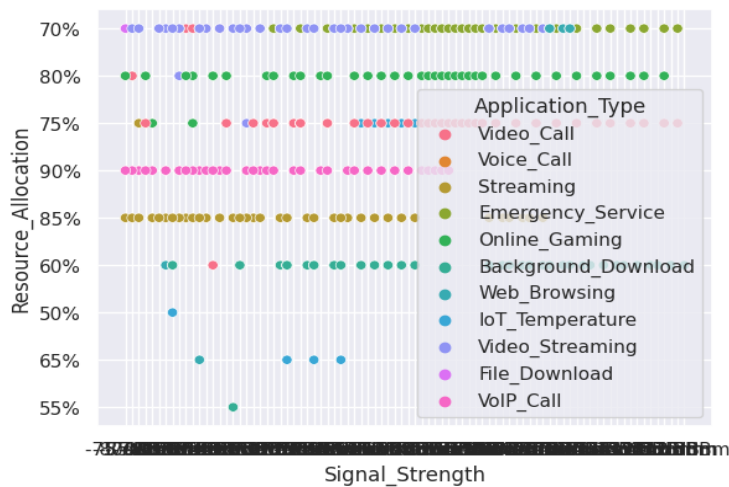


Figure 5 . Percentage of Resource Allocation on Application Types

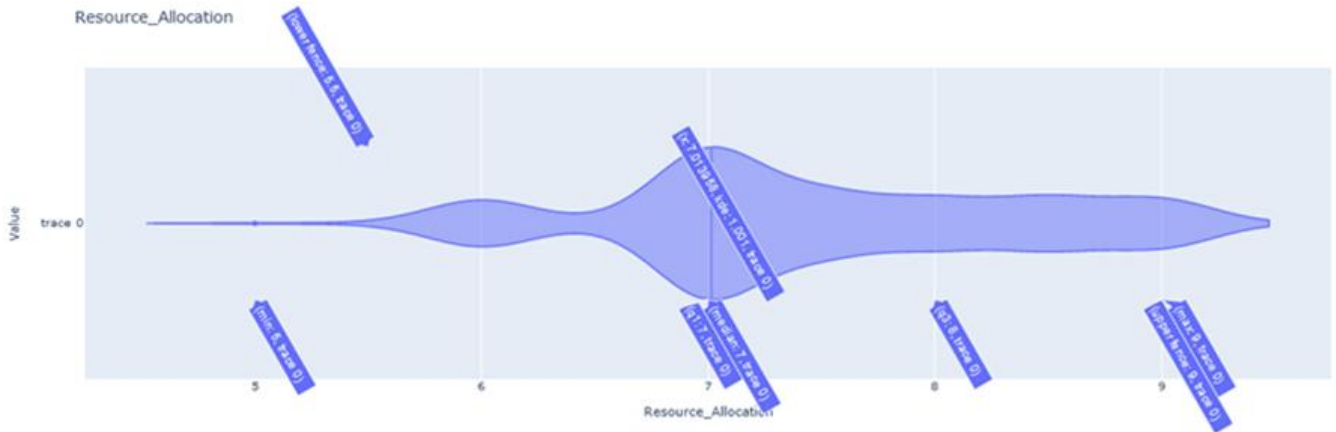


Figure 6 . Distribution on resource allocation

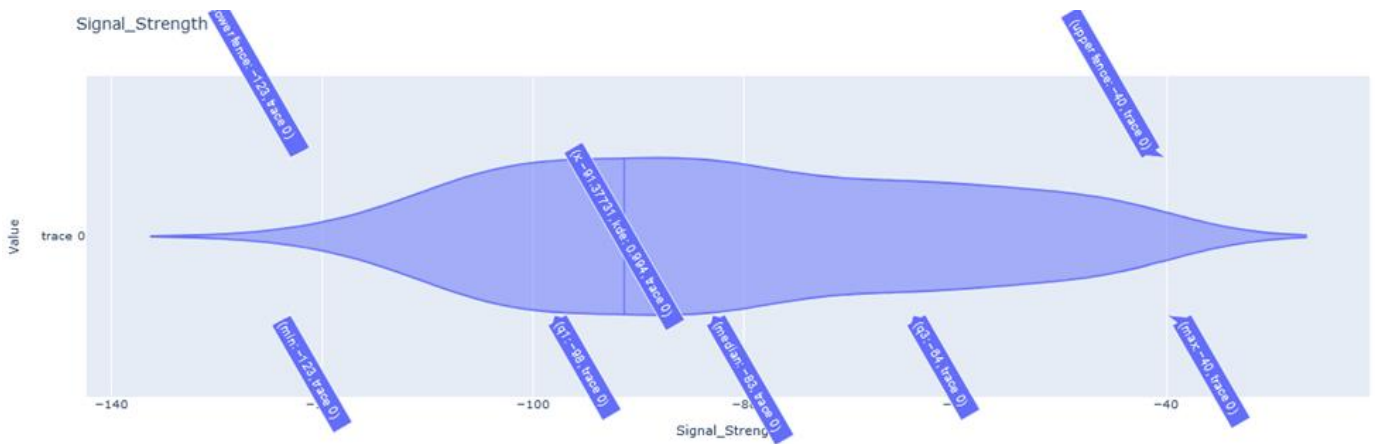


Figure 7 . Distribution on application type on signal strength

Violin plots are plotted as shown in Figure 6 and Figure 7 to compare and obtain insights to the distributional of the data across various application types on resource allocation and signal strength. The density of data points at a certain value is represented by the width of the violin at that position. Areas that are narrower imply lower density, whereas those that are wider indicate higher density. It shows the statistics such as Kernel Density Estimation (KDE) as 1.001 at the center which indicates the estimated density is slightly above 1 implying a moderate density of data points.

