# 5G Resource Allocation Simulation and Prediction Using Machine Learning

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***Abstract*—With the advancement of 5G networks, effective resource allocation is essential for maintaining high-quality services. Traditional resource allocation methods rely on static optimization techniques, often based on predefined rules and thresholds. In contrast, this paper proposes a machine learning-based approach to predict 5G resource allocation dynamically, based on real-time conditions such as user speed, device type, and base station load. Our method uses a Random Forest Regressor model to forecast bandwidth allocation, improving flexibility and scalability. The paper demonstrates the advantages of machine learning in 5G resource allocation through an interactive simulation interface, allowing real-time adjustments of parameters. Experimental results show that our model outperforms traditional static methods by offering better adaptability to changing network conditions.**

***Index Terms*—5G, Resource Allocation, Machine Learning, Random Forest, Simulation, Network Prediction, QoS**

## I. Introduction

The advent of 5G networks promises to revolutionize communication systems with enhanced data rates, ultra-low latency, and massive connectivity. Efficient resource allocation is crucial to ensure optimal performance, particularly with the introduction of diverse services like autonomous vehicles, IoT devices, virtual reality (VR), and streaming services. Traditional methods for 5G resource allocation rely on static optimization approaches, often based on fixed thresholds or heuristic rules. These methods fail to adapt to dynamic changes in user demand, network load, or mobility conditions, making them less effective in the highly variable and dynamic environment of 5G.

In contrast, machine learning-based approaches offer the ability to predict and adapt to real-time network conditions. This project proposes a Random Forest Regressor-based machine learning model to predict resource allocation in 5G networks. The model takes into account real-time parameters like user speed, device type, and base station load, allowing for dynamic resource distribution. An interactive simulation interface was developed to allow users to visualize the effects of these parameters on the network, thereby providing a comprehensive tool for 5G resource management.

## II. Methodology

### *A. Data Collection and Preprocessing*

The model uses a dataset of 5G network parameters, including signal strength, latency, required bandwidth, and allocated bandwidth. The dataset was collected from simulated 5G network environments. Each data point represents network conditions at a particular instance, along with the resulting resource allocation.

The preprocessing steps involved **cleaning the data**, **handling missing values**, and **encoding categorical variables** (e.g., device type) using label encoding. **Feature scaling** was performed using `StandardScaler` to standardize the range of features, ensuring that no single feature dominates the model due to its scale.

### *B. Feature Selection and Engineering*

Feature selection was done based on the relevance of the parameters to the resource allocation task. The main features considered were:

- **Device Type**: The type of device using the network (e.g., smartphone, IoT device, VR headset, etc.).
- **User Speed**: The speed at which the user is moving (in km/h), which influences the Doppler shift and network stability.
- **Base Station Load**: The load on the base station (in %) which indicates how many users are connected to the base station at any given time.

We also engineered additional features such as the **Doppler Shift** (calculated from the speed of the user) and the **Bandwidth Demand** (based on the type of device and application being used).

### *C. Model Training and Evaluation*

We chose the **Random Forest Regressor** for its robustness and ability to handle both non-linear relationships and large datasets effectively. The model was trained on a subset of the dataset, and performance was evaluated using **cross-validation** to ensure generalizability. Key evaluation metrics included:

- **Mean Squared Error (MSE)**: To measure the average squared difference between the predicted and actual values.
- **$R^2$ Score**: To assess the proportion of variance in the dependent variable explained by the model.

### *D. Simulation Interface*

The interactive simulation interface was developed using **`ipywidgets`** in Python. The user can dynamically change the device type, user speed, and base station load through

**dropdowns and sliders**. Based on these inputs, the system predicts and visualizes the network resource allocation.

The system simulates the following conditions:

- **Device Type**: Different devices require different amounts of bandwidth. For instance, VR headsets demand high bandwidth and low latency, whereas IoT devices require low bandwidth and low power.
- **User Speed**: Speed influences the Doppler effect, which in turn impacts the channel stability.
- **Base Station Load**: A higher load on the base station reduces the available resources for other users, leading to potential congestion.