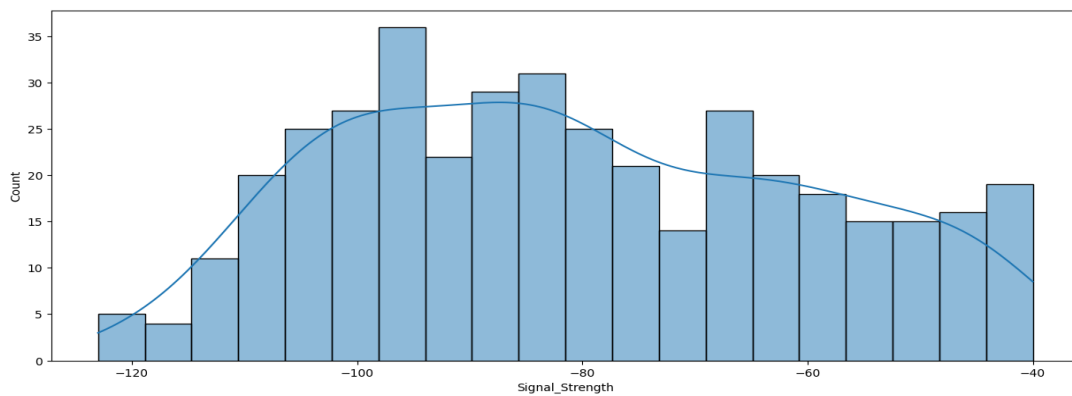


Figure 8 . HistoPlot on signal strength

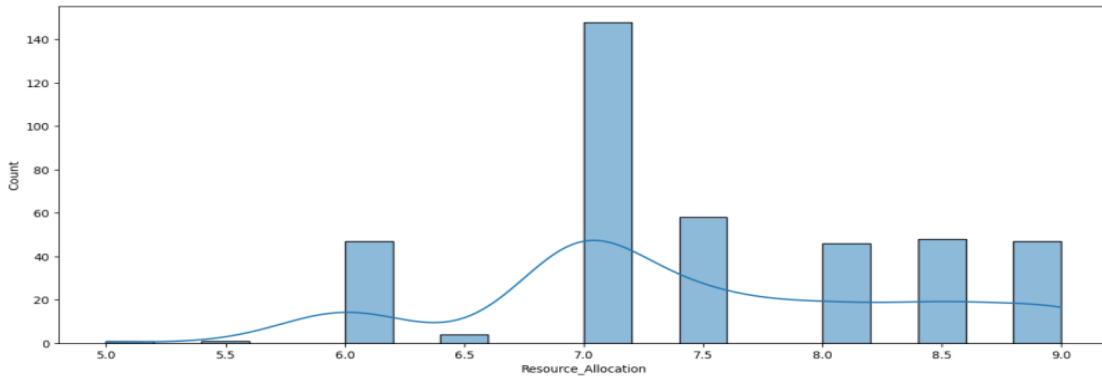


Figure 9. Histogram on Resource Allocation

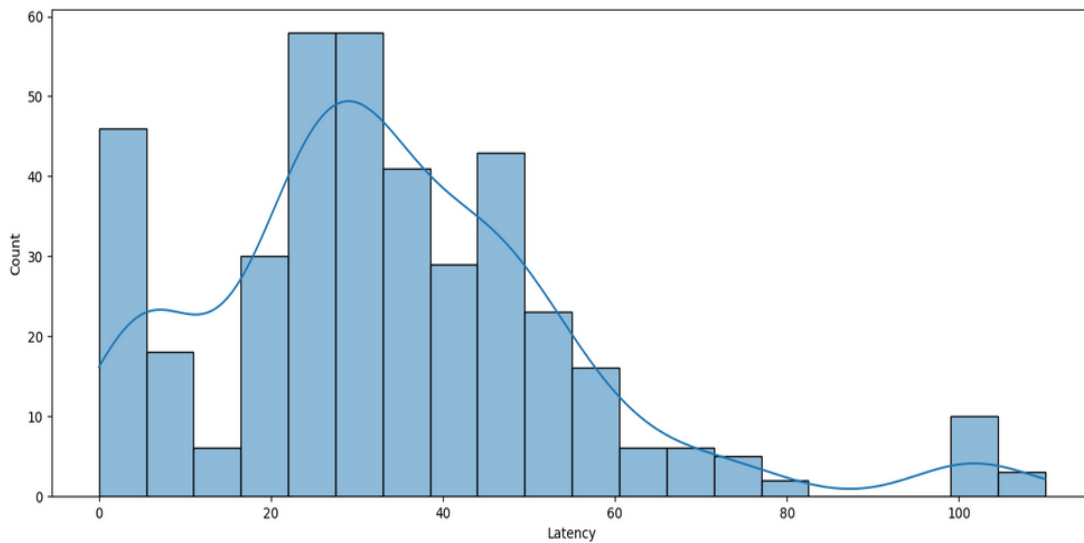


Figure 10. Histogram on Latency

HistoPlot is illustrated in the Figure 9. It is observed that central tendency is at 7.0 of resource allocation. Figure10 shows the low latency on the downfall of curve which is same proposition of 70. So it is inferred that potential relationship among best resource allocation and low latency is seen in the graph. Moderate skewness can be depicted in Figure 8 that shows the efficient spread of data on signal strength.

The line plot understands how changes in one feature affect another and suggests the potential optimizations or improvements in resource allocation and network performance to be done. The graph illustrates the impact of resource allocation, signal strength, allocated bandwidth and latency as shown in the figure 11, figure 12, and figure 13.

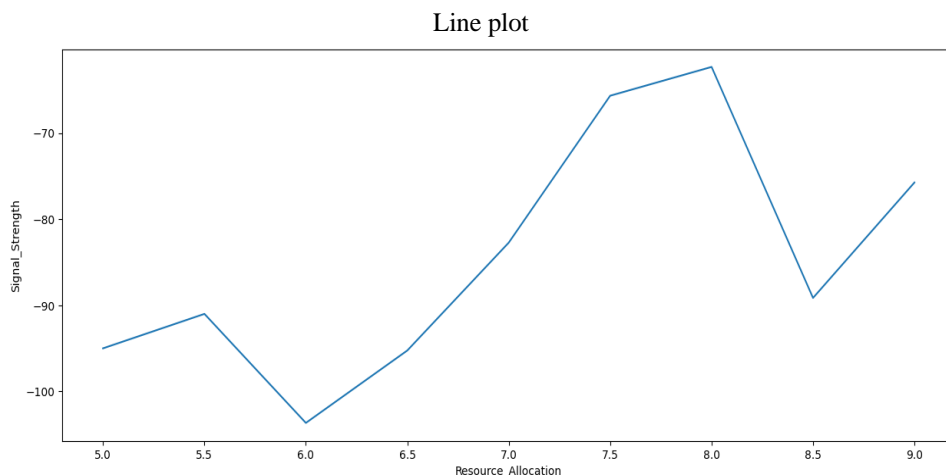


Figure 11. LinePlot Resource allocation on signal strength

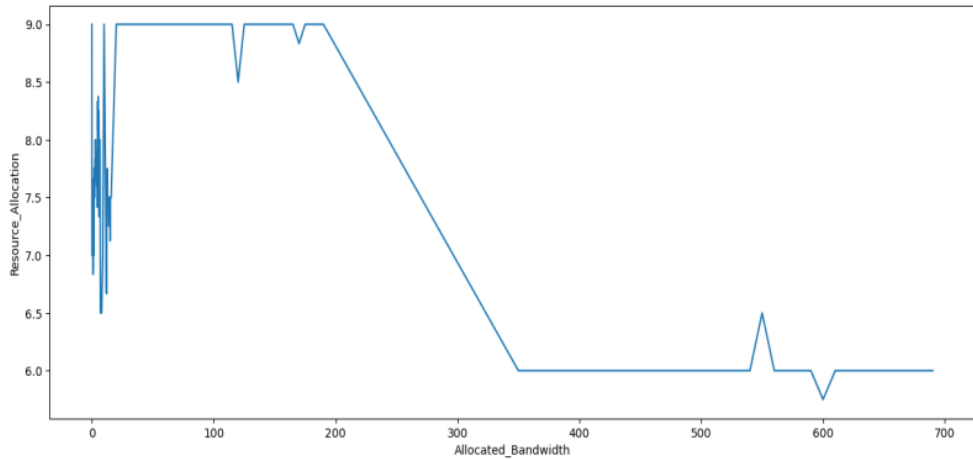


Figure 12. LinePlot Allocated Bandwidth on Resource allocation

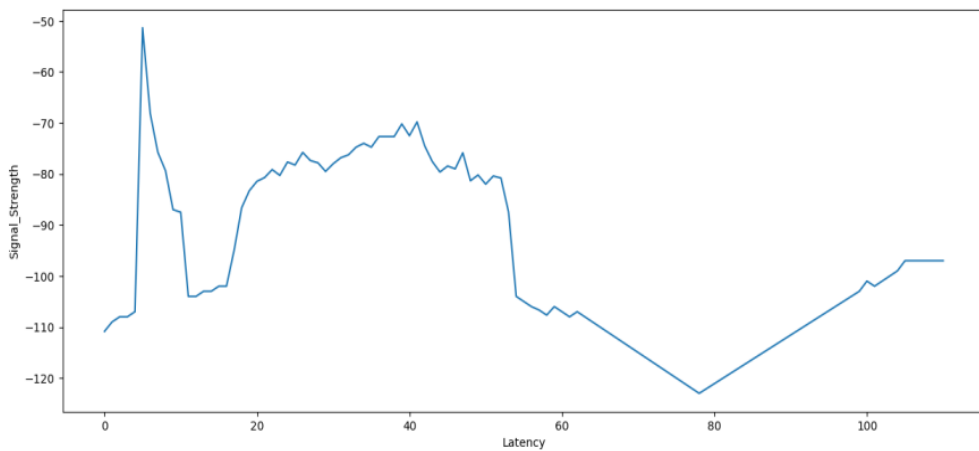


Figure 13. LinePlot latency on signal strength

In the figure 12 sudden slope and drop in the line graph could be noticed significantly at (9, 200). This is a rapid transition in resource allocation has impact on allocated bandwidth. This infers the