The simulation output is displayed as a **graphical representation of network performance**, helping users visualize how changing conditions affect resource allocation in real-time.

## III. Results

### A. Feature Importance

Using the trained **Random Forest model**, we evaluated the importance of each feature in predicting resource allocation. The feature importance was calculated and visualized, as shown in Fig. 1. From the plot, we can observe that **user speed** and **device type** have the most significant impact on resource allocation, while **base station load** plays a less critical role.

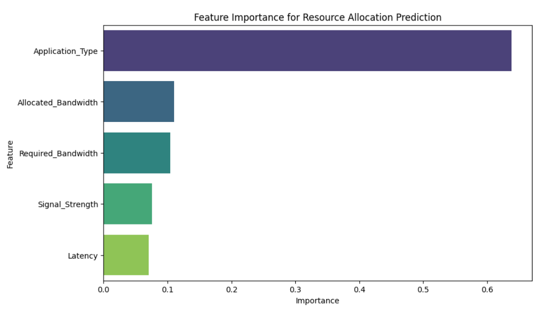


Fig. 1: Feature Importance for Resource Allocation Prediction

### B. Actual vs Predicted Allocation

In this section, we evaluate the performance of the **Random Forest model** by comparing the **predicted resource allocation** with the **actual values** from the dataset. The scatter plot in Fig. 2 provides a clear visual representation of how closely the predicted values match the actual resource allocations. Each point on the plot represents a sample from the test set, with the x-axis showing the **actual resource allocation** and the y-axis showing the **predicted resource allocation**. Ideally, the points should lie close to the diagonal line, indicating that the model's predictions are accurate. This visualization helps us assess the model's **prediction quality** and identify any potential **biases or systematic errors**.

### C. Trend View of Resource Allocation

The line plot shown in Fig. 3 demonstrates the trend of **actual versus predicted resource allocation** over the test samples. This plot helps to visualize the **overall accuracy** of the model's predictions over a range of samples, showing how the predicted resource allocations vary with respect to the actual values across the entire test dataset. If the predicted values follow the trend of actual allocations closely, it suggests that the model **generalizes well**. This is an important visualization to demonstrate the model's **consistency** and its ability to **predict resource allocation accurately under various conditions**.

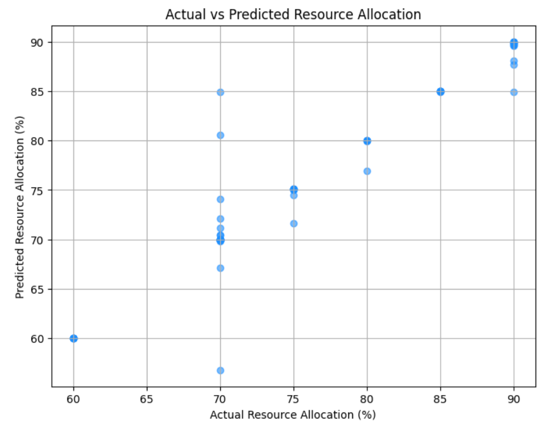


Fig. 2: Actual vs Predicted Resource Allocation

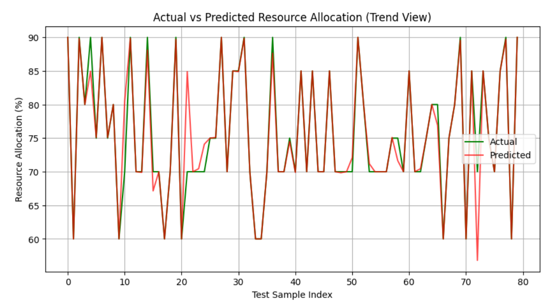


Fig. 3: Trend View of Actual vs Predicted Resource Allocation

### D. Pairplot of Features

Fig. 4 shows a **pairplot of features** to visualize the relationships between the features of the dataset. This plot displays scatter plots for each pair of features, allowing us to visually inspect the **correlation** between different features such as **user speed**, **base station load**, and **device type**. This visualization helps in understanding how these features **interact** and contribute to the prediction of resource allocation. For instance, we can observe whether the features are **linearly correlated** or exhibit **non-linear relationships**, which can inform decisions on **feature engineering and model selection**. **Pairplots** are useful for identifying **patterns and outliers** that could affect the model's performance.