existence of resource constraints that affect the efficiency of resource allocation in relation to bandwidth provisioning. Figure 14 depicts how the changes in resource allocation impact signal strength, which can be valuable for optimizing resource allocation strategies 5G networks. So higher levels of resource allocation tend to be associated with higher signal strength that is seen at 7.0

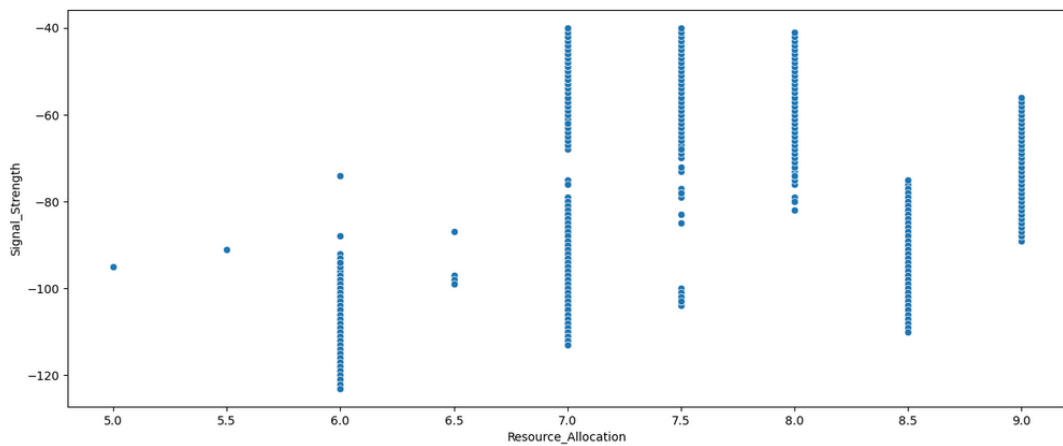


Figure 14. Scatter Plot on Resource Allocation on signal strength.

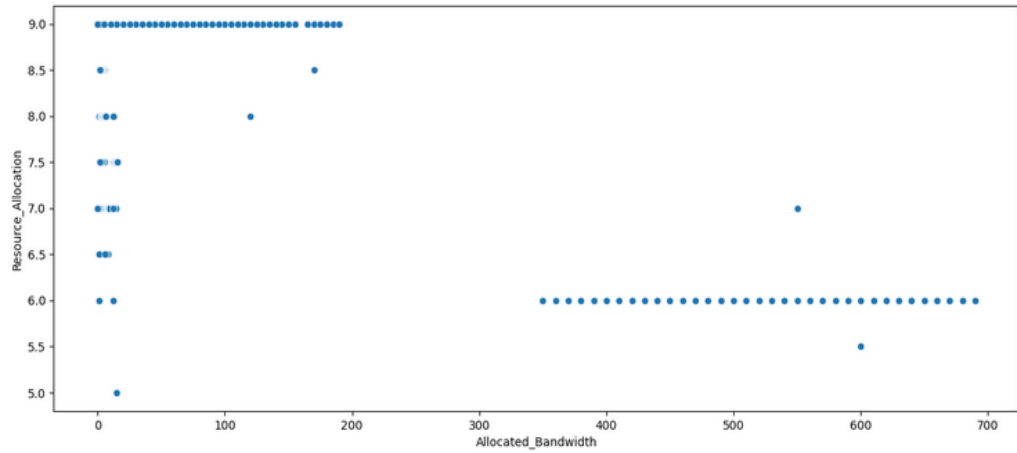


Figure 15. Scatter Plot on Allocated Bandwidth and Resource Allocation

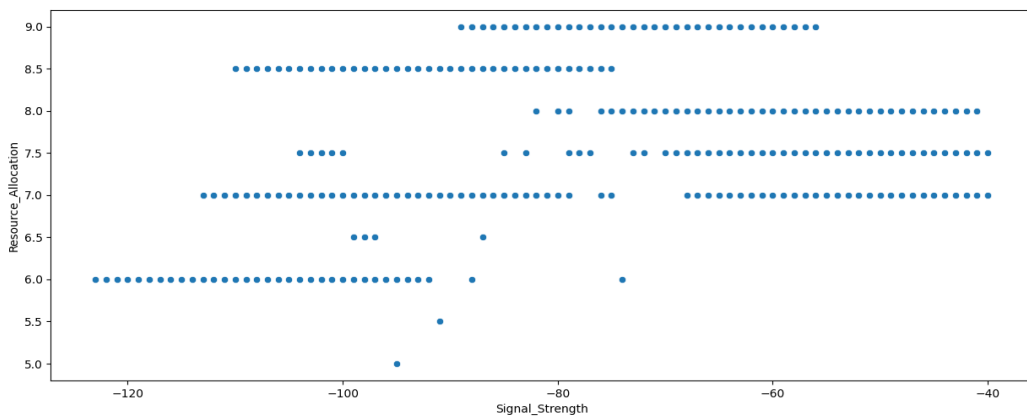


Figure 16. Scatter Plot on signal strength and Resource Allocation

The resource constraint shown in Figure 12 is seen evidently seen in Figure 15. Other scatter plot is shown in Figure 15 and Figure 16. Cluster of points is noticed at various signal strength which give better resource allocation. Graphs such as latency over time- Figure 17, signal strength over Timestamp in Figure 18, Resource Allocation over Timestamp in Figure 19 illustrates the relationship examined over the timestamp