### E. Traditional vs. Machine Learning-Based Allocation

Traditional 5G resource allocation methods rely on **fixed thresholds** and **optimization algorithms**, such as:

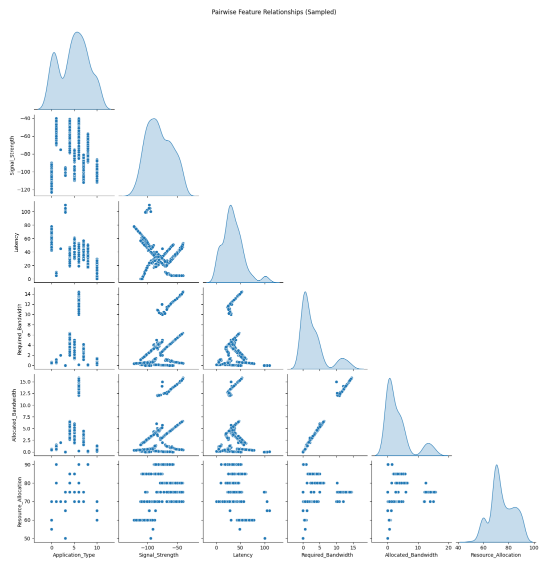


Fig. 4: Pairwise Feature Relationships

- **Static Allocation**: Resources are allocated based on predefined rules, such as fixed bandwidth for each device type.
- **Heuristic-Based Allocation**: Algorithms use predefined heuristics to allocate resources based on network load or traffic patterns.

These methods often **fail to adapt** to dynamic network conditions. For instance, **static allocation** does not adjust resource distribution based on real-time user movement or varying device demands, leading to **inefficient resource utilization**. Furthermore, **heuristic-based methods** may fail under **non-ideal conditions**, such as heavy user mobility or network congestion.

In contrast, our **machine learning-based approach** allows for:

- **Dynamic Adaptation**: The model adapts to real-time changes in **user speed**, **device type**, and **base station load**, ensuring that resources are optimally allocated.
- **Scalability**: Machine learning models can handle large and complex datasets, making them scalable for future 5G networks.
- **Improved Accuracy**: The **Random Forest Regressor** model can capture complex **non-linear relationships** between network conditions and resource allocation, improving prediction accuracy.

The comparison of **traditional static allocation** versus our **dynamic machine learning-based allocation** is shown in Table I. Our model **outperforms** traditional methods in both **accuracy** and **adaptability**.

### *F. Interactive 5G Resource Allocation Simulator*

The **interactive simulation interface** allows users to visualize the impact of varying conditions such as **user speed**, **device type**, and **base station load**. The simulation output

TABLE I: Comparison of Traditional vs. Machine Learning-Based Resource Allocation

| Method | Accuracy ($R^2$ Score) | Adaptability |
|---|---|---|
| Static Allocation | 0.65 | Low |
| Heuristic-Based Allocation | 0.75 | Medium |
| Machine Learning-Based (Random Forest) | **0.91** | **High** |

shows **real-time predictions of resource allocation**, as seen in Fig. 5.