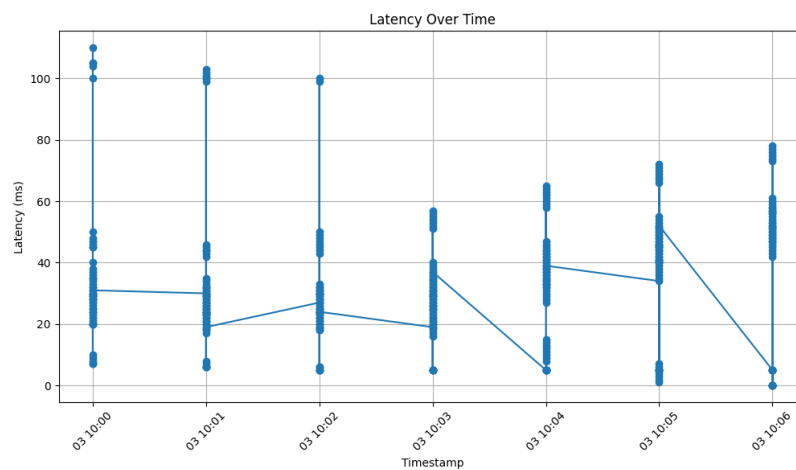


Figure 17. Latency over Timestamp

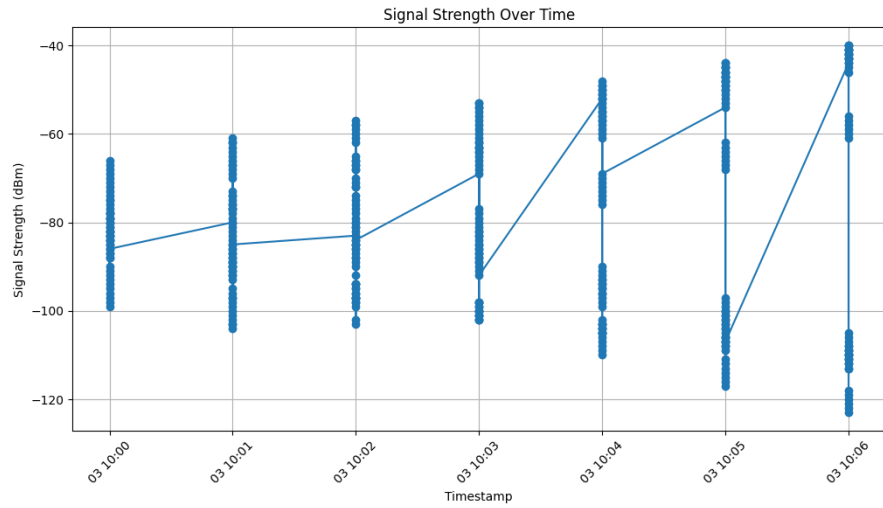


Figure 18. Signal strength over Timestamp

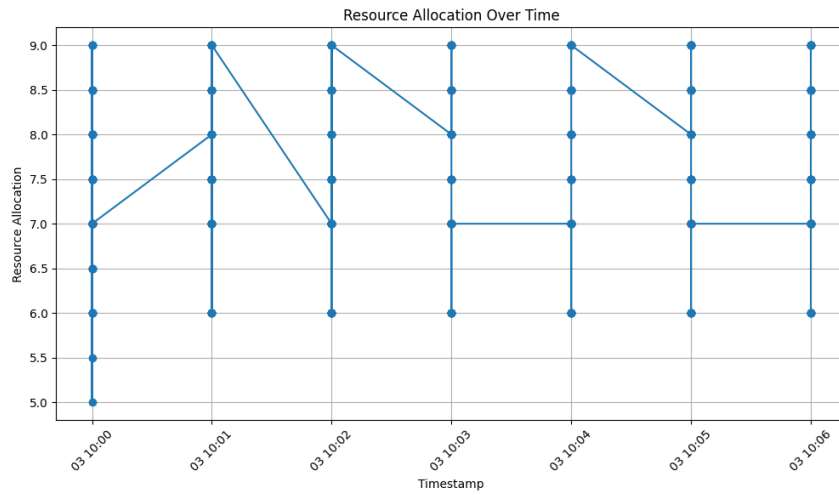


Figure 19. Resource Allocation over Timestamp

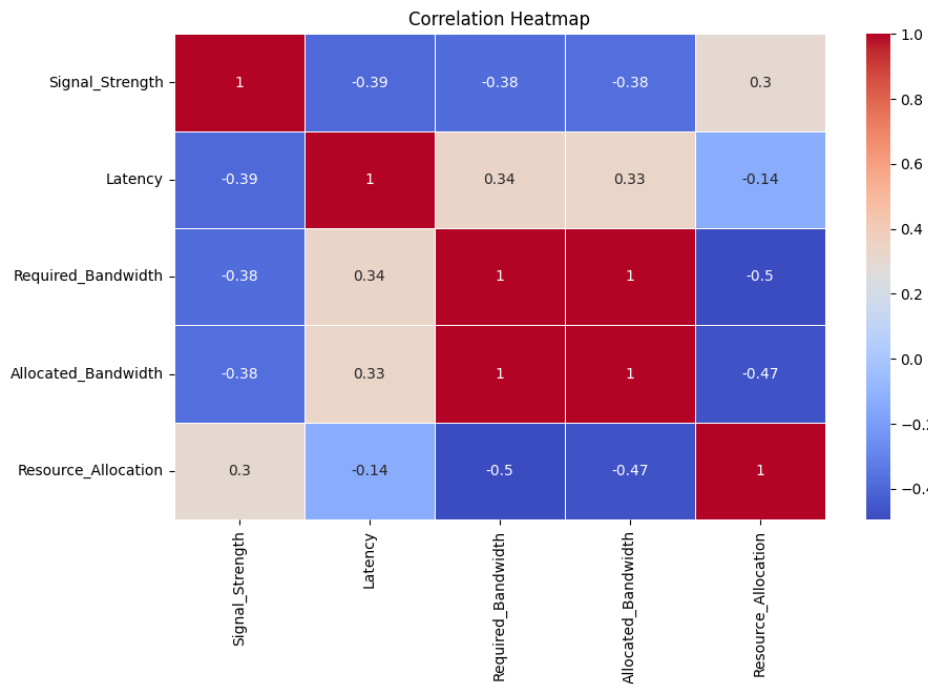


Figure 20. Correlation Heat Map

Correlation heat map as shown in Figure. 20 provides valuable insights into the relationships between different variables such as signal strength, latency, required bandwidth, allocated bandwidth that influence resource allocation decisions. The correlation coefficients values are ranging from -1 to 1.