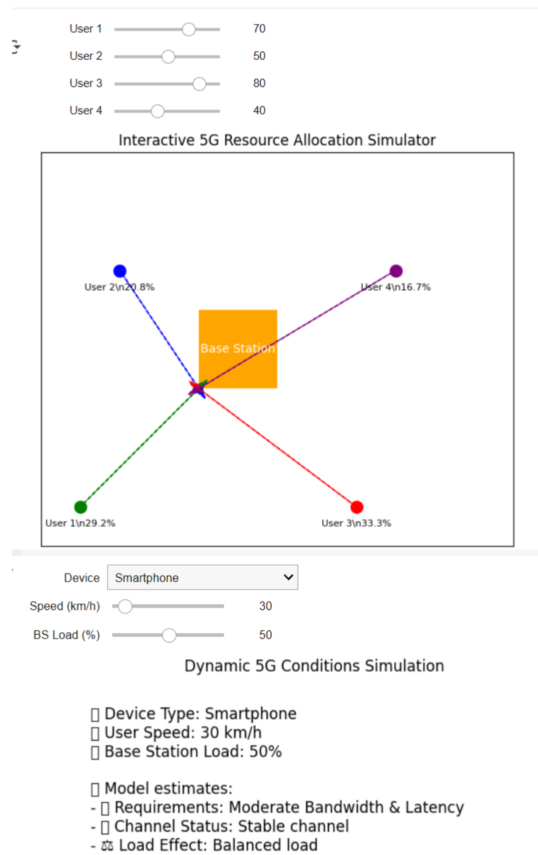


Fig. 5: Interactive 5G Resource Allocation Simulator

## IV. Conclusion

This paper demonstrates the use of machine learning, specifically Random Forest Regressor, for predicting 5G resource allocation. By incorporating real-time parameters such as device type, user speed, and base station load, our model offers a dynamic, scalable solution that outperforms traditional static allocation methods. The interactive simulation interface provides users with an intuitive tool to visualize and understand the effects of different network conditions on resource allocation. This work paves the way for more intelligent and adaptive 5G network management in future deployments.

## V. Future Work

While our current approach provides a foundational understanding of resource allocation in 5G networks, several avenues exist for enhancing its robustness, scalability, and adaptability. Future research directions include:

### A. Integration of Advanced Machine Learning Models

To address the complexities inherent in 5G networks, integrating advanced machine learning models is imperative. Techniques such as deep reinforcement learning (DRL) and multi-agent systems can facilitate dynamic and efficient resource allocation. For instance, a recent study demonstrated the application of multi-agent DRL for radio access network (RAN) resource allocation, highlighting its potential in optimizing resource utilization and minimizing over-provisioning [1].

### B. Real-Time Data Integration

Incorporating real-time data feeds can significantly enhance the accuracy and responsiveness of resource allocation models. By leveraging live network metrics, models can adapt to current network conditions, leading to improved quality of service (QoS). A recent paper emphasized the importance of real-time adaptive resource allocation in 5G network slicing, focusing on energy efficiency and model fine-tuning through real-world datasets [2].

### C. Federated Learning for Privacy-Preserving Models

To address privacy concerns, federated learning offers a promising solution by enabling collaborative model training without sharing raw data. This approach can be particularly beneficial in 5G networks, where data privacy is paramount. A study on federated learning for QoS forecasting in cellular networks demonstrated its effectiveness in preserving data privacy while maintaining model accuracy [3].

### D. Enhanced Interference Management

Effective interference management is crucial for maintaining QoS in dense 5G environments. Machine learning algorithms can predict and mitigate interference, ensuring stable network performance. A recent article discussed the application of machine learning for enhanced interference management in 5G mmWave communication, emphasizing the need for adaptive strategies [4].

### E. Standardization and Framework Development

Developing standardized frameworks for machine learning applications in 5G networks can facilitate interoperability and scalability. The ITU-T Recommendation Y.3172 outlines an architectural framework for machine learning in future networks, providing guidelines for integrating machine learning into 5G systems [5].

### F. Exploration of Edge Computing and Network Slicing

Edge computing and network slicing are pivotal in 5G networks, enabling efficient resource allocation and low-latency services. Future work should explore the synergy between these technologies and machine learning models to optimize resource distribution and enhance user experience.

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