Perfect correlation is seen at the diagonal. Positive correlation value 0.45 is observed between signal strength, resource allocation. Also, 0.46 with Allocated bandwidth moderate relationship of 0.3 between signal strength and resource allocation. As the value is positive, the other factors also influence the resource allocation aside from signal strength. A negative correlation between resource allocation and latency of -0.14 and -0.39 with signal strength. This suggests that increasing resource allocation leads to a decrease in latency, which can improve overall network performance and user experience without the need for additional infrastructure investments. Other metrics with negative correlations benefited for 5G network revealed in the matrix are signal strength with latency, allocated bandwidth, required bandwidth with -0.39, -0.38 and -0.38. Here signal strength plays a crucial role in performance of various application types. There is also a weak correlation of 0.0029, 0.0033. It is observed that the signal strength have the most significant impact on the resource allocation with the correlation value of 0.3 from the studied dataset.

This correlation suggests that network operators might allocate more resources to areas with stronger signal strength to improve overall network performance and user experience. Also factors such as network congestion, user demand, and application requirements may also play significant roles. Optimizing signal strength can lead to improvements in latency, bandwidth efficiency, and resource allocation. By focusing on enhancing signal strength in network planning and deployment, service providers can achieve the same to enhance the quality of service for users. Optimizing signal strength can help conserve bandwidth resources and improve network efficiency, help reduce latency and improve overall network responsiveness. Areas with stronger signal strength, network resources are allocated more efficiently, leading to reduced bandwidth allocation.

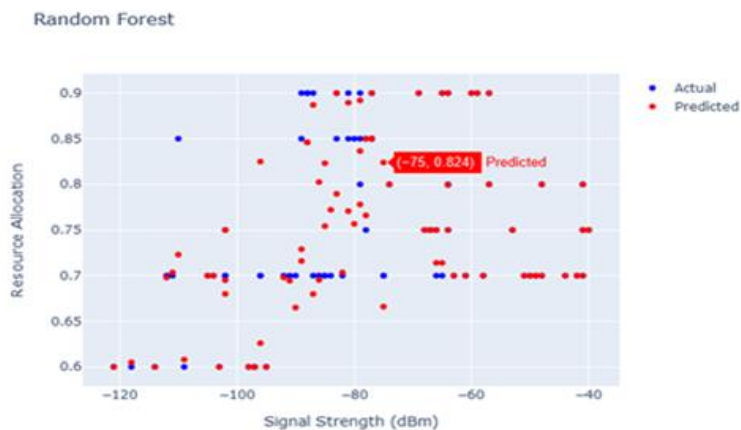


Figure 21. Prediction using Random Forest

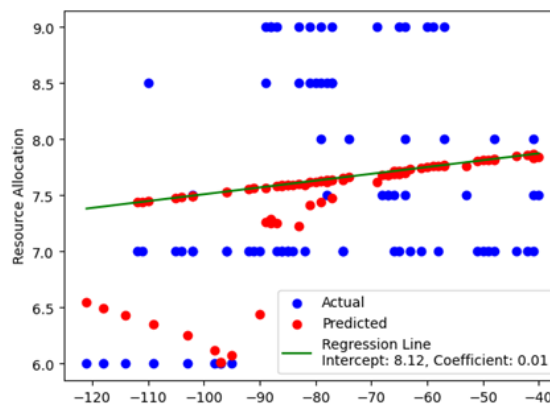


Figure 22. Linear Regression

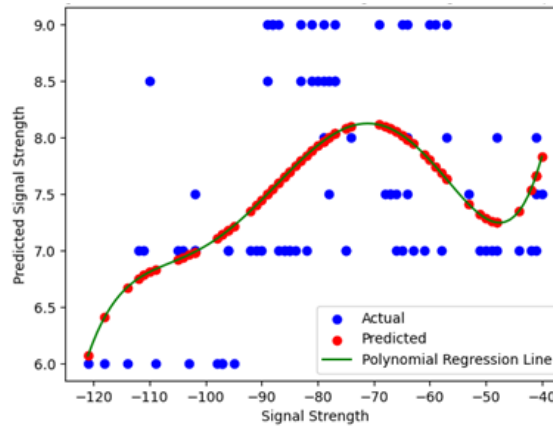


Figure 23. Polynomial Regression

The robustness of the resource allocation is tested on 5G dataset. This includes data acquisition, preprocessing, feature engineering, model selection that involved the steps of training the model and test it with several ML model to minimize the loss and improve predicted accuracy.

The graph shown in the Figure 21, depicts the predicted resource allocation against signal strength. The red colored dot shows the predicted values. For the signal strength of 75, the random forest machine learning algorithm demonstrates generally 82.4 percentage of resource allocation which is a good prediction for the further optimization. The linear regression graph is shown in Figure 22. The analysis is made to quantify the relationship between resource allocation and signal strength to get the insights into how changes in resource allocation affect signal strength. Each dot in the graph represents a pair of actual and predicted signal strength values. The regression line is the best-fit line that minimizes the differences (errors) between the predicted values and the actual values. The graph infers the best fit as the predicted values takes the regression line. We found the intercept value 8.12 and coefficient 0.01. In the same way Figure 23 depicts the polynomial regression predicted values fitting the regression line.

In our study we have further improvise, invent and predict some more insights by applying various ML complex algorithms for optimization. it is found that MSE and R^2 values are valuable metrics for evaluating the performance of models used in resource allocation for 5G networks. So the dataset was tested on the Machine learning models to predict the overall fit. In the Table 1, the results obtained are depicted row wise. Better MSE values, is found with the Random Forest model that predicts an efficient allocation as it gives lowest MSE (0.00205). It indicates that it is providing the best overall fit to the resource among the other models. When Neural networks with more epochs of around 200 shows 0.8235 R^2 value, efficient for better performance. So random forest model and neural networks gives improvement and predict for enhanced resource allocation. So solution is given for service providers to deploy at base station.

Table I. Comparison of ML Models on Resource Allocation

ML Model	MSE	R Squared Value
Linear Regression	0.0079	0.0895
Polynomial Regression	0.0022	0.7375
Decision Tree	0.0047	0.4632
Gradient boosting Regressor	0.0023	0.7280
Random Forest	0.0020	0.7654
Support vector Machine	0.0063	0.2727
KNN	0.0041	0.5293
Neural Networks (100 epochs)	0.0024	0.7293
Neural Networks (200 epochs)	0.0015	0.8235

Figure 24 illustrates flow diagrams, outlining the systematic steps involved in enhancing resource allocation efficiency using various ML models .

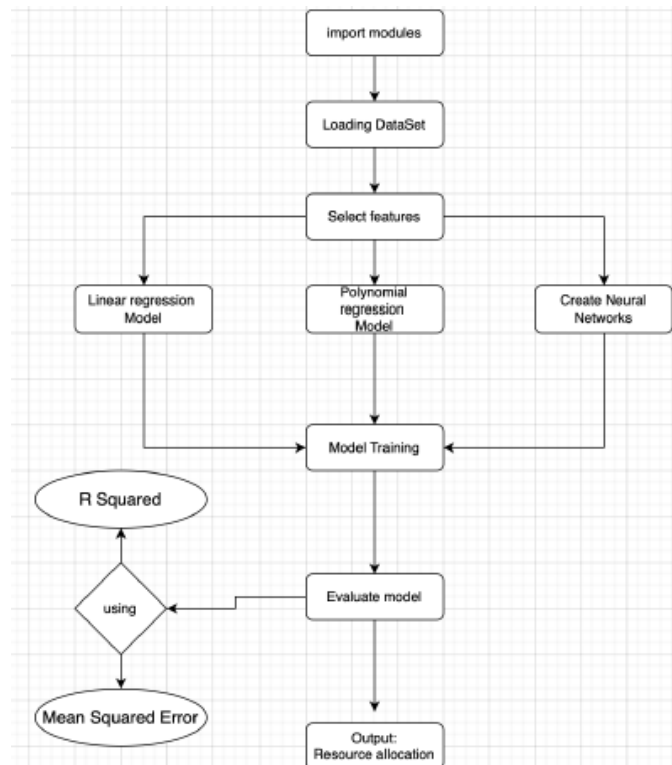


Figure 24 . Flow chart on resource allocation

V. CONCLUSION

In this research paper, we have explored the complexities and challenges associated with resource allocation in 5G networks and discussed various factors influencing this critical aspect of network management. By analyzing signal strength, user demand, network capacity, application requirements, and other relevant variables, we aimed to provide insights into optimizing resource allocation strategies to improve network performance and enhance user experience. Prioritizing signal strength enhancement can lead to reduced latency, improved reliability, and optimized bandwidth utilization, ultimately enhancing the quality of service (QoS) for users. Evaluation metrics such as R-squared (R^2) and mean squared error (MSE) were utilized to assess the performance of models. In future work, ML based resource allocation can be further focused on the study of F1 score, Recall, Precision, deep neural network to find the best accuracy which gives further substantiation to the resource allocation.

ACKNOWLEDGEMENT

My research work is non funded by any of the organization.